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Changing routinized household energy consumption using the example of washing, cooking, and standby: A randomized controlled field experiment of home energy advice

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ABSTRACT

Despite advances in understanding routines, there is little knowledge about which aspects of routinized behavior people adjust during interventions. In this study, we applied an adjusted social practice theory framework to disentangle routinized energy consumption, focusing on energy services related to washing, standby, and cooking. We investigate the potential of home energy advice to change elements of routinized behaviors, namely meanings, knowledge, and technologies. Using a randomized controlled field trial on a probabilistic sample of households, we found short-term treatment effects related to increased usage of lids during cooking and improved knowledge of IT-related energy consumption, as well as negative effects regarding multi-sockets and washing frequency. Our findings suggest that meanings (e.g., preferences underlying routinized behaviors) are less subject to change, and that sociodemographic variables are associated with routinized behaviors in complex ways. Our disentangling of energy demand into elements of routines enables us to show how home energy advice may change behaviors and knowledge. This study highlights the benefits of a multifaceted perspective for understanding household energy consumption and can be used to inform intervention and policy design.

1. Introduction

Many behaviors are habitual, such as the use of entertainment equipment, eating, and cleaning (Marien et al., 2018). These habitual behaviors are of interest in behavior-oriented energy research because frequent activities are related to a considerable amount of energy consumption (Dietz et al., 2009). They are difficult to change, and researchers only partly understand how they can be changed (Klöckner, 2015). Moreover, research suggests that routine/habitual behavior is not only related to daily life, but also to investment decisions, as people tend to stick to the same brand, heating system, or drive technology (Burger et al., 2019; Nayum and Klöckner, 2014), or are less likely to invest in renewable energy systems when they age (Zalega, 2017). A better understanding of habitual behaviors is therefore key in fostering policy solutions that change these toward less energy-intense behavior.

Although socio-psychological approaches and social practice theory (SPT) have different understandings of habits and routines, researchers agree that they need to be conceptualized differently to deliberate decisions, and that there is a need to disentangle their complexity to better understand mechanisms for behavior change (Kurz et al., 2015; Spurling et al., 2013; Verplanken and Wood, 2006).

Despite progress in conceptualizing routines in psychology and SPT, little is known about which factors people alter as a result of interventions. Most studies, that aim to identify intervention effects, focus on overall kWh consumption, which is advantageous in that tangible treatment effects in kWh units can be estimated (Allcott and Kessler, 2019; Delmas et al., 2013; Fowlie et al., 2018; Winett et al., 1982). Nevertheless, these studies are often unable to identify which behavior change leads to an overall change in kWh consumption. While it was found that smart meter displays and home energy social comparison reports have the potential to reduce household electricity consumption, it remains unclear which elements within habits people adjust (Allcott and Rogers, 2014; Degen et al., 2013). Moreover, focusing only on kWh as the target dimension risks overlooking that energy demand at home is a "by-product of practices such as cooking, showering […] or doing the laundry" (Higginson et al., 2015, p. 951). Households ask for energy services (e.g. a heating system), rather than for kWh (e.g. the fuel for the heating system) (Burger et al., 2015; Halloran et al., 2021; Jonsson et al., 2011).

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For this research, we rely on an adjusted SPT-approach. Our motivation to do so is twofold (cf. the elaborated argument above as well as our operationalization of SPT, also in relation to psychology in section 3). First, with regard to changing routinized energy consumption behavior and taking into account the technical dimension within energy services, researchers suggest considering a socio-technical approach (e.g., Breukers et al., 2013). This means acknowledging that individual behavior is nested in social and physical contexts and that habitual behavior may be changed when addressing individual motivations and contextual factors together (Breukers et al., 2013; Klöckner, 2015; Verplanken and Wood, 2006). Second, theories of practice also highlight the reasons for energy consumption, i.e. the use of energy services (Gram-Hanssen, 2014; Shove and Walker, 2014). Reasons are internal elements in "demand for energy service".

We chose home energy advice as intervention type, because the literature suggests this has the potential to stimulate broad change in knowledge, meanings, and technologies (Salo et al., 2016). Home energy advice can be characterized as a high-involvement, information-based intervention in which the household participates (Delmas et al., 2013).

By analyzing the effects of home energy advice on a set of routinized behaviors, we contribute to the literature on interventions in household energy consumption and specifically, on changing habitual behaviors. Our study highlights the benefits of disentangling demand and analyzing intervention effects separately for different practices. The results suggest that a high-involvement, information-based intervention has the potential to change routinized cooking behavior and IT-related energy consumption knowledge in the short term. However, we also found that the intervention did not affect behavioral meanings. This suggests that policies aimed at reducing household energy consumption should consider routinized energy consumption as consisting of different elements. Acknowledging and addressing these elements could help to better identify and understand leverage points for and barriers to changing routinized actions in the home.

The paper is structured as follows: a literature review in Section 2, followed by section 3 giving the reasoning behind our SPT-framework as well as expectations of intervention effects. Section 4 describes the sample, measures, and methods, and section 5 comprises the description of the results and discussion. Section 6 provides conclusions and potential policy implications.

2. Literature review

In this section, we present existing knowledge about home energy advice interventions to change household energy consumption behavior. Home energy advice provides personalized and specific information in an interactive face-to-face setting (Abrahamse et al., 2005). Personal interaction between advisors and households can support household members in better understanding their energy consumption and engaging in meaningful actions to reduce it (Salo et al., 2016).

The evidence about home energy advice is mixed, depending on context, intervention design, and target group. In a comprehensive meta-analysis of information-based energy conservation experiments, Delmas et al. (2013) showed that individualized audits and consulting are effective for conservation behavior. Others found that advice did not reduce consumption, but increased knowledge on savings, consumption patterns, and carbon footprint (Degen et al., 2013; Salo et al., 2016). Revell's (2014) study revealed that home energy advice had a negligible effect on behavioral change, but households made minor technological adjustments. Shen et al. (2020) found that face-to-face consultation had an effect on energy savings when the household head perceived that there were sufficient non-material incentives and opportunities to perform energy-conservation behavior. This finding supports Revell and Stanton (2017), who urged that tailored advice should consider variations not just in demographics and attitudes, but in the thought processes that carry intentions into actions.

Many studies on information-based interventions have focused on kWh as the dependent variable to estimate treatment effects, but it often remains unclear which behaviors or technologies people changed. Few studies have evaluated interventions targeting particular consumption habits. Tiefenbeck et al. (2016) studied the effect of real-time feedback on the resource consumption of showering. They found that addressing a particular behavior led to larger conservation gains than providing aggregate feedback on resource use.

Spurling et al. (2013) re-frame policy approaches to practice-based interventions. In their view, the approach of re-crafting practices is similar to intervention strategies for behavior change, but the re-crafting practices framing suggests a systematic intervention and analysis in the different components of practices to make existing practices more sustainable. We take that as point of departure. In addition, we assume that analyses of different practice components need to provide evidence beyond qualitative findings when striving to inform policy. However, there are few papers using a SPT framework to quantitatively assess routinized behaviors. Higginson et al. (2015), for example, applied a practice network analysis to identify core and peripheral elements of the laundry practice. However, to the authors' knowledge only a few papers exist (e.g., for clinical trials Frost et al., 2020) that analyzed effects of an intervention employing the method of a randomized controlled field experiment with a practice-based approach.

The abovementioned research indicates that it is not sufficient to look at outcome targets such as kWh and cognitive and emotive mechanisms, but that a broader set of factors has to be considered. Behavioral information and educational programs should be considered alongside technological improvements and structural changes to reduce energy consumption (Cotton et al., 2021). The literature suggests that to take full advantage of the potential for changed behavior, interventions should address particular behaviors and their related performance contexts.

3. Framework and expectations

In this section, we present how we operationalize SPT as our theoretical framework. Then we derive expectations about the effects of home energy advice on energy consumption, focusing on washing, standby usage, and cooking. We focus on these three activities as aspects of household energy consumption, because considerable savings can be expected when adjusting these practices towards less energy use. For example, standby consumption reduction can result in energy savings of 600 TWh on a global level, which corresponds to the annual electricity supplied by 200 mid-sized coal-fired power plants (IEA, 2014).

3.1. Theoretical framework

The literature on routinized energy consumption can be assigned to two theoretical strands—environmental/social psychology and SPT. The term "habit" is defined differently within these two approaches. Moreover, the term "behavior" is also laden with different meanings within the different strands of the literature, and some scholars in SPT (e.g., Shove, 2011) even reject its use. In addition, there are also variations within the strands (see Hess et al., 2018 for a description of variations). Against this backdrop, we provide the rationale for our operationalization of SPT as theoretical basis for the study in the following.

Generally speaking, our attempt to study changes of routines by relying on SPT enriched with socio-psychological factors stands in the tradition of Giddens' theory of structuration arguing for an interplay between structural/institutional and individual factors (Giddens, 1984). In addition, this theoretical argument is in line with empirical evidence on the interplay between structural and individual factors in changing routines (see Section 1 and 2). Moreover, interventions like home-energy-advice are not directed to change established socio-cultural practices as such, but at individuals as activators of such practices. Such interventions can be understood as leading to niches that may upscale to become dominant practices (considering that as with technological changes practice changes start from niches rather than disruptively from one day to another (see Geels, 2005, 2002 for an evolutionary transition approach). On an empirical level, there is also evidence for individual or sub-group variations in the performance of collectively shared practices (Browne et al., 2014; Gram-Hanssen, 2008), which can be understood as basis for possible niches. Hence, to understand possible effects for change, the structural and the individual level need to be considered. Eventually, the advantage of following SPT rather than social-psychology as theoretical background is that socio-technical contexts are an endogenous part of the unit of analysis, whereas in psychology it would be an exogenous part.

In SPT, practices are the smallest unit of analysis (Reckwitz, 2002). They are for example defined as “routinized types of behaviors” that are shaped by interlinked elements, such as meanings, skills, and technologies (Reckwitz, 2002). This means that not a single element, such as knowledge, or emotions, are analyzed, but rather the interplay between these elements which constitute a practice (Reckwitz, 2002; Shove et al., 2012). Shove (2012) defines the terms habit and routine in relation to practices. A habit is conceptualized as a mode of enactment, i.e., a regular, consistent and frequent performance of a practice. A routine, in turn, refers to “the way in which multiple practices are ordered and scheduled” (Shove, 2012, p. 103). In their widely applied SPT framework, Shove et al. (2012) suggest three “elements of practice”: materials (infrastructure, tools, hardware), meanings (mental activities, emotions, motivational knowledge), and competences (know-how, background knowledge, skills). Practices can be perceived as routinized behaviors embedded in existing infrastructure/technology, preferences/social conventions, and knowledge. Washing as an energy service for example is motivated by wanting clean clothes. Connected to this is the need to have a washing machine, and the behavior related to its use (setting the temperature).

In SPT the change of practices amounts to re-crafting them as a unit (Spurling et al., 2013). In line with what we have already generally claimed, output targets like reducing kWh are side effects of re-crafting practices. The approach to re-crafting practices emphasizes the need to look at all elements of a practice and their interrelationships (Spurling et al., 2013). For example, technological elements need to be integrated into people’s daily lives to be effective in changing routines (Eon et al., 2018). The advantage of looking at routinized behavior change through a practice lens is that it enables the inclusion of those contexts in which routinized behaviors are embedded and to zoom out on behavior and include related devices, knowledge, and meanings in our analysis.

Arguably, some versions of SPT neglect an analytic role of the individual in studying practices (e.g., Shove et al., 2012). Given the arguments above on change of practices, however, it is reasonable to integrate individual factors and to rely on social-psychology research to represent them (not the least because there is a rich psychological body of literature on effects of interventions (Abrahamse et al., 2005)). This is also the reason why we use the term “behavior”, namely to ensure connectivity to behavioral determinants from social psychology, although SPT often does not use the term.

The psychological approach defines habits as repeated, automated, and identity-expressing actions (Verplanken and Orbell, 2003) performed without much conscious thought (Klöckner, 2015). Individuals are still able to reflect on their habits, both while they perform them and retrospectively (Kilpinen, 2012), however mostly habits are exerted automatically, and stabilized by external contextual and structural factors (Klöckner, 2015; Verplanken and Wood, 2006). In an earlier paper we successfully developed a framework to operationalize SPT constructs along social-psychological items like knowledge, values, norms etc. (Hess et al., 2018), which we also use here.

3.2. Expectations of intervention effects

Our expectations of how home energy advice influences routinized behaviors rest on the literature showing that information-based interventions are more effective when they include personal interaction as compared to just written information (Delmas et al., 2013). The rationale behind the higher effect is that people have the opportunity to ask questions and also advisors can tailor their recommendations to the particular situation of households (Salo et al., 2016). As such, we expect, that not only knowledge, but the different elements of a practice are affected by home energy advice.

We draw on previous findings to formulate expectations about intervention effects on routinized behaviors and related materials, knowledge, and meanings. Given the exploratory nature of our design and the previous literature, we refrain from stating explicit hypotheses. Fig. 1 provides an illustration of our conceptual framework, specifically the relation between energy advice, practice elements, and routinized behaviors. We elaborate on the elements of our framework and their relation in the following sections.

3.2.1. Routinized behaviors

Home energy advice intervenes in a household’s situational context because advisors visit people’s homes, meaning advice should be remembered when they perform tasks later. The advice may serve as a reminder to interrupt old habits and perform new ones (Lally and Gardner, 2013). For example, when household members do laundry, they may remember that advisors mentioned the benefits of washing clothes at 30°C instead of 40°C.

3.2.2. Materials

The intervention in this study provided information rather than technology. Advisors did not change the material context of households, but provided information that changing materials may facilitate less energy use (e.g., installation of multi-sockets to facilitate standby behavior). If investment is not too costly, information is expected to have an effect (Stern, 1986). Dietz et al. (2009) estimated that about 80% of households would change their appliances if encouraged to do so. Hence, we expect that our intervention will change the materials related to routinized behaviors.

3.2.3. Knowledge

When estimating the energy use of appliances, people rely on simple heuristics, such as thinking larger appliances use more energy (Baird and Brier, 1981; Steg, 2008). Information-based interventions have the potential to increase knowledge (Abrahamse et al., 2005). In line with previous research, we expect advice to enhance device-related knowledge.

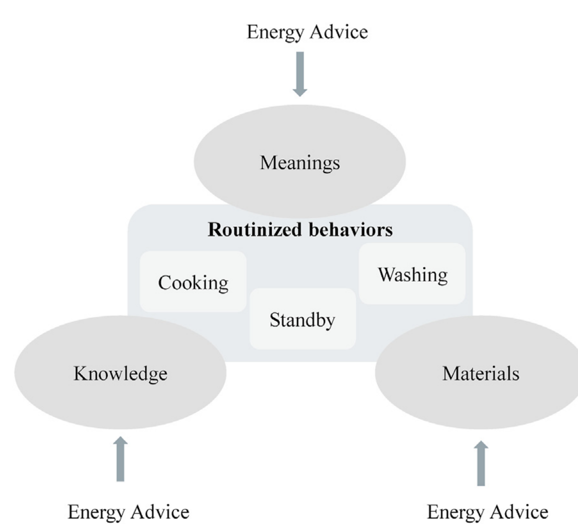

Fig. 1. Framework illustrating the relations between home energy advice and practice elements.

3.2.4. Meanings

Meanings include symbolic meanings, ideas, and aspirations (Shove et al., 2012). Like values or preferences, meanings are components of a particular lifestyle (Klöckner, 2015). The change of meanings is considered an important component of sustainability strategies (Burger et al., 2019); for example, a change in an individual's preference structure may also drive the alteration of meanings associated with a practice (Samadi et al., 2017). Energy advice can challenge meanings, such as the importance of switching off electronic devices when not in use, which can be seen as a change in "rules" (Hargreaves, 2011). In line with previous research, we assume that meanings of a routinized action are more resistant to change than competences and materials.

4. Material and methods

4.1. Sample and procedure

We ran a home energy advice field experiment from January to October 2018. We randomly sampled 1,000 households in Basel, Switzerland's third most populous city. Each household was offered a selection of energy-saving items after completion of the study. A total of 161 (16.1%) households agreed to participate, of which 17 did not provide an e-mail address and were excluded. The remaining 144 households were randomly assigned to the treatment (T) or control group (C). All participants were asked to complete three online surveys at three points in time: a baseline survey (March 2018) before the advice took place, a second survey (May 2018) about four weeks after the advice, and a third survey (October 2018) about six months after the advice. Treatment households that answered the baseline survey were contacted by a student trained to provide energy advice to schedule a 1-h advice session. Some households that were assigned to the treatment group did not participate (n = 11) because they were absent during the intervention period, or could not be contacted. The second survey was administered to all households from the control group who had answered the baseline survey, and to all participating households from the treatment group. The third survey was administered to all households that answered the baseline survey.[1] Table 1 summarizes the stages of the experiment and the corresponding number of responses.

4.2. Energy advice

A municipal energy advisor trained students, mainly recruited from the Sustainable Development Master's program at the University of Basel, in a one-day workshop to provide home energy advice. Afterwards, the students practiced the consultation process with test households. They were accompanied by a project team member and received feedback from them and the test household. All home visits were conducted with two students trained to provide energy advice, using a checklist developed with the municipal energy advisor. Advice focused on structural and technical aspects, as well as behavior. The advice included specific tips on washing, standby, and cooking. Advisors recommended properly filling the washing machine and washing clothes at 30°C (instead of 40°C) and at 60°C (instead of 90°C). They emphasized the importance of switching off all electronic devices when not in use and recommended multi-sockets to facilitate this. Advice regarding cooking focused on using a lid, not preheating the oven, and defrosting frozen food in the fridge. Knowledge about electricity-related practices was provided by emphasizing, for example, that it is more efficient to boil water in an electric kettle than in a pot with a lid (except for pasta, where the pot will be used anyway), and that a desktop computer uses more electricity than a laptop (see Appendix A for detailed information on the advice). Overall, advice aimed to increase knowledge about the energy intensity of routinized behaviors and how to change them.

Table 1
Timeline of the experiment and number of responses.

Invitation: 31.01.18	1st survey: 07.03–02.04	Treatment: 09.03–27.04	2nd survey: 02.05–27.05	3rd survey: 10.10–31.10
1,000 households randomly selected in Basel; 144 included	Data from 1st survey to estimate baseline effects	T-group households who finished 1st survey received treatment	Data from 2nd survey to estimate short-term effects	Data from 3rd survey to estimate medium-term effects
Groups: T: n = 73 C: n = 71	Responses: T: n = 41 C: n = 42	Responses: T: n = 30	Responses: T: n = 27 C: n = 34	Responses: T: n = 24 C: n = 31

Legend: T = treatment group, C = control group, n = number of observations in the respective experimental stage.

4.3. Measures

The three surveys included the same questions on routinized behavior related to heating, water, and electricity use (the focus of this paper), available equipment, characteristics of the accommodation, and sociodemographic variables. Furthermore, we asked questions to assess people's knowledge and meanings in relation to the practices. All households received the same survey. In the second survey, the treatment group was asked to provide information on energy.

Items were mainly based on the Swiss Household Energy Demand Survey (SHEDS), which was designed in a large-scale multidisciplinary project (Weber et al., 2017). We developed additional items—to measure washing, cooking and standby practices more specifically—based on the energy advice checklist developed with the municipal energy advisor (see Appendix A).

4.3.1. Washing

4.3.1.1. Washing frequency and washing temperature. Households were asked how frequently they washed clothes and at what temperature (range: 20°C–90°C). We created one variable for washing frequency by summing all wash cycles. For the average washing temperature, we divided the total wash temperature by the number of cycles.

4.3.1.2. Washing-related meanings. We asked participants how important it was for them to wear freshly washed clothes daily. Answers were given on a five-point Likert scale ranging from 1 "not at all important" to 5 "very important." For the data analysis, we combined categories 1 and 2, as well as 4 and 5, to create an ordinal variable with three categories: 1 "not important," 2 "neither important nor unimportant" and 3 "important."

4.3.2. Standby

4.3.2.1. Standby behavior. People were asked how often they switched off (not standby mode) the following devices when not in use: TV, set-top box, stereo system, modem, PC, printer, laptop, and tablet. The five-point Likert scale ranged from 1 "never" to 5 "always." We calculated the mean standby behavior for all available devices.

4.3.2.2. Automated behavior. To evaluate the automaticity of standby behavior, we asked respondents to indicate the extent to which they agreed with the following statement: "To completely switch off electronic

[1] We dropped the 11 households from the treatment group sample that did not receive the treatment (i.e. the never-takers) because we did not collect follow-up data on this group. Thus, we were unable to estimate alternatives to the average treatment effect for one-sided non-compliance, such as the intent-to-treat effect or the local average treatment effect (Gerber and Green, 2012). Consequently, we limited the analytical sample to households (both treatment and control groups) who participated in all three surveys.

devices (not standby) is something that I a) do automatically and b) do without thinking." These items were based on the automaticity subscale of the Self-Report Habit Index (Gardner et al., 2012), but we used two instead of four items to reduce respondent burden. The Likert scale ranged from 1 "do not agree at all" to 5 "totally agree." We created a mean score for the two items.

4.3.2.3. Multi-sockets. We asked participants to indicate whether they had installed multi-sockets to switch household devices and multimedia devices on/off (0 = no, 1 = yes).

4.3.2.4. Standby-related meanings. We asked participants how important it was for them that all electronic devices were switched off when not in use. The Likert scale ranged from 1 "not at all important" to 5 "very important." We created an ordinal variable with three categories: 1 "not important," 2 "neither important nor unimportant", and 3 "important".

4.3.3. Cooking

We measured cooking behavior by asking respondents how often they 1) used a lid, 2) preheated the oven, and 3) defrosted frozen food in the fridge. The scales ranged from 1 "never" to 5 "always." The item on preheating the oven was recoded so that the highest number corresponded to the least energy-intense behavior. We used the items separately as outcome variables.

4.3.4. Knowledge

Knowledge related to electricity practices was determined by asking respondents, "In the following pairs, which of the two consumes more electricity?" The pair to assess cooking-related knowledge was a) "Bringing 1 L of water to the boil in an average pot with a lid" compared to b) "Bringing 1 L of water to the boil in an electric kettle". The pair to assess IT-related knowledge was a) "Running a desktop PC for 1 h" compared to b) "Running a laptop for 1 h". Additional answer categories for each pair were c) "both consume about the same" or d) "I don't know". We created a dummy variable for each pair, where 1 corresponded to the correct answer and 0 to incorrect and "I don't know" answers.[2]

4.3.5. Sociodemographic variables

We included the following sociodemographic characteristics in our models: gender, age, education in years, log of income midpoints,[3] household size, household size squared to account for the non-linear relationship between household size and electricity consumption (Longhi, 2015), a children dummy, and an owner/tenant dummy.

4.3.6. Outcome-specific control variables

As outcome-specific controls for our washing models, we included a dummy variable for washing machine ownership (1) versus sharing (0).[4] We included this variable because we assumed that people washed differently when sharing a machine, e.g., higher temperature settings for hygiene reasons, and less frequency due to availability.

To analyze cooking behavior, we included the number of hot meals per household per week because households that cook more might have different cooking and cooling habits than households who cook less. To estimate the probability of defrosting frozen food in the fridge, we included a freezer dummy variable,[5] because households with additional freezers might be more likely to freeze and defrost food and thus might have different defrosting practices.

4.4. Descriptive statistics and randomization checks

Our treatment and control groups were balanced according to variables at the baseline, (Table 2). However, there was a tendency toward a higher level of automated standby behavior in the treatment group ($p = 0.06$), and more households with their own washing machines in the control group ($p = 0.06$).

As with other panel surveys, we observed attrition. Eighteen households dropped out after the baseline survey, and a further 10 after the second survey, resulting in a total dropout rate of 33.7%. This rate is comparable to attrition in similar studies (e.g., Abrahamse et al., 2007). Based on additional analyses, we found four variables associated with dropout—being assigned to the treatment group, being a woman, having children in the household, and higher income (Table B1). We discuss possible limitations with regard to attrition in Section 5.4.

4.5. Analytical strategy

We estimated the average effect of the treatment among compliers. Compliers are the subgroup assigned to the treatment group who actually received the treatment (Gerber and Green, 2012). We based our analysis of the average treatment effect (ATE) on the differences in means (difference-in-probabilities for binary and ordinal outcome variables) between the treatment and control group after the second survey (short-term effects) and the third survey (medium-term effects).

To obtain the ATE for each dependent variable (continuous, binary, and ordinal), we ran random-effects models to allow for the estimation of time-invariant covariates.[6] Estimating these associations enabled us to understand the role of (time-invariant) sociodemographic factors in routinized behavior beyond treatment effects.

For each dependent variable, we estimated three models. First, we ran a basic model using the treatment and time variable plus their interaction (treatment × time) as independent variables. Second, we estimated a model where we added relevant time-varying (age, education, income) and time-invariant (gender, household size, children, and ownership) sociodemographic independent variables (see Section 4.3.5). This set of independent variables was the same for all models to allow for comparisons between dependent variables. Including covariates in the regression reduces the size of the error term and enables a more precise estimation of the treatment effect (Gerber and Green, 2012), as presented in our results section. Third, we ran a model in which we additionally included time-varying outcome-specific variables (own washing machine, number of hot meals cooked per week, additional freezer) in the models on routinized washing and cooking behavior (see Section 4.3.6). This model assessed whether the inclusion of these covariates had a consequence on the estimated size of the treatment effect (sensitivity analysis; see Section 5.4). Complete tables of all covariate-adjusted estimates, difference-in-means estimates, and difference-in-probabilities estimates are included in Appendix C.

The specification for a continuous dependent variable is as follows:

$$\ln(y_{it}) = \beta_0 + \beta_1 D_i + \beta_2\, T_t + \beta_3 (D_i \times T_t) + \delta x_{it}' + \gamma z_i' + c_i + u_{it}$$

[2] Correct answers were: Cooking-related energy consumption knowledge: a), IT-related energy consumption knowledge: a).

[3] The question was: What is the gross monthly income (CHF) of your household? Answer options were 3000 or less, 3000–4459, 4500–5999, 6000–8999, 9000–12000, 12000 or more, no answer, I don't know. The latter two were treated as missing values. From the six income categories, a midpoint was taken, i.e., 1500, 3729.5, 5249.5, 7499.5, 10500, and 12000 and the logarithms of these midpoints were taken.

[4] In Switzerland, it is common that households in multi-family homes share a washing machine in the basement.

[5] We assumed that each household had a freezer compartment in the fridge.

[6] Fixed-effects models control for time-invariant characteristics by including an individual-specific intercept. The estimations of the regression coefficients are based on variation within the same person over time. However, fixed-effects models may be less appropriate when there is only little within-variation in individual level predictors and when there are only few measurement points (Hill et al., 2019), as is the case with our data.

Table 2
Descriptive statistics for baseline measures in the full sample, control group, and treatment group.

Variable	Full sample	Control group	Treatment group	Difference between control group and treatment group: p-value [a] and 95% confidence interval
Washing frequency (mean)	37.95	34.21	41.78	0.22 (−4.53–19.66)
Washing temperature (mean)	50.56	52.00	49.08	0.17 (−7.10–1.24)
Importance on wearing fresh clothes every day (%)	33.73	33.33	34.15	0.94 (0.42–2.58)
Often/always using a lid (%)	81.93	83.33	80.49	0.74 (0.27–2.53)
Never/seldom preheating the oven (%)	27.50	24.39	30.77	0.52 (0.51–3.69)
Often/always defrosting frozen meals in the fridge (%)	25.30	21.43	29.27	0.41 (0.56–4.12)
Standby behavior (mean)	3.47	3.45	3.49	0.86 (−0.41–0.50)
Standby automated behavior (mean)	3.55	3.27	3.83	0.06* (−0.02–1.15)
Multi-sockets installed (%)	45.78	40.48	51.22	0.33 (0.65–3.68)
Importance on all electronic devices being switched off when not in use (%)	69.88	61.90	78.05	0.11 (0.83–5.75)
Correct answers for cooking-related knowledge (%)	61.45	54.76	68.29	0.21 (0.73–4.36)
Correct answers for IT-related knowledge (%)	56.63	50.00	63.41	0.22 (0.72–4.17)
Women (%)	58.54	58.54	58.54	1.00 (0.42–2.41)
Age (mean)	51.09	52.98	49.15	0.26 (−10.55–2.90)
Monthly income (mean CHF)[b]	7596.71	7858.74	7316.60	0.52 (−2226.32–1142.04)
Education (mean years)	14.12	13.98	14.27	0.51 (−0.59–1.17)
Household size (mean)	2.31	2.33	2.29	0.91 (−0.76–0.68)
Households having at least one child (%)	24.10	28.57	19.51	0.34 (0.22–1.68)
Tenants (%)	75.90	73.81	78.05	0.65 (0.29–2.18)
Own washing machine (%)	54.22	64.29	43.90	0.06* (0.18–1.05)
Hot meals cooked per week per household (mean)	8.85	9.23	5.06	0.57 (−3.39–1.87)
Having an additional freezer (%)	55.42	54.76	56.10	0.90 (0.44–2.51)

*$p < 0.10$. Source: own calculation.

[a] We tested continuous variables using linear regression, binary variables using logistic regression and ordinal variables assessing differences between treated and control group for the highest value, again using logistic regression.
[b] 23 missing values.

Our dependent variable $\ln(y_{it})$ is the logarithm of the continuous variable, which we took to assess the treatment effect in percentage change. β_0 is the intercept and estimates the average log outcome in the control group at baseline. β_1 is a dummy variable: 1 for the treatment group and 0 for control group. T_t is our time variable and β_2 estimates the time-specific effect at the second and third survey, compared to the baseline. We included an interaction term $D_i \times T_t$ to gauge whether the treatment effect was different for a short versus medium timeframe after the intervention. x'_{it} is a row vector for time-varying and z'_i is a row vector for time-invariant sociodemographic and outcome-specific variables. δ and γ are column vectors of parameters. c_i is an individual-specific effect—a random variable that is assumed to be uncorrelated with the explanatory variables. u_{it} is an idiosyncratic error term. We used cluster-robust standard errors to allow for heteroscedasticity and serial correlation. We estimated random-effects logistic regression models and random-effects ordered logistic regression models for binary and ordinal dependent variables, respectively.

ATE was then calculated as the difference between the treatment and control groups in means or probabilities, as appropriate. Short-term treatment effects refer to differences between the estimates obtained from the second survey, and medium-term treatment effects to differences obtained from the third survey. In the results section, we present the ATE for compliers graphically along with 95 and 90% confidence intervals to facilitate the assessment of treatment effects across time and between dependent variables (in addition, ATE for compliers based on the basic model and the models with outcome-specific covariates can be found in Appendix C).

5. Results and discussion

5.1. Description and interpretation of the results

We found a short-term effect of a 13% reduction in washing temperature. However, the washing temperature in the treatment group was 11% lower ($p = 0.076$) than the control group at the baseline (see also Model 2, Table C2).[7] Hence, these results should be interpreted cautiously. We also found that the treatment group washed more frequently than the control group at the medium-term evaluation. This finding contradicts our expectations and might be due to outliers.[8]

Contrary to our expectations, the treatment group was 30 percentage points less likely to install multi-sockets in the short term. Regarding cooking, there was a short-term treatment effect for using a lid. The treatment group had an 11 percentage point higher probability of using a lid than the control group, and was more likely to defrost frozen meals in the fridge at each measurement point (Table C.19).

The treatment group increased their IT-related energy consumption knowledge in the short term compared to the control group, being 32 percentage points more likely to know that running a desktop computer consumes more electricity than a laptop. This effect was no longer present in the medium timeframe.

The intervention increased lid use when cooking and IT-related energy consumption knowledge, in line with our expectations, but only short term. As expected, the intervention did not change the meanings related to routinized washing and standby behaviors. Contrary to expectations, the treatment group reported higher washing frequency in the medium term. It might be that the treatment led to an increase in

[7] All models are displayed in Appendix C.
[8] Washing frequency: baseline: control group (C) = 39, treatment group (T) = 46, short term: C = 37, T = 39, medium term: C = 28, T = 50.

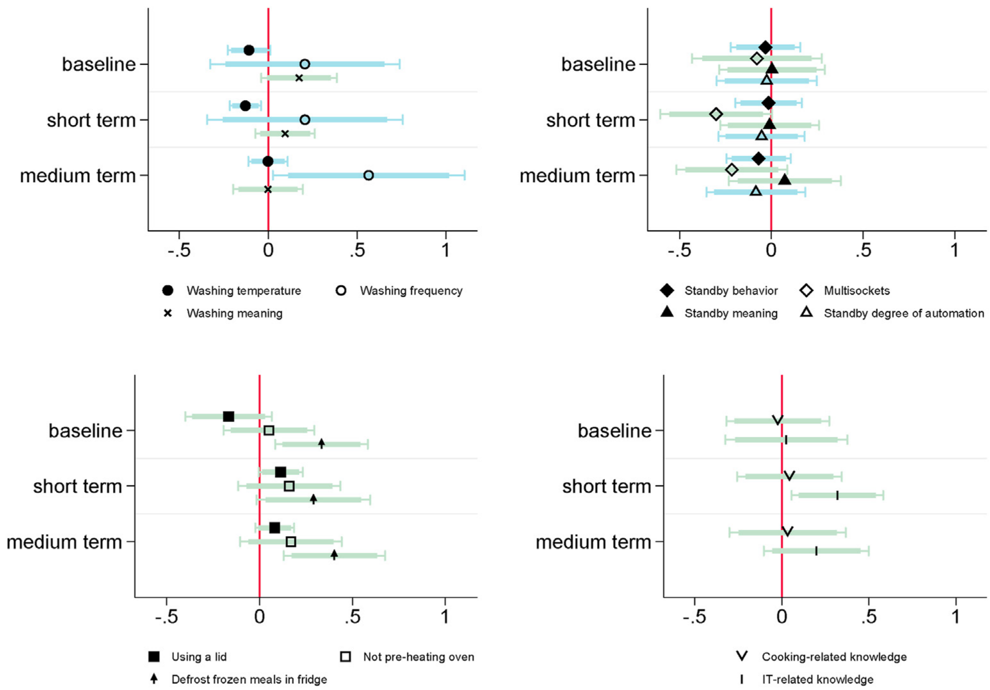

Fig. 2. Average treatment effects of energy advice for the short and medium term and differences at baseline.

Note: Estimates shown in Fig. 2 are based on regression models (see Appendix C, Models 2). Continuous variables are displayed in blue, and their effects should be interpreted as percentage change in the respective variable, e.g., washing temperature was reduced by 13% in the short term (see top left panel). Binary and ordinal variables are displayed in green, and their effect should be interpreted as a change in percentage points regarding the probability of observing a positive outcome (for binary variables) and of observing the highest outcome (for ordinal variables), e.g., the treatment led to an 11 percentage point higher probability of often/always using a lid (see bottom left panel). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

reporting accuracy due to increased mindfulness of behavior. Mindfulness has been found to increase recall, so those who received the advice might recall their behavior more accurately in the medium term than the control group (Mrazek et al., 2013). Our expectation was not supported with regard to the material element. The intervention led to a *reduced* probability of installing multi-sockets. It might be that treatment households were confused because advisors explained that multi-sockets consume only 0.1 W, i.e., they wanted to emphasize that multi-sockets do not overconsume the electricity saved.

In general, the effects of the intervention were mixed. Washing temperature decreased in the treatment group, but frequency remained higher compared to controls. Besides the abovementioned possibility of the treatment group having a higher reporting accuracy, mixed evidence may also be a result of energy advice leading to some sort of moral licensing or negative spillover effect (Sorrell et al., 2020), i.e., reducing energy consumption in one behavioral element of the washing practice but increasing consumption in another. The mixed evidence suggests that it is important to disentangle demand and zoom into practices. Further research is needed to determine why people responded positively in one domain, but contrary to expectations in another.

The estimates of the treatment effects were robust across a wide range of model specifications.[9] This was not the case for washing temperature (Table C2), using a lid (Table C.16), and IT-related energy consumption knowledge (Table C.24), where the estimates of the treatment effect differed according to the basic and full models, respectively. The inclusion of outcome-specific variables did not change the model results substantially compared to the inclusion of sociodemographic variables.

5.2. *Predictors of the elements of routinized behavior*

In the following section, the relationships between sociodemographic and outcome-specific variables are discussed with regard to washing, standby, and cooking practices.

5.2.1. *Washing*

Income was negatively correlated with washing temperature (Table C1), but positively with frequency (Table C.3). Previous studies have found that high-income households have higher overall energy consumption and higher energy consumption related to washing and drying clothes (Kleinhückelkotten et al., 2016; Schaffrin and Reibling, 2015). However, previous studies have considered washing frequency but not temperature (Kleinhückelkotten et al., 2016). Our results indicate the advantage of disentangling the practice into different components to get a differentiated picture of the correlations between socioeconomic predictors and parts of the washing practice.

Similarly, level of education was positively correlated with washing temperature, and negatively correlated with washing-related meanings. One additional year of education was associated with a 3% increase in average washing temperature (Table C1). Each extra year of education was associated with a lower importance of wearing fresh clothes daily (3 percentage point lower probability of finding it important (Table C.5). Our findings are in line with previous literature (e.g., Holden and Linnerud, 2010), showing that years of education are correlated with energy-intense behavior (higher washing temperature) and with washing-related meanings, which are a component of green lifestyle and environmental attitudes (not finding it important to wear freshly washed clothes daily).

Having at least one child in the household was associated with a higher probability of finding it (very) important to wear fresh clothes every day. This might be due to different practices (such as playing outside with children), leading to different connections between such practices and washing (Shove et al., 2012).

5.2.2. *Standby*

Income was negatively correlated with switching off devices when not in use (Table C.7), in line with previous findings that high-income households consume more energy (Schaffrin and Reibling, 2015). Households with children were 38 percentage points less likely to have multi-sockets installed (Table C.9). Children in the household were also negatively correlated with standby-related meanings (Table C.11) and automatic switching off gadgets (Table C.13). Households with children might have other priorities and perceive it as too much effort, or children probably interfere in energy-saving endeavors (Gram-Hanssen, 2010).

[9] All estimates of basic (Models 1) and full models (Models 2–4) can be found in Table C1-Table C.24, and Appendix C. Full models include sociodemographic covariates (Models 2) or sociodemographic covariates and outcome-specific covariates (Models 3 and 4).

Education was positively correlated with importance of switching off devices. As with washing-related meanings, this result suggests that education might be positively related to energy-saving preferences.

5.2.3. Cooking

Years of education were positively correlated with using a lid and defrosting food in the fridge. One additional year of education was associated with a 3.3 percentage point increase in probability of using a lid (Table C.15, Model 2) and a 6.1 percentage point increase in probability of defrosting food in the fridge (Table C.19, Model 2). For cooking behaviors, education was positively correlated with energy-saving practices.

Education was also positively associated with cooking-related energy consumption knowledge. One more year of education increased the probability of knowing that boiling water in a pot with a lid consumed more energy than an electric kettle by 7.3 percentage points (Table C.21). A positive association between education and *knowledge* as well as education and *meanings* suggests that education is positively correlated with energy saving. However, when looking at energy-relevant *behaviors,* the pattern is less uniform, as seen in the positive correlation between education and lid use (energy-saving), compared to the positive correlation between education and washing temperature (energy-intense).

Having children was negatively correlated with lid use. It could be that some practices are unique to households with children; for example, being less likely to use a lid and have multi-sockets installed.

There was a time effect for preheating the oven. At short and medium term, all respondents were less likely to preheat the oven compared to the baseline. This time effect might relate to seasonal patterns, e.g., preheating the oven may be less common in summer than in winter.

Being a homeowner was negatively correlated with using a lid and positively correlated with not preheating the oven. Regarding energy intensity, this is an inconsistent pattern, which further shows the advantage of disentangling demand to detect such patterns.

Women had a lower probability of consistently (often/always) defrosting frozen food in the fridge, indicating gender differences in freezing and defrosting behaviors. It could be that women use different defrosting methods, or cook less frozen food.

The number of hot meals cooked per week and the availability of an additional freezer did not explain the differences in routinized cooking and cooling behaviors. Our expectations concerning these variables were not supported (see Section 4.3.6).

5.3. Interpretation of the findings from an SPT perspective

The problem framings and targets of interventions by Spurling et al. (2013) were taken as point of departure. Thus, the aim of this intervention was to re-craft practices, by reducing the resource-intensity of existing practices through changing the components, or elements, which make up those practices. Energy advice showed the potential of re-crafting one element of the cooking practice towards less energy use. People who received energy advice were more likely to use lids – although this was only during a short timeframe after the intervention. The advice on using lids was rather easy to understand ("always use a lid", see Guide/Checklist in Appendix A), which might explain why it was followed. Besides being easy to understand, it might also be easy for households to implement, as most households have lids.

In contrast, advice had a negative effect on the probability of installing multi-sockets. It might be that the advice was too complicated in showing potential kWh savings through installing multi-sockets. However, it could also be that following this advice would have been too much effort in the view of households (buying multi-sockets, and then initially remembering to switch them off until this becomes integrated into daily routines). Energy advice was also less effective in changing meanings. Research on sufficiency suggests it might be a long way to go to achieve changes in meanings (Burger et al., 2019; Shove, 2018).

The present research further reveals insights into how practices might differ according to socio-demographic characteristics, for example, education, income, and gender. Exploring these heterogeneities seems promising for future research. Previous research has also proposed making socio-demographic difference more central in practice-based research (Hess et al., 2018). This might also allow for a segmentation approach in practice-based research.

5.4. Limitations and prospects for future research

Eleven households in the treatment group did not receive treatment after answering the baseline survey (26.8% non-response rate; see Section 4.1). Future studies could try to improve compliance (Gillingham and Tsvetanov, 2018) and address perceived non-monetary costs preventing participation (Fowlie et al., 2015).

Connected to this, the sample size was rather small. Further research should aim to recruit more participants to reduce noise and the risk of false negatives, while carefully considering selection bias. A bigger sample size would also allow heterogeneity of treatment effects to be examined and, eventually, lay the foundation for group-specific interventions.

Our intervention was based on voluntary participation and informed consent, and we used a selection of energy-saving items as incentives. This might have led to self-selection bias, possibly affecting the external validity of our results. Keeping these limitations in mind, our results can still be generalized beyond the confines of our sample.

Our survey design did not allow further investigations of the complier average causal effect, where the outcome is observed for those assigned to the treatment—whether they actually receive it or not (Gerber and Green, 2012). Future studies should collect data on those assigned to, but not receiving the treatment. This would enable researchers to use an instrumental variables approach to account for the possibility that compliers share some unobserved factors that may affect dependent variables (Gerber and Green, 2012).

Our research relied on self-report data.[10] While new technologies to gather detailed consumption data are being developed, there is currently no alternative for collecting such fine-grained data on behavioral routines with a revealed preference approach (i.e., through "hard" consumption measures). Although smart meters can collect detailed data on energy consumption for different appliances, there are still two shortcomings of this approach. First, device-related smart meter technologies have not been rolled out on a large scale in Switzerland, where our experiment was conducted. Second, this data would still not allow disentangling practices into their elements. The higher kWh consumption of a washing machine measured over a certain period would not reveal insights into which behavioral components people actually changed, and whether negative spillover effects occurred (i.e., saving energy in one behavior and higher usage in another). Therefore, self-report data is a valuable approach for understanding the elements of routines that are altered by an intervention.

We cannot rule out that the lower level of expertise of students compared to professional energy advisors may have impacted our results—although advisors were perceived as competent by most households.[11] Prior research found moderately more consistent and lasting behavior change, but no differences in mean kWh reductions when advice was provided by an energy technician compared to agents who were trained by technicians (Winett et al., 1982).

Future research could apply our approach to disentangle demand when evaluating a behavior change intervention and assess the mechanisms underlying ambiguous treatment effects, such as negative spillover

[10] See Steg and Vlek (2009) as well as Vining and Ebreo (2002) for further perspectives on the use of self-report data in environmental psychology.

[11] Most households found the advisors competent, with just one household stating they would have appreciated more expertise.

or non-conformity between meanings and behaviors. Spillover effects can be positive (when energy saving behavior is adopted in a different domain) or negative (when energy behavior in one domain makes it less likely that energy is saved in another domain). Positive spillover is more likely (and negative spillover less likely) when people have strong environmental values (Sorrell et al., 2020).

Finally, future research could run a longitudinal study with a multi-group multi-treatment design, for example including financial incentives as well, while maintaining one pre and two post measurements.

6. Conclusions and policy implications

In this study, we suggest a framework to disentangle energy demand when evaluating the effects of an intervention. We analyzed home energy advice to change routinized washing, standby, and cooking behaviors, as well as meanings, technology, and knowledge related to these behaviors. We designed the study as a randomized controlled field experiment.

Our results indicate that routinized behaviors and device-related knowledge can be changed within the course of an intervention. We found treatment effects showing more frequent use of lids during cooking and improved knowledge of IT-related energy consumption. However, we also found opposite treatment effects regarding higher washing frequency and a lower probability of installing multi-sockets. Furthermore, we found that meanings were unlikely to change during the intervention.

We found significant differences in relation to income, education, gender, owner vs. tenant status, having children in the household, and household size. The direction and effect size of the correlations varied according to the particular element of a routine, highlighting the advantage of looking at particular routinized behaviors and related materials, meanings, and knowledge, rather than aggregated kWh. These findings also indicate potential opposing effects within certain segments of a population. On an aggregated level, these opposing effects may cancel themselves out, thereby covering up the mechanisms underlying energy demand. We also discovered contrasting associations between education and routinized washing and cooking behaviors, meanings, and knowledge. This again points to the importance of disentangling energy demand and use of energy services.

We derive three main policy implications from our research. First, our approach allows us to disentangle energy demand, which is key to advancing our understanding of routines and which elements can be changed during such interventions. Breaking down behaviors and their contexts into different components can be applied to any type of intervention to change household energy consumption behavior. Our study suggests a possible way forward, but more research is needed to develop according policies or interventions. For example, research may focus on how policies could change meanings for energy saving behaviors through intervention programs. Program planners who want to use energy consulting as a tool to reduce energy consumption should carefully consider which aspects of practices they want to address and evaluate whether an absolute reduction in energy consumption is associated with the intervention. Likewise, interventions based purely on social-psychological models should be evaluated in terms of which aspects of practices they target and how effectively they change them.

Second, as with all voluntary programs, opt-in interventions like home energy advice risk attracting the already "converted." Ethically, energy advice can only be designed as an opt-in intervention, which is likely to enroll fewer people than an opt-out approach (Allcott and Kessler, 2019). It was beyond our scope to estimate the cost-effectiveness of the intervention studied in this paper. Nevertheless, program planners might face the challenge of developing a cost-effective program by reaching a considerable number of households at low cost or by targeting high-consumption households that are highly responsive to treatment (Andor et al., 2020).

Third, our study adds to the literature that single-shot interventions, even if they require high involvement from households, are not very effective in changing habitual energy consumption. However, the intervention could be adapted by setting up reminders for households. Previous studies suggest that reminders can have a positive reinforcing effect to change routinized behaviors (Shen et al., 2020). Further research is needed to evaluate the effect of reminders on routinized behaviors, as well as related meanings, materials, and knowledge.

The additional value of our research is that we looked at particular elements of routinized behaviors. We hope that our study prompts researchers and policy designers to apply a multifaceted perspective by including the components of routinized behaviors when developing and testing policies to change energy demand.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Guide/Checklist for students trained to provide energy advice

Preparation

- Go again through the training manuals, if necessary print important slides and take them with you to the consultation

Start

- Present yourself and explain the procedure

- Go through the household room-wise (e.g., start with living room or kitchen)

Electricity tariff and total electricity consumption

- Ask households when household members are usually at home (to give advice accordingly which tariff would be more beneficial for the household)
- Recommend to change from normal tariff to budget tariff (i.e. flexible tariff) if household members are at home predominantly in the evenings (after 8 p.m.) and on weekends
  → Households (tenants) need to coordinate with the landlord when they want to change their tariff; an electrician needs to install a different electricity meter (the question is who pays for the electrician, the landlord or the tenant)
  o Normal tariff: 8.56 cents/kWh
  oBudget tariff: normal tariff (Mo–Fr. 6 a.m. to 8 p.m.): 9.48 cents/kWh, budget tariff (for the rest of the time): 7.70 cents/kWh
  oplus grid fees, contributions and VAT
  o[Remark for you: try it yourselves with your electricity bill, fill in your annual electricity consumption in this online mask and look whether the price changes when you select the budget tariff option: https://www.iwb.ch/Fuer-Zuhause/Strom/Strompreisrechner-Privatkunden.html#/start]

Lighting

- Replace 60 W light bulbs with 6 W LED (90% less energy consumption) → please note the efficiency label
- *Calculation example:*
  oLED: 6Wx750h = 4500 Wh = 4.5 kWh → 4.5 × 0.27[12] = 1.22 CHF per year
  oLight bulb: 60Wx750h = 45 kWh → 45 × 0.27 = 12.15 CHF per year
  → I.e. replacing one single light bulb with a LED saves 10.93 CHF per year - this adds up to 100 CHF with 10 light bulbs
- Halogen light bulbs are often built into the ceiling, often you do not see the difference between halogen light bulbs and LED, but you can feel it (halogen lamps are getting warm, LED not)
- To change to LED is always a good advice, but when households have a dimmable lighting system, they should leave the task to an electrician
- Explain the price advantage according to the lifetime of LED (slide 22 in your training manual)
- Disposal of LED via hazardous waste (contains a toxic phosphor layer)

Electronic devices

This is mainly about consumer electronics, such as TV, PC, printer, router, set-top-box, etc.

- Switch-off all electronic devices when not in use
- use multi-sockets (these consume only 0.1 W, accordingly they do not overconsume the saved electricity)
- check whether devices are warm or not (warm means they still run in stand-by)
- take together your consumer electronics where this makes sense on one multi-socket to avoid standby consumption of multiple devices
- *Calculation example (network devices such as set-top-box or printer):*
  o*8W stand-by consumption x22hx365* = 64240 Wh = *64*.24 kWh → *64x0.27 = 17.28 CHF/year*
- A desktop computer consumes more energy than a laptop and this in turn consumes more energy than a tablet/smartphone
- Adapt the screen brightness (for all devices who have a screen)
- Do not use the TV as radio because it consumes a lot more energy than a radio
- Exchange a plasma or tube TV with a LED, be aware of the screen diagonal → smaller screens consume less energy
- If you plan to buy a new device → pay attention to the efficiency label

Cooking and doing the dishes

- Use good (usually heavy pots) and put them on the fitting hotplate
- Always use a lid
- Use the kettle to boil water instead of a pot (slide 34 in training manual), except for pasta where you can boil the water in the pot that is to be used for the pasta
- Also in the kitchen switch off all devices (especially turn the coffee machine off – no standby)
- Fill the dishwasher to the maximum
- If you wash up hand → do not leave the water running, but fill the sink once

Cooling and freezing

- Choose devices with A+++ labels (with every plus you have approximately 30% less energy consumption)
- Efficiency is related to the isolation (you can check the thickness of the fridge wall)
- Make sure that your fridge or freezer stays in a cool place without direct sunlight and not next to the oven
- When you have a layer of ice → defrost! A layer of ice reduces the cooling capacity, food can go bad (freezer burn food)
- Not less than 6°C in the fridge
- Defrost: let food from the freezer defrost in the fridge

[12] Assumption: 27 cents/kWh electricity costs in Basel (incl. grid fees and contributions) (https://www.strompreis.elcom.admin.ch/PriceComparison.aspx?Period=2018&PlaceNumber=2701&OpID=624&CatID=2&ProdID=10&CPeriod=2017&CPlaceNumber=2701&COpID=624&CCatID=2&CProdID=1).

- Cool down: do not put warm meals into the fridge

Washing and drying

- Fill washing machine and dryer if possible to a maximum
- 30°C is sufficient for normal laundry, bed linen etc. can be washed at 60°C (instead of 90°C)
- Line drying saves a lot of energy → if possible always line dry the clothing
- If your building has an indoor air dryer in the basement → close the doors when in use

Warm water

- A water saving shower head can halve the water consumption
- Install water economizers in the tabs in the bath and kitchen
- If you have an own boiler: do not set the temperature above 60°C (60°C is sufficient to avoid legionella)
- Showering (if not too long) is more energy efficient than taking a bath

Heating and airing

Especially in winter (heating season)

- Recommend electronic (programmable) thermostats
- Do not cover the radiator with furniture
- If you leave the house, turn down the thermostat, or program your electronic thermostat accordingly
- If you are absent for a longer time (e.g. holidays) set the thermostat to *
- Open all windows for a short time (5 min to create a through draught) → do not tilt the windows, as 2 min opening all windows creating a through draught = 50 min airing with tilt windows
- Set your room temperature a few degrees lower and put on a pullover to warm up
- Set your thermostat appropriately (Position 3, approximately 20°C)
- According to usage heat rooms more or less → sleeping room cooler than living room

Especially in summer (avoid overheating)

- Air conditioner is not necessary if you follow some recommendations:
  - oAir at night
  - oDuring the day close all windows, close the (roller) blinds (should be fixed outside)
  - oSwitch-off electronic devices if possible (avoid waste heat)
  - oA fan can help to cool down when temperatures are very hot

Conclusion

- Sum up the most important/most relevant points for the households

After the consultation

- Document the energy advice in the prepared template and sent it at energieimalltag-fnf@unibas.ch
- If necessary send the household further information
- Look up any information that was unclear or that you were unsure about

Appendix B

Table B.1
Results of logistic regression assessing attrition

	Dependent variable: dropout (1 = yes)
Assigned to treatment group (reference: control group)	0.127* (0.067)
Woman (reference: man)	0.133* (0.071)
Age	0.000 (0.003)
Income (log of midpoints from categories)	0.179** (0.076)
Education (years)	−0.018 (0.017)
Household size	−0.035 (0.030)
Children in household (reference: no child in household)	0.302*** (0.109)
Owner (reference: tenant)	0.038 (0.095)
Prior advice before the study took place (reference: no prior advice)	0.190 (0.185)
N	182

Standard errors in parentheses.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table B.2
Analytical sample: Descriptive statistics for baseline measures in the analytical sample, control group, and treatment group

Variable	Analytical sample	Control group	Treatment group	Difference between control group and treatment group: p-value[3] and 95% confidence interval
Washing frequency (mean)	42.10	38.88	46.00	0.49 (−13.51–27.74)
Washing temperature (mean)	47.84	49.17	46.23	0.33 (−9.07–3.19)
Importance on wearing fresh clothes every day (%)	16.13	11.76	21.43	0.47 (0.29–14.39)
Often/always using a lid (%)	83.87	82.35	85.71	0.80 (0.18–9.02)
Never/seldom preheating the oven (%)	25.81	23.53	28.57	0.75 (0.26–6.52)
Often/always defrosting frozen meals in the fridge (%)	29.03	17.65	42.86	0.13 (0.68–17.96)
Standby behavior (mean)	3.46	3.49	3.44	0.89 (−0.74–0.64)
Standby automated behavior (mean)	3.40	3.47	3.32	0.73 (−1.04–0.74)
Multi-sockets installed (%)	54.84	58.82	50.00	0.62 (0.17–2.91)
Importance on all electronic devices being switched off when not in use (%)	74.19	70.59	78.57	0.61 (0.29–7.94)
Correct answers for cooking-related knowledge (%)	67.74	64.71	71.43	0.69 (0.30–6.28)
Correct answers for IT-related knowledge (%)	58.06	52.94	64.29	0.53 (0.38–6.82)
Women (%)	54.84	52.94	57.14	0.82 (0.29–4.92)
Age (mean)	48.87	51.82	45.29	0.25 (−17.85–4.77)
Monthly income (mean CHF)[4]	7229.05	7493.79	6907.57	0.61 (−2962.21–1789.77)
Education (mean years)	14.39	13.94	14.93	0.16 (−0.42–2.40)
Household size (mean)	2.01	2.24	1.93	0.57 (−1.40–0.79)
Households having at least one child (%)	19.35	23.53	14.29	0.52 (0.08–3.51)
Tenants (%)	80.65	76.47	85.71	0.52 (0.08–3.51)
Own washing machine (%)	58.06	76.47	35.71	0.03** (0.04–0.82)
Hot meals cooked per week per household (mean)	7.32	7.53	7.07	0.77 (−3.63–2.71)
Having an additional freezer (%)	38.71	35.29	42.86	0.67 (0.33–5.88)

**p < 0.05.

Appendix C. All tables are based on own calculations. Tables with even numbers display ATEs that were estimated based on the random effects models; the corresponding random-effects models are displayed in the odd numbered tables

Table C.1
Washing temperature: Results of random-effects model: average marginal effects

	Dependent variable: washing temperature (log)		
	Model 1	Model 2	Model 3
Treatment group (reference: control group)	−0.031 (0.046)	−0.078 (0.049)	−0.078 (0.048)
Short term (reference: baseline)	0.008 (0.020)	0.008 (0.019)	0.008 (0.020)
Medium term (reference: baseline)	0.028 (0.021)	0.029 (0.020)	0.029 (0.020)
Women (reference: men)		−0.042 (0.047)	−0.042 (0.049)
Age in years		−0.001 (0.001)	−0.001 (0.001)
Income (log of midpoints from categories)		−0.044* (0.023)	−0.044* (0.023)
Education in years		0.030*** (0.011)	0.030*** (0.011)
Household size		0.043 (0.066)	0.043 (0.066)
Household size squared		−0.001 (0.009)	−0.001 (0.009)
Children in household (reference: no children in household)		−0.076 (0.083)	−0.076 (0.084)
Owner (reference: tenant)		−0.070 (0.069)	−0.070 (0.072)
Own washing machine (reference: shared washing machine)			0.001 (0.028)
N	100	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 2
Washing temperature: Average treatment effect at short term and medium term and difference between treatment and control group at the baseline

	Dependent variable: washing temperature (log)		
	Model 1	Model 2	Model 3
Baseline	−0.056 (0.058)	−0.109* (0.061)	−0.108* (0.061)
Short term	−0.084** (0.042)	−0.129*** (0.045)	−0.129*** (0.044)
Medium term	0.045 (0.055)	−0.002 (0.056)	−0.001 (0.056)
N	100	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 3
Washing frequency: Results of random-effects model: average marginal effects

	Dependent variable: washing frequency (log)		
	Model 1	Model 2	Model 3
Treatment group (reference: control group)	0.282 (0.189)	0.332 (0.210)	0.366* (0.215)
Short term (reference: baseline)	−0.093 (0.128)	−0.089 (0.134)	−0.073 (0.143)
Medium term (reference: baseline)	−0.079 (0.156)	−0.075 (0.165)	−0.059 (0.171)
Women (reference: men)		0.168 (0.186)	0.159 (0.187)
Age in years		0.003 (0.007)	0.002 (0.008)
Income (log of midpoints from categories)		0.302* (0.163)	0.301* (0.172)
Education in years		−0.020 (0.061)	−0.023 (0.062)
Household size		−0.481* (0.279)	−0.487* (0.280)
Household size squared		0.076** (0.032)	0.077** (0.032)
Children in household (reference: no children in household)		0.093 (0.298)	0.085 (0.301)
Owner (reference: tenant)		−0.004 (0.237)	−0.064 (0.231)
Own washing machine (reference: shared washing machine)			0.128 (0.157)
N	100	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 4
Washing frequency: Average treatment effect at short term and medium term and difference between treatment and control group at the baseline

	Dependent variable: washing frequency (log)		
	Model 1	Model 2	Model 3
Baseline	0.160 (0.267)	0.206 (0.272)	0.247 (0.282)
Short term	0.160 (0.244)	0.206 (0.281)	0.239 (0.282)
Medium term	0.508** (0.254)	0.565** (0.275)	0.596** (0.278)
N	100	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 5
Washing-related meanings: Results of ordinal logistic random-effects model: average marginal effects

	Dependent variable: washing-related meanings (probability of finding it (very) important to wear fresh clothes every day)		
	Model 1	Model 2	Model 3
Treatment group (reference: control group)	0.022 (0.075)	0.085 (0.079)	0.083 (0.080)
Short term (reference: baseline)	0.037 (0.047)	0.038 (0.045)	0.036 (0.046)
Medium term (reference: baseline)	−0.031 (0.057)	−0.027 (0.057)	−0.029 (0.059)
Women (reference: men)		0.005 (0.079)	0.007 (0.077)
Age in years		−0.002 (0.003)	−0.002 (0.003)
Income (log of midpoints from categories)		−0.074 (0.076)	−0.073 (0.075)
Household size		0.203* (0.116)	0.204* (0.117)
Household size squared		−0.048** (0.019)	−0.048** (0.019)
Children in household (reference: no children in household)		0.370* (0.193)	0.374** (0.189)
Owner (reference: tenant)		0.053 (0.100)	0.058 (0.106)
Own washing machine (reference: shared washing machine)			−0.010 (0.051)
N	100	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 6
Washing-related meanings: Average treatment effect at short term and medium term and difference between treatment and control group at the baseline

	Dependent variable: washing-related meanings (probability of finding it (very) important to wear fresh clothes every day)		
	Model 1	Model 2	Model 3
Baseline	0.090 (0.107)	0.173 (0.108)	0.170 (0.110)
Short term	0.023 (0.091)	0.095 (0.085)	0.092 (0.085)
Medium term	−0.039 (0.087)	−0.002 (0.100)	−0.003 (0.100)
N	100	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 7
Standby behavior: Results of random-effects model: average marginal effects

	Dependent variable: standby behavior (log)	
	Model 1	Model 2
Treatment group (reference: control group)	−0.059 (0.094)	−0.040 (0.087)
Short term (reference: baseline)	0.003 (0.033)	0.005 (0.033)
Medium term (reference: baseline)	0.035 (0.026)	0.037 (0.023)
Women (reference: men)		−0.066 (0.092)
Age in years		0.004 (0.003)
Income (log of midpoints from categories)		−0.172*** (0.044)
Education in years		0.027 (0.021)
Household size		0.085 (0.135)
Household size squared		−0.003 (0.015)
Children in household (reference: no children in household)		−0.102 (0.129)
Owner (reference: tenant)		−0.029 (0.135)
N	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 8
Standby behavior: Average treatment effect at short term and medium term and difference between treatment and control group at the baseline

	Dependent variable: standby behavior (log)	
	Model 1	Model 2
Baseline	−0.045 (0.106)	−0.032 (0.096)
Short term	−0.033 (0.104)	−0.016 (0.092)
Medium term	−0.096 (0.090)	−0.070 (0.089)
N	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 9
Multi-sockets: Results of logistic random-effects model: average marginal effects

	Dependent variable: multi-sockets (1 = yes)	
	Model 1	Model 2
Treatment group (reference: control group)	−0.174 (0.134)	−0.203 (0.140)
Short term (reference: baseline)	0.086 (0.068)	0.072 (0.078)
Medium term (reference: baseline)	0.036 (0.066)	0.029 (0.069)
Women (reference: men)		−0.180 (0.150)
Age in years		0.001 (0.005)
Income (log of midpoints from categories)		0.011 (0.112)
Education in years		0.014 (0.036)
Household size		0.047 (0.201)
Household size squared		0.001 (0.025)
Children in household (reference: no children in household)		−0.380** (0.184)
Owner (reference: tenant)		−0.150 (0.214)
N	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 10
Multi-sockets: Average treatment effect at short term and medium term and difference between treatment and control group at the baseline

	Dependent variable: multi-sockets (1 = yes)	
	Model 1	Model 2
Baseline	−0.044 (0.160)	−0.079 (0.180)
Short term	−0.282* (0.147)	−0.301* (0.155)
Medium term	−0.184 (0.161)	−0.216 (0.154)
N	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 11
Standby-related meanings: Results of ordinal logistic random-effects model: average marginal effects

	Dependent variable: standby-related meanings (probability of finding it (very) important to switch-off devices)	
	Model 1	Model 2
Treatment group (reference: control group)	0.091 (0.115)	0.024 (0.119)
Short term (reference: baseline)	0.011 (0.054)	0.005 (0.056)
Medium term (reference: baseline)	−0.018 (0.085)	−0.019 (0.079)
Women (reference: men)		−0.115 (0.126)
Age in years		−0.002 (0.005)
Income (log of midpoints from categories)		−0.068 (0.118)
Education in years		0.063* (0.034)
Household size		0.515*** (0.168)
Household size squared		−0.054*** (0.019)
Children in household (reference: no children in household)		−0.549*** (0.111)
Owner (reference: tenant)		−0.168 (0.149)
N	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 12
Standby-related meanings: Average treatment effect at short term and medium term and difference between treatment and control group at the baseline

	Dependent variable: standby-related meanings (probability of finding it (very) important to switch-off devices)	
	Model 1	Model 2
Baseline	0.066 (0.146)	0.003 (0.147)
Short term	0.038 (0.140)	−0.010 (0.137)
Medium term	0.164 (0.149)	0.073 (0.155)
N	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 13
Automaticity of standby behavior: Results of random-effects model: average marginal effects

	Dependent variable: automaticity of standby behavior (log)	
	Model 1	Model 2
Treatment group (reference: control group)	−0.030 (0.142)	−0.056 (0.112)
Short term (reference: baseline)	0.133* (0.068)	0.131* (0.070)
Medium term (reference: baseline)	0.079 (0.053)	0.082 (0.057)
Women (reference: men)		−0.163 (0.139)
Age in years		−0.001 (0.004)
Income (log of midpoints from categories)		−0.056 (0.087)
Education in years		0.022 (0.022)
Household size		0.376** (0.185)
Household size squared		−0.041** (0.020)
Children in household (reference: no children in household)		−0.365** (0.169)
Owner (reference: tenant)		−0.082 (0.214)
N	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 14
Automaticity of standby behavior: Average treatment effect at short term and medium term and difference between treatment and control group at the baseline

	Dependent variable: automaticity of standby behavior (log)	
	Model 1	Model 2
Baseline	0.003 (0.165)	−0.025 (0.139)
Short term	−0.030 (0.144)	−0.053 (0.120)
Medium term	−0.059 (0.162)	−0.085 (0.137)
N	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 15
Using a lid: Results of ordinal logistic random-effects model: average marginal effects

	Dependent variable: probability of often/always using a lid		
	Model 1	Model 2	Model 3
Treatment group (reference: control group)	0.105* (0.061)	0.016 (0.046)	0.008 (0.048)
Short term (reference: baseline)	0.085 (0.075)	0.067 (0.073)	0.071 (0.073)
Medium term (reference: baseline)	0.083 (0.079)	0.091 (0.074)	0.090 (0.072)
Women (reference: men)		−0.098 (0.072)	−0.106 (0.069)
Age in years		−0.002 (0.002)	−0.002 (0.003)
Income (log of midpoints from categories)		0.057 (0.076)	0.066 (0.066)
Education in years		0.033** (0.015)	0.038*** (0.014)
Household size		−0.030 (0.136)	−0.057 (0.136)
Household size squared		0.030 (0.033)	0.036 (0.034)
Children in household (reference: no children in household)		−0.467*** (0.053)	−0.477*** (0.044)
Owner (reference: tenant)		−0.224** (0.089)	−0.205** (0.098)
Number of hot meals cooked per week			0.006 (0.011)
N	100	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 16
Lid: Average treatment effect at short term and medium term and difference between treatment and control group at the baseline

	Dependent variable: probability of often/always using a lid		
	Model 1	Model 2	Model 3
Baseline	0.034 (0.126)	−0.167 (0.119)	−0.197 (0.130)
Short term	0.135 (0.108)	0.114* (0.061)	0.107* (0.060)
Medium term	0.138* (0.078)	0.081 (0.053)	0.084 (0.051)
N	100	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 17
Preheating oven: Results of ordinal logistic random-effects model: average marginal effects

	Dependent variable: probability of never/seldom preheating the oven		
	Model 1	Model 2	Model 3
Treatment group (reference: control group)	0.134 (0.196)	0.129 (0.122)	0.129 (0.123)
Short term (reference: baseline)	0.106* (0.059)	0.104* (0.054)	0.104* (0.054)
Medium term (reference: baseline)	0.116* (0.068)	0.104* (0.058)	0.104* (0.056)
Women (reference: men)		−0.003 (0.110)	−0.003 (0.109)
Age in years		−0.001 (0.004)	−0.001 (0.004)
Income (log of midpoints from categories)		−0.024 (0.094)	−0.024 (0.095)
Education in years		−0.010 (0.028)	−0.010 (0.028)
Household size		−0.123 (0.177)	−0.122 (0.192)
Household size squared		0.018 (0.020)	0.018 (0.022)
Children in household (reference: no children in household)		−0.173 (0.126)	−0.173 (0.125)
Owner (reference: tenant)		0.484*** (0.130)	0.483*** (0.141)
Number of hot meals cooked per week			−0.000 (0.011)
N	100	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C18
Preheating oven: Average treatment effect at short term and medium term and difference between treatment and control group at the baseline

	Dependent variable: probability of never/seldom preheating the oven		
	Model 1	Model 2	Model 3
Baseline	0.040 (0.212)	0.050 (0.125)	0.050 (0.125)
Short term	0.178 (0.196)	0.160 (0.140)	0.160 (0.140)
Medium term	0.173 (0.212)	0.169 (0.139)	0.169 (0.143)
N	100	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 19
Defrosting food: Results of ordinal logistic random-effects model: average marginal effects

	Dependent variable: probability of often/always defrosting frozen food in the fridge			
	Model 1	Model 2	Model 3	Model 4
Treatment group (reference: control group)	0.354*** (0.108)	0.343*** (0.120)	0.334*** (0.125)	0.345*** (0.122)
Short term (reference: baseline)	0.099 (0.070)	0.096 (0.065)	0.099 (0.064)	0.104 (0.065)
Medium term (reference: baseline)	0.094 (0.062)	0.085 (0.057)	0.081 (0.055)	0.087 (0.058)
Women (reference: men)		−0.289** (0.115)	−0.285** (0.116)	−0.276** (0.112)
Age in years		0.004 (0.004)	0.003 (0.004)	0.003 (0.004)
Income (log of midpoints from categories)		−0.134 (0.091)	−0.137 (0.096)	−0.113 (0.096)
Education in years		0.058** (0.024)	0.061** (0.024)	0.057** (0.024)
Household size		0.071 (0.151)	0.022 (0.151)	0.025 (0.150)
Household size squared		0.001 (0.017)	0.006 (0.017)	0.006 (0.017)
Children in household (reference: no children in household)		−0.125 (0.139)	−0.125 (0.138)	−0.128 (0.134)
Owner (reference: tenant)		−0.096 (0.151)	−0.070 (0.153)	−0.082 (0.151)
Number of hot meals cooked per week			0.010 (0.011)	0.010 (0.011)
Additional freezer (reference: not having an additional freezer)				−0.056 (0.065)
N	100	100	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 20
Defrosting food: Average treatment effect at short term and medium term and difference between treatment and control group at the baseline

	Dependent variable: probability of often/always defrosting frozen food in the fridge			
	Model 1	Model 2	Model 3	Model 4
Baseline	0.350*** (0.115)	0.333*** (0.127)	0.329** (0.128)	0.341*** (0.124)
Short term	0.306** (0.153)	0.290* (0.156)	0.287* (0.158)	0.298* (0.156)
Medium term	0.403*** (0.132)	0.403*** (0.139)	0.382*** (0.147)	0.392*** (0.149)
N	100	100	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 21
Cooking-related energy consumption knowledge: Results of logistic random-effects model: average marginal effects

	Dependent variable: cooking-related energy consumption knowledge (1 = yes)	
	Model 1	Model 2
Treatment group (reference: control group)	0.106 (0.138)	0.020 (0.134)
Short term (reference: baseline)	−0.007 (0.051)	0.002 (0.039)
Medium term (reference: baseline)	−0.038 (0.077)	−0.031 (0.077)
Women (reference: men)		−0.085 (0.148)
Age in years		−0.000 (0.005)
Income (log of midpoints from categories)		−0.068 (0.071)
Education in years		0.073*** (0.027)
Household size		−0.259 (0.200)
Household size squared		0.033 (0.025)
Children in household (reference: no children in household)		0.053 (0.236)
Owner (reference: tenant)		0.065 (0.187)
N	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 22
Cooking-related energy consumption knowledge: Average treatment effect at short term and medium term and difference between treatment and control group at the baseline

	Dependent variable: cooking-related energy consumption knowledge (1 = yes)	
	Model 1	Model 2
Baseline	0.085 (0.164)	−0.023 (0.151)
Short term	0.130 (0.158)	0.044 (0.153)
Medium term	0.101 (0.170)	0.033 (0.171)
N	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 23
IT-related energy consumption knowledge: Results of logistic random-effects model: average marginal effects

	Dependent variable: IT-related energy consumption knowledge (1 = yes)	
	Model 1	Model 2
Treatment group (reference: control group)	0.312*** (0.110)	0.187* (0.109)
Short term (reference: baseline)	0.131 (0.102)	0.143 (0.101)
Medium term (reference: baseline)	0.029 (0.104)	0.029 (0.103)
Women (reference: men)		0.042 (0.111)
Age in years		−0.006 (0.004)
Income (log of midpoints from categories)		0.123 (0.099)
Education in years		0.036 (0.024)
Household size		−0.264* (0.145)
Household size squared		0.030 (0.018)
Children in household (reference: no children in household)		0.140 (0.149)
Owner (reference: tenant)		0.001 (0.124)
N	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table C 24
IT-related energy consumption knowledge: Average treatment effect at short term and medium term and difference between treatment and control group at the baseline

	Dependent variable: IT-related energy consumption knowledge (1 = yes)	
	Model 1	Model 2
Baseline	0.160 (0.177)	0.026 (0.179)
Short term	0.434*** (0.134)	0.319** (0.134)
Medium term	0.327** (0.155)	0.198 (0.154)
N	100	100

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

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