Energy Policy 161 (2022) 112731

Contents lists available at ScienceDirect

Energy Policy

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

The effect of information nudges on energy saving: Observations from a randomized field experiment in Finland

Enni Ruokamo [a,b,*], Teemu Meriläinen [a,b], Santtu Karhinen [a,b], Jouni Räihä [a,b], Päivi Suur-Uski [c], Leila Timonen [c], Rauli Svento [b]

[a] Finnish Environment Institute, University of Oulu, PL 413, FI-90014, Finland
[b] Department of Economics, Accounting and Finance, University of Oulu Business School, University of Oulu, P.O.Box 8000, FI-90014, Finland
[c] Motiva Ltd, P.O. Box 489, FI-00101, Helsinki, Finland

ARTICLE INFO

JEL classification:
C33
D12
L94
Q41

Keywords:
Behavior
Conservation
Electricity
Energy advice
Experiment
Finland
Intervention
Nudging
Randomized field trial
Social norm

ABSTRACT

Field experiments have shown that information nudging can help households to save energy, however, the effectiveness varies depending on aspects such as information content, delivery mode and study area. This article evaluates the impacts of information nudges on residential electricity consumption with a randomized field experiment. This opt-in experiment was conducted in Finland. Information was administered via monthly email newsletters and an online energy service platform. The aim is to find out whether i) energy saving tips combined with and without online energy service platform providing electricity consumption information, and ii) peer comparisons (i.e., social norm) influence households' electricity consumption. The results show a high seasonal variation in the treatment effects within the groups who were registered users of the online energy service platform. Those with access to usage feedback and versatile energy savings tips (without the social norm comparisons) reduced their electricity consumption around 10% in wintertime. The results imply challenges in encouraging energy saving behavior among households less interested in following their electricity consumption.

1. Introduction

Electricity remains a relatively poorly understood area of spending among households (Brounen et al., 2013; Ruokamo et al., 2019), and thus, households are likely to miss out on potential energy savings. Meanwhile, successful field trials have shown the potential of behavioral interventions and nudging to induce electricity saving among households (see, e.g., Allcott, 2011; Aydin et al., 2018; Byrne et al., 2018).

Electricity consumption is an interesting application for nudging. The aim of nudging is to alter behavior without prohibiting alternatives or significantly changing economic incentives (Thaler and Sunstein, 2008). As a consumption decision, electricity consumption is challenging because household uses electricity indirectly when utilizing various devices (e.g., television, lighting) and services (e.g., heating). The electricity itself is invisible to the end user and it is hard to estimate the consumption of different devices (Lesic et al., 2018) and similarly the costs. This study employs informational nudges that aim to make the effects of electricity consumption choices more visible to households and make the energy conservation easier. In addition, a social norm nudge is utilized to inform households of others' electricity consumption with respect to their own.

Generally, informational nudges include feedback, personalized advice and energy saving tips (Buckley, 2020). Usage and/or price information makes electricity costs more salient that, in turn, should guide consumers to change the level of their consumption. Sharing energy saving tips aims to influence household consumption behavior by lowering the threshold for energy saving measures and increasing knowledge of available solutions. The underlying assumption is that a lack of information can lead to sub-optimal consumption behavior. The idea of a social norm nudge based on peer comparisons is that consumers

* Corresponding author. Finnish Environment Institute, University of Oulu, PL 413, FI-90014, Finland.
E-mail addresses: enni.ruokamo@syke.fi (E. Ruokamo), teemu.merilainen@oulu.fi (T. Meriläinen), santtu.karhinen@syke.fi (S. Karhinen), jouni.raiha@oulu.fi (J. Räihä), paivi.suur-uski@motiva.fi (P. Suur-Uski), leila.timonen@motiva.fi (L. Timonen), rauli.svento@oulu.fi (R. Svento).

https://doi.org/10.1016/j.enpol.2021.112731
Received 24 June 2021; Received in revised form 4 November 2021; Accepted 22 November 2021
Available online 10 December 2021

seek to shape their consumption towards a more socially acceptable direction.

This study evaluates the effectiveness of information nudges on residential electricity consumption in a cold climate location where electric heating is widely used. Finland is different from most of the previously studied areas due to its northern location and being a part of the Nordic energy market with 100% smart meter deployment.[1] The majority of previous studies have been conducted in the UK and USA, but there are also many studies from e.g., Japan and Netherlands (Buckley, 2020) that all have warmer climate than Finland. Typically, the winter begins in Finland in November and the mean temperature remains below zero Celsius degrees until the end of March (Finnish Meteorological Institute, 2021). Furthermore, Andor et al. (2020) demonstrate that the effects of similar information nudges may differ between countries and contexts,[2] in turn, implying the importance of country and context-specific investigation.

With a randomized field experiment, this study investigates whether i) email energy saving tip newsletters combined with and without usage of an online energy service platform providing electricity consumption information, and ii) a provision of comparative electricity consumption information (i.e., social norm) influence households' electricity consumption. Randomized field experiment (RFE) enables accurate impact analyses of the examined information nudges. In RFE, the target population is randomly divided to treatment and control groups. The randomization ensures that the observed differences in the electricity consumption between groups are specifically due to the exposure of the studied treatment.

This study contributes to the existing literature in the following ways. First, the experiment employs emails and an online service as delivery methods for the information steering, solutions which are highly scalable and not as extensively studied (Bird and Legault, 2018). Second, the experimental setting of the study allows for analyzing treatment effects between users and non-users of an online energy service platform. The previous research is limited on how the voluntary usage of an already existing online electricity consumption monitoring service is linked with the efficacy of the energy saving tips (see Section 2). In addition, no RFEs on information nudges on electricity use have been conducted in Finland before, and generally, we lack knowledge on the topic in the distinct Nordic climate conditions with high seasonal variation in electricity consumption (see recent study from Kažukauskas et al. (2020) for Sweden). The study findings are particularly relevant for regions with long and cold winters where behavioral changes during high electricity consumption periods can result in significant electricity savings.

Overall, the findings of this study imply that email delivered energy saving tips reduce electricity consumption of households who are involved in following their electricity consumption via an online service. Among such households there is a clear variation in the treatment effects between months with wintertime particularly showing good results. On the other hand, the findings demonstrate that households with less interest in following their electricity consumption do not respond to the energy saving tips. Similar observations about the linkages between monitoring and nudge efficacy is made by Aydin et al. (2018), whereas Kažukauskas et al. (2020) show similar evidence related to seasonal differences in the treatment effects. Furthermore, the findings indicate that peer comparisons decrease electricity consumption only when combined with energy saving tips. Contrary to this, De Dominicis et al. (2019) and Dolan and Metcalfe (2015) find peer-to-peer comparisons to work relatively well.

The remaining article is organized as follows. Section 2 overviews the existing literature relevant to this study. The experiment design, data and modeling approach are described in Section 3. Section 4 presents the results and Section 5 continues with discussion. Section 6 concludes the article with policy implications.

2. Literature

This section focuses on previous experiments with non-price interventions as well as results on settings which were selected on the basis of their relevance to the RFE study conducted here. More precisely, the studies presented in this section cover the effects of general saving tips, social norm and the effects of the chosen delivery method.

Generally, the literature suggests that information nudging can induce changes in energy consumption behavior, but there is a clear variation in the magnitude of the estimated effects between different studies (Andor et al., 2020; Carroll et al., 2014; Houde et al., 2013; Kua and Wong, 2012; Gans et al., 2013; Gleerup et al., 2010; Schleich et al., 2013) with more robust results showing average savings from 2% to 4% (Buckley, 2020; Delmas et al., 2013). There are many possible reasons for the varying results. For example, the studies have used different types of nudges and information delivery methods. Some studies have used home energy reports (e.g., Allcott, 2011; Andor et al., 2020) for feedback, some had in-home displays installed (e.g., De Dominicis et al., 2019; Kažukauskas et al., 2020), whereas others relied on other channels, such as text messaging (e.g., Gleerup et al., 2010). Moreover, experiments have had varying target groups and locations as well as sample sizes and analysis methods that make it difficult to properly identify the sources of the differences. Studies of higher quality utilizing more controls (i.e., control groups, demographic information, and weather variables) in the analysis have generally found smaller treatment effects (Delmas et al., 2013).

In addition to the size and direction of the effects, it is also important to understand how fast and long the nudges work. It has been found that peer comparisons can cause a reduction in energy consumption relatively quickly (Dolan and Metcalfe, 2015) and some studies have found the effects to be surprisingly long-lasting and continuous over the duration of intervention (Ayres et al., 2013; Allcott and Rogers, 2014; Dolan and Metcalfe, 2015). On the other hand, studies have also found that the nudge effects are not permanent after the end of the intervention, disappearing for the most part within a month (see e.g., Brandon et al., 2017). Overall, studies have yielded mixed results on long-term effects of information nudges (Andor and Fels, 2018).

The nudges examined in this study include general energy saving tips and peer comparisons. In other experiments the interventions have often mixed general tips, consumption information and social norm components (Andor and Fels, 2018). Social norm in these settings has been found to affect household electricity consumption in several different studies: either in energy reports combined with conservation tips (Allcott, 2011), or via real-time displays (Kažukauskas et al., 2020; Schultz et al., 2015). Studies on the large-scale intervention by Opower in the US agree on an average reduction in energy use of around 2% (Allcott, 2011; Ayres et al., 2013), but even higher reductions between 6% and 7% have been found (Dolan and Metcalfe, 2015; Kažukauskas et al., 2020). Studies looking at social norm, in the form of peer comparisons, and with a setting isolating its effect have found it to be effective (De Dominicis et al., 2019; Dolan and Metcalfe, 2015; Ayres et al., 2013). There are also potential risks and problems in utilizing social norms. One noteworthy problem is the so-called "boomerang effect", in which low-consumption households increase their consumption closer to the average when receiving peer-to-peer data (Byrne et al., 2018). The boomerang effect can be mitigated by using message elements that

[1] The residential electricity consumption covers just over a quarter of the total electricity consumption in Finland (OSF, 2020a, b).

[2] Andor et al. (2020) suggest that the effects of similar information nudges can differ between countries (here US and Germany) due to different electricity metering aspects (quarterly vs. annual metering) and different overall electricity consumption levels among households (lower baseline consumption in Germany than in the US). Thus, the effects of information nudging in Finland may differ to other countries, because of hourly smart metering of electricity consumption and high electricity consumption levels.

support good behavior (e.g., emoticons in home energy reports) for those households that consume less than average (Schultz et al., 2007).

Previous studies have often had some sort of component of giving feedback with tips on how to save energy. The evidence in the literature on the effectiveness of energy saving tips is both for (Allcott, 2011; Aydin et al., 2018) and against (Buckley, 2020). Aydin et al. (2018) found that households that tried energy saving tips and actively monitored their consumption were more likely than others to reduce their consumption. According to a meta-analysis of Buckley (2020), giving general energy-saving tips could also lead to increased electricity consumption. The reason for this may be, for example, a reaction when the recipient of the guidance finds the received tips restrictive or patronizing. Externally issued general guidelines can also supersede other more effective motives for energy saving that already exist. Overall, it has been found that personalized and targeted energy saving tips work better than general tips (Buckley, 2020).

This study uses both email and online portals to provide information and feedback, with already existing user base of the online service. Previous literature has shown that the method of delivery has an impact on the effectiveness of nudge, but no clear recommendation can be identified from the literature as the most effective channel to approach households. Studies have found that emails and separate in-home displays produce stronger treatment effects than letters (Andor and Fels, 2018). As one example of a study also looking at an online web portal, Schleich et al. (2013) found no significant difference when compared to delivery by post. Other studies have found that email is less effective in conveying the impact of a social norm (Dolan and Metcalfe, 2015). Study location can also impact the effectiveness of the delivery mode. For instance, online-based feedback solutions have worked well in the Nordic countries (Gleerup et al., 2010; Vassileva et al., 2012). The scalability of online delivery methods like emails and web portals makes them interesting options for interventions and nudges. Online methods might prove even more important in the future as we move towards smart grids. When using online services (web portals or apps) the cost for the household is also significantly lower compared to having e.g., in-home-displays installed and maintained. This study contributes to the research on the effect of different mediums of feedback also, as studies looking at online portals and services have not been as common (Andor and Fels, 2018).

The efficacy and viability of given nudges are linked with the characteristics and consumption patterns of treated households. For example, Aydin et al. (2018) show for Netherlands that energy saving is concentrated more outside the hours of high consumption, among older households, and those already familiar with energy saving. In the US, on the other hand, it was found that the impact of energy reports on electricity savings was greater among high electricity-consuming households and those living in cheaper locations (Ayres et al., 2013). In Austria, the effects were strongest in households with 30–70 percentile electricity consumption, and outside this nudging had little effect (Schleich et al., 2013). In addition, the effectiveness has also been found to depend on the values and attitudes of individuals. A study conducted in the US found that the energy report induced a larger reduction in electricity consumption among liberals than among conservatives (Costa and Kahn, 2013). The amount and persistence of savings also appear to be higher when conservation is motivated by health-related arguments rather than economic ones (Asensio and Delmas, 2016). This study accounts for differences between households, for example, different income and different electricity consumption levels.

3. Methodology and data

3.1. Experiment design

The plan to examine the efficiency of energy advice in the Finnish context was initiated in a Finnish Energy Authority led workshop on demand response in September 2017. Motiva Ltd, a Finnish state company, tasked to promote sustainable use of energy and materials, and the BCDC Energy research group joined in to plan and conduct the experiment. An electricity distribution partner was found from Porvoo when Porvoo Energia, a southern Finnish utility with around 36 000 customers connected to its 3700-km distribution network,[3] expressed their willingness to participate in the study. The Porvoo region lies on the southern coast of Finland under 50 km from Helsinki. The most densely populated area is the city center of Porvoo, which has just below 40 000 inhabitants. The other areas under study are more scarcely populated with plenty of detached housing in a lush area including seashore, archipelago and countryside. Porvoo region is bilingual with roughly 30% Swedish speaking minority that necessitated doing the entire study in both Finnish and Swedish languages.

Fig. 1 depicts timeline of the experiment. After thorough pre-testing and steering group input during the planning phase, a joint decision was made to examine two kinds of treatments directed at household electricity use: energy advice and social norm, with a RFE in an opt-in setting.

The implementation of the survey began in the summer of 2018, when about 9600 of Porvoon Energia's customers[4] were asked to take part in an online survey via email or text messages. The survey included questions about demographics, house specifications and equipment, energy use, environmental attitudes, and consumption behavior. A GDPR-compliant opt-in question was included for agreeing to join the experiment and to allow the researchers access to the household's electricity consumption data. In total 1277 households responded to the survey, of which 671 agreed to participate in the experiment and provide their electricity consumption data.[5]

As is required by law in Finland, all experiment participants could sign-up to access their hourly electricity consumption data via an online energy service platform, but not everyone does so. This online registration is trackable by all DSO's in Finland, and it is a key differentiator and a notable research question in this experiment. Within signed-up users of the online platform, i.e. registered users (R), we randomized the participant sample (N=393) into i) energy-saving tip treatment (Tip-R), ii) social norm plus reduced energy saving tip treatment (Norm-R), and iii) control (Control-R). Those who had not registered (NR) (N=298) were randomized into: i) energy-saving tip treatment (Tip-NR), and ii) control (Control-NR). Division to users and non-users of the online platform enables us to test, whether those more familiar with their electricity consumption patterns are more receptive for the tested treatments. Aydin et al. (2018) find that those already familiar with energy saving are more responsive to nudging.

Table 1 lists the randomized group composition coupled with descriptive statistics. It shows that the randomization within groups succeeded very well. The registered and non-registered groups differ somewhat as expected. On average, the registered households have higher income, live in larger houses and are more likely to identify as men.

The information treatments provided in the experiment were

[3] The network covers the entire city of Porvoo, southern parts of Pornainen and Western Loviisa.

[4] All roughly 7500 customers who had provided their email address were contacted with an email. The rest were contacted with a text message. As a precondition the recipients also had to have both distribution and electricity sales contracts with the company. This was done in order to make sure that we would be able to gather reliable electricity consumption data and provide the comparison tool for use.

[5] We tested for differences between the opt-in and not participating groups using t-tests and chi-squared tests. We found that those of younger age, higher education and income, and larger family size, as well as households living in a larger house were more likely to opt-in to the experiment. Households that had already registered to the online energy service platform were also more likely to join the experiment. This may relate to their higher level of electricity consumption, and thus, greater interest in following and controlling consumption.

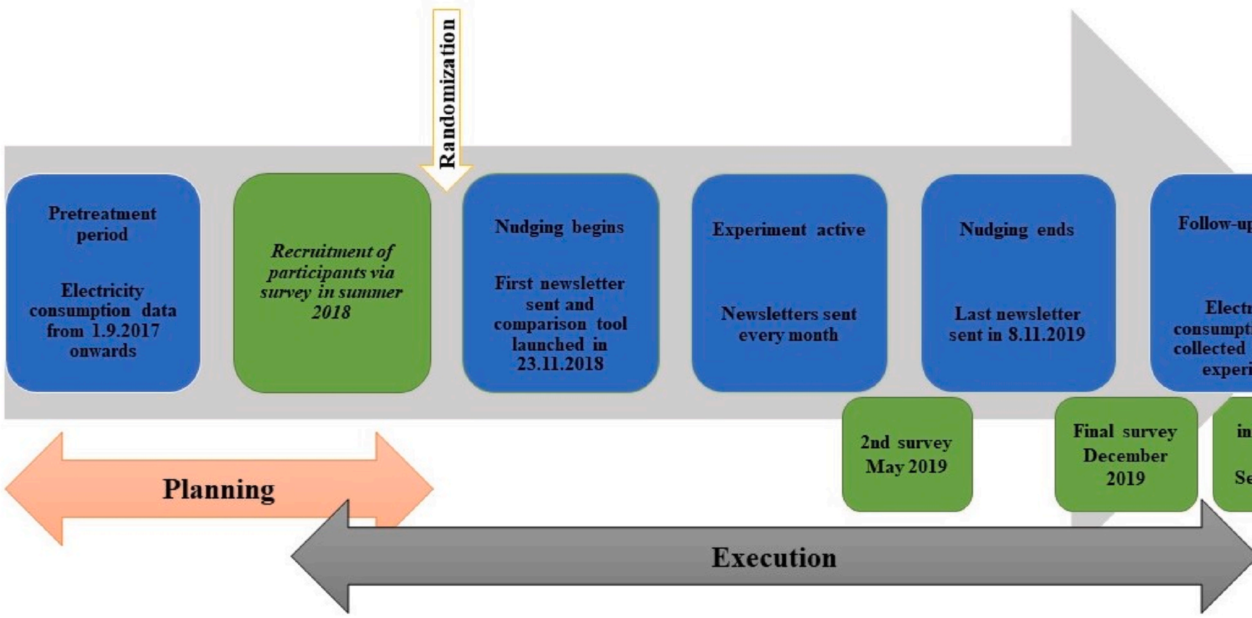

Fig. 1. Experiment timeline.

Table 1
Descriptive statistics for treatment and control groups.

	Non-registered		Registered		
	Tip-NR	**Control-NR**	**TiP-R**	**Control-R**	**Norm-R**
N	139	139	131	131	131
Age (average years)	52.7	53.9	51.2	52.3	52.7
Household size (average persons)	2.50	2.0	2.8	3.0	3.0
Heat floor space (average m^2)	114.7	114.5	146.4	151.2	143.5
	(%)	*(%)*	*(%)*	*(%)*	*(%)*
Female	46.0	38.8	22.9	19.1	26.2
Household monthly income <6000€	69.8	64.7	45.0	45.0	43.5
University degree	67.7	61.2	62.6	62.6	65.4
Opted for Swedish content	30.2	23.7	26.7	33.6	33.1
Detached house	61.2	64.7	81.7	80.9	78.6
Electric heating	33.1	38.8	42.0	43.5	51.5

carefully designed and targeted. The information sources available for the treated groups are presented in Table 2. For Norm-R group, a specially designed peer comparison tool enabling electricity consumption comparison with other similar households was opened to the online energy service platform. Within the tool the Norm-R group members were presented with a timeline of their own consumption with weather information and a timeline of consumption of a group of similar households. The views were available at hourly, daily, and monthly resolutions. The tool also enabled to change the comparison group with house characteristics of one's own choosing (heating system, floor area, and year of construction). The Norm-R group also received reduced energy saving tips in the monthly newsletter. Tip-R and Tip-NR groups received monthly newsletters and had access to a themed website providing additional information on energy saving measures. All the information treatments used in this study are highly replicable and scalable.

The energy advice newsletters were provided by Motiva Ltd. The newsletters were sent every month between November 2018 and November 2019.[6] The newsletters covered seasonal topics related to electricity and energy use (see Table 3). In addition to the seasonal tips, Tip-R received reminders to check electricity consumption from the online service platform and Tip-NR instructions on registering to the online service. The Norm-R group got reminders to check electricity

Table 2
Sources of information.

Treatment	Data content provided			
	Newsletter	**Online service**	**Comparison tool**	**Themed website**
Norm-R	x	x	x	
Tip-R	x	x		x
Tip-NR	x	x		x

Table 3
Content of newsletters.

Newsletter number	Brief description of the newsletter theme
1: Nov 2018	Introduction of the experiment, initial information, motivation – benefits of participation
2: Dec 2018	Temperature control, ventilation
3: Jan 2019	Benefits of consumption monitoring, heating
4: Feb 2019	Timing of electricity consumption
5: Mar 2019	Solar power, consumption monitoring, personalized consumption data
6: Apr 2019	Invitation to the mid-point survey, home automation
7: May 2019	Consumption monitoring, energy-efficiency measures
8: Jun 2019	Electric heating, cooling
9: Aug 2019	Consumption of electrical equipment, consumption monitoring
10: Sep 2019	Preparation for the heating season, carbon footprint, electric heating extra (exact information for electrically heated homes)/ consumption comparison data among other participants in the study
11: Oct 2019	Peak consumption and its timing, tip for room temperature
12: Nov 2019	Compilation of the experiment, top 6 general tips and new good electrical practices

[6] Excluding July because of the summer holiday period in Finland. Newsletters are available upon request.

consumption and use the peer comparison tool. The structure of all newsletters followed a similar pattern: seasonal information content, a monthly tip, a part marketing the online service, and a content-related poll aimed to activate the recipient.

In addition to the initial survey, mid-point and end surveys detailing experiences during the entire experiment were conducted to gather feedback. The mid-point feedback survey targeted the treatment groups (N=398) and sought feedback on the newsletters and comparison tool. It received 144 answers. The end survey was sent to both treated and control groups, and it sought information on behavioral changes, investments, and actions. A total of 303 answers were returned. After the active experiment, attempt was made to reach all the participants, who were identified as having successfully completed the study (N=586) with separate phone interviews for validation purposes. A total of 347 interviews were successfully completed.

3.2. Experiment monitoring and survey feedback

The newsletter open rates were closely monitored throughout the experiment and the conducted surveys gathered feedback related to the content of the newsletters and the functionality of the comparison tool. In general, the newsletter content was well-received according to the mid-point survey,[7] and the open rates (Fig. 2) were relatively high throughout the experiment with over half of the recipients opening them. There was some variation in the newsletter opening rates between the groups. Tip-R and Norm-R groups had consistently higher open rates compared to the Tip-NR group. Email was found as a functioning channel to deliver information and the monthly cadence was considered good for the newsletters. All in all, the newsletters received positive feedback in every metric: length, how interesting, easy to understand and useful the content was. Participants liked especially general and seasonal energy saving tips. Only video content did not receive positive feedback from the households (Fig. 3).

Visits to the online service and the peer comparison tool were also monitored. The comparison tool was not used as extensively as hoped. On average, the tool was used just over 3 times during the one-year trial,[8] and about 40% of households in the Norm-R group did not use the service at all. Feedback in the midpoint survey indicated that the tool was considered a little slow and unclear. Only roughly a fifth said that the comparisons had affected their energy consumption behavior. The low engagement with the comparison tool prompted us to include more detailed tips and comparative information in the newsletters for the Norm-R group during the last autumn period of the experiment.

3.3. Data

The original electricity consumption data provided to the researchers included a total of 657 households. Households (N=127) that had moved outside Porvoo Energia's distribution area, holiday homes and households with business operation[9] were removed from the data. In addition, two households dropped out from the experiment and were removed from the remaining material. The final data includes a total of 9,250,560 hourly electricity consumption observations for 528 households. The data contains a total of 9,320 (0.1% of all observations) missing hourly consumption observations that were imputed with a 5-h moving average.

Hourly electricity consumption was summed up as daily consumption and converted into panel data, which combined survey data and the Finnish Meteorological Institute's daily weather observations from the Porvoo Harabacka observation station. Missing survey observations were imputed based on the observed properties of other data (predictive mean matching). In the final data, 528 household observation units were divided between the different groups as follows: the unregistered energy saving tip group (Tip-NR) contained 100 and the corresponding control group (Control-NR) contained 100 households; the registered energy saving tip (Tip-R) had 110, the social norm plus reduced energy saving tip treatment group (Norm-R) had 108 and the corresponding control group (Control-R) had 110 households. The final sample descriptive statistics are available in Appendix A.

Fig. 4 presents the average daily consumptions at the monthly level for the treated and control households during the pre-treatment and treatment periods. In the figures, the treatment starts at the dashed line. The pre-treatment period began on November 23rd in 2017 and ended on November 22nd in 2018, and the treatment period began on November 23rd in 2018 and ended on November 22nd in 2019. The figures show the average daily consumption is highest in January and lowest in the summer months. The unregistered households (Tip-NR and Control-NR groups) consume less electricity than the registered households (Tip-R, Norm-R and Control-R groups).

The experiment was carried out in the operation area of one electricity distributor in Finland. In addition, the experiment consists of households who had agreed to participate to the experiment (opt-in setting). Table 4 presents background information on the participants and compares their representativeness in relation to all Finnish households and households in the Porvoo region.

The experiment participants are not fully representative of Finnish citizens in general. The households participating in the experiment were slightly smaller than the average in Finland and the Porvoo region. In addition, participants in the experiment were more educated. In terms of living environment, the participants in the experiment correspond to the Finnish average with urban and rural division. In terms of house types, those living in detached houses and semi-detached houses are overrepresented and there are relatively fewer people living in apartment buildings than in the whole country. The share of electric heated homes was the same as the national average. The final group of households used in the analysis differed slightly from the national average in terms of the share of electric heating. The size of households in the final group is almost the same as the Finnish average.

3.4. Econometric model

The randomized field trial makes the assessment of the effect straightforward: the treated groups are compared with their control groups. The differences-in-differences model (DiD), which is a linear regression model, is used to estimate the treatment effect of the information nudges. The estimated equation is:

$$\ln(kWh_{it}) = \alpha + \beta T_i P_t + \tau T_i + \gamma P_t + \mu \Omega_i + \tau \Delta_t + \varepsilon_{it}. \tag{1}$$

The explanatory variable in the model (Eqn 1) is the daily $t = (1, \ldots, 730)$ electricity consumption kWh_{it} of the household i, obtained by aggregating the hourly consumption data of the households for each day. A logarithm is taken of the dependent variable so that the effects on electricity consumption can be interpreted as percentage changes[10]. T_i is an indicator for the treated group and P_t is an indicator for the treatment period. Ω_i includes household and building-specific background variables observed before the treatment period, and Δ_t presents weather-related variables from both the pretreatment and treatment periods. In addition, monthly indicators for both periods are included. ε_{it} is the error

[7] The content was interesting to 81% of the respondents, 84% thought it was easy to understand, 59% stated it contained new information, and 56% said that the newsletters contained tips that they needed.

[8] Unfortunately, the visit count for the comparison tool did not work during the first five months of the experiment due to a technical issue. Only the last visit was recorded, and thus, the recorded three visits is likely a slight underestimate.

[9] Business can be related to, for example, agricultural production, in which case controlling consumption is challenging.

[10] The results are not sensitive to taking the logarithm.

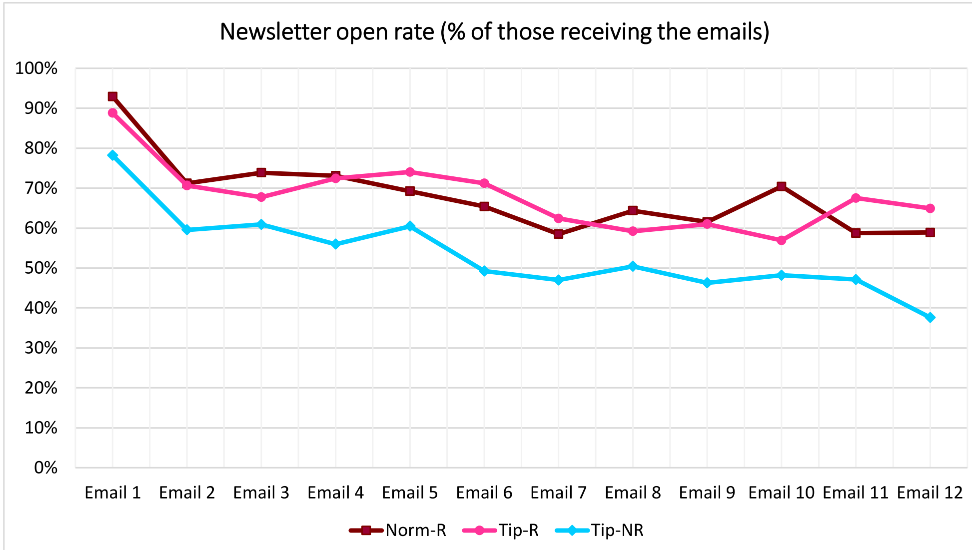

Fig. 2. Email newsletter open rates (%) of those successfully receiving the newsletter.

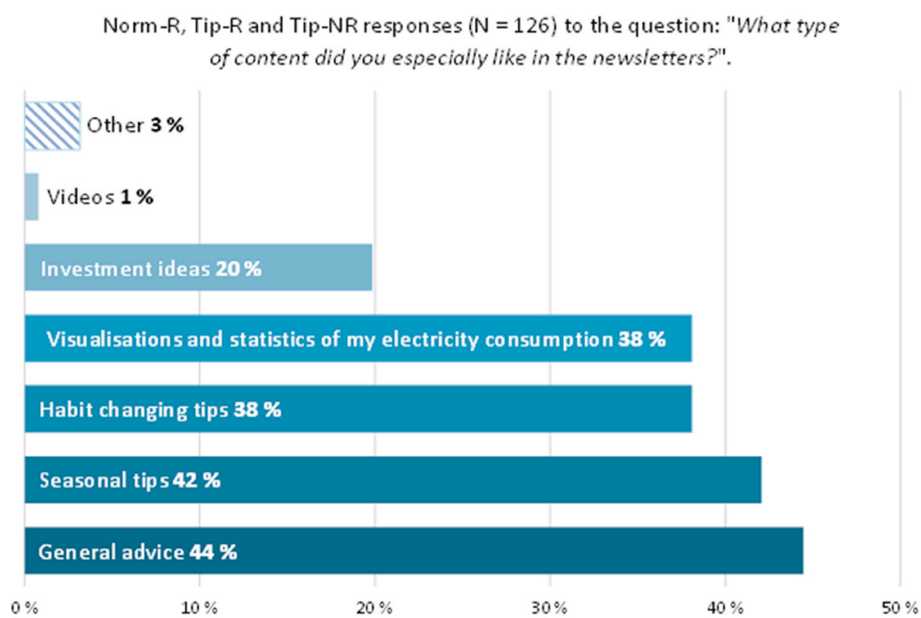

Fig. 3. Respondent preferences over newsletter content types.

term. The treatment effect is interpreted from the β estimate. Household and building-specific background data as well as weather-related data serve as control variables in the model.[11] Heteroskedasticity and auto-correlation robust household-level clustered standard errors are used.

The study uses an intention to treat setting i.e., the effect of receiving an e-mail delivered information letter is analyzed, not the effect of reading the letter. It is not possible to identify how well the energy saving tips have actually been read among the targeted households.

The key DiD assumption of common pre-treatment trends between the treatment and control groups is valid in this experiment (see Fig. 4). It is noteworthy that the common pre-treatment trends assumption does not require the groups (see Appendix A Table A1) to be otherwise completely similar in properties (Angrist and Pischke, 2014; Frölich and Sperlich, 2019).

The average treatment effect was identified on an annual basis. Moreover, the monthly treatment effect variation was examined by dividing the treatment period indicator into twelve monthly periods. For example, the effect of the treatment in December was identified by determining the December treatment indicator, which received a value of 1 in December 2018 and otherwise 0. The monthly model includes the same control variables as the annual model (temperature, humidity, and household and building characteristics).

4. Results

4.1. Annual treatment effect

The annual results of the experiment are shown in Table 5. The

[11] Electricity prices are not included in the analysis because the experiment participants did not have hourly varying spot-price electricity sales contracts available.

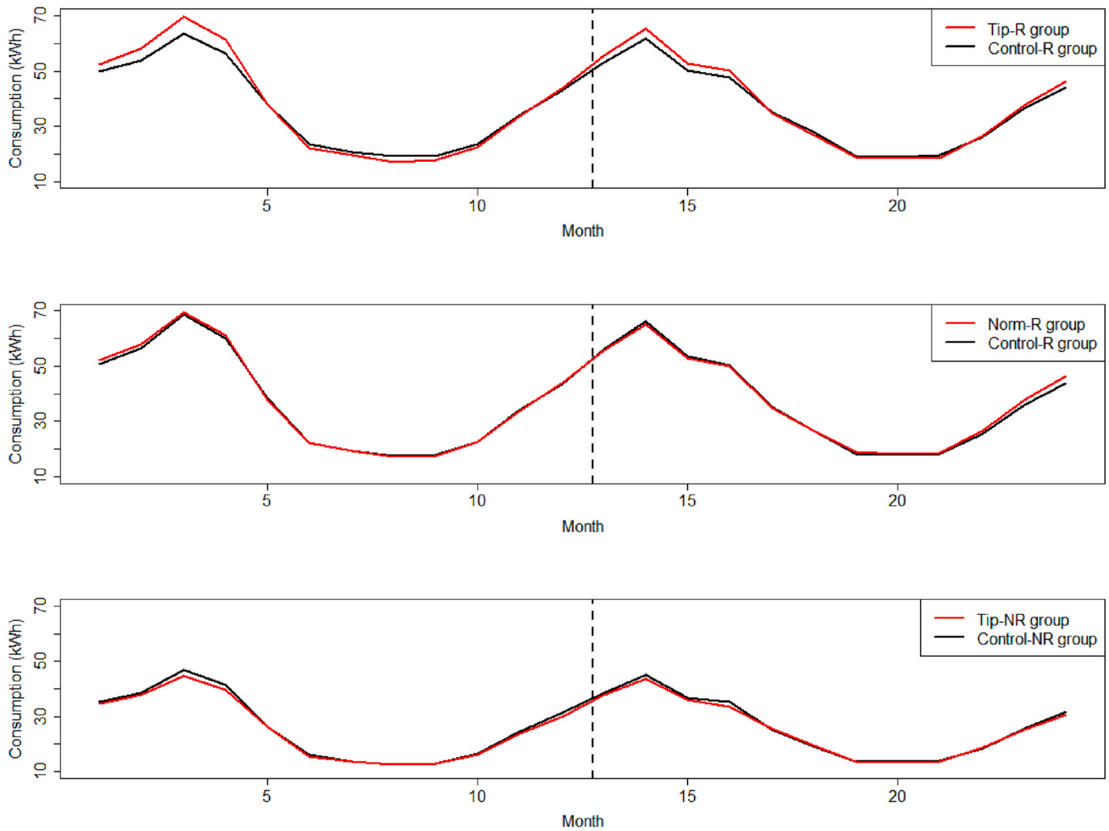

Fig. 4. Average daily electricity consumption at the monthly level for treatment and control groups.

Table 4
Descriptive statistics of the participants in the experiment and comparison with Finnish households.

	Agreed to the experiment	Final experiment group	Corresponding statistics: Finns	Corresponding statistics: Porvoo residents
N	671	528		
	Average	***Average***	***Average***	***Average***
Age (years)	53.1[g]	54.2[g]	42.9 [a g]	42.5[a g]
Household size (persons)	2.58[g]	2.67	2.75 [b]	2.80 [b g]
Apartment size (m^2)	134	140	NA	NA
	Percent (%)	***Percent (%)***	***Percent (%)***	***Percent (%)***
Household income (gross, €/month)				
under 4000 €	27.7	25.6	NA	NA
4000–5999	27.8	26.5	NA	NA
6000–7999	20.6	21.0	NA	NA
8000–9999	12.8	13.3	NA	NA
over 10,000 €	11.0	11.0	10.7	NA
Highly educated	63.9[g]	64.6[g]	31.8[d g]	32.8[d g]
Living environment				
Urban	69.0	62.9[g]	70.3[c]	87.8[c g]
Countryside	31.0	37.1[g]	28.4[c]	11.0[c g]
House type				
Detached or semi- detached house	74.5[g]	79.4[g]	39.3[e g]	NA
Terraced house	10.6[g]	9.8[g]	13.9[e g]	NA
Apartment building	14.9[g]	10.8[g]	46.8[e g]	NA
Electric heating				
Yes	41.7	43.6[g]	38.6[f g]	NA
No	58.3	56.4[g]	61.4[f g]	NA

NA: No information available.
[a] 11ra – Key figures on population by region 1990–2019 (Official Statistics of Finland, 2020c).
[b] 12c1 - Key figures on families by family type and area, 2006–2018 (Official Statistics of Finland, 2019a).
[c] 11s3 – Population according to urban-rural classification by age and sex, 2000–2018 (Official Statistics of Finland, 2019b).
[d] 12bs - Population aged 15 or over by level of education, municipality, region, gender and age, 2007–2018. (Official Statistics of Finland, 2019c).
[e] Appendix Table 1. Number of buildings, dwellings and persons by type of building and number of storeys Dec. 31, 2017 (Official Statistics of Finland, 2017a).
[f] Appendix Table 3. Number of buildings by heating fuel 1970–2017 (Official Statistics of Finland, 2017b).
[g] The means or proportions are not equal at the 5% level according to the *t*-test or chi-squared test (experimental group compared to the corresponding statistics of Finns and Porvoo residents).

Table 5
Annual treatment effects.

	Dependent variable: ln(daily electricity consumption)		
TREATMENT	Tip-NR	Tip-R	Norm-R
Average treatment effect: estimate (s.e.)	0.013 (0.021)	−0.015 (0.019)	−0.005 (0.016)
Controls			
Household characteristics (household size, income, education, language, work)	✓	✓	✓
Building characteristics (house type, type of ownership, floor area, building age, location, heating mode, level of electricity consumption)	✓	✓	✓
Weather variables (outdoor temperature, rainfall)	✓	✓	✓
Adjusted R^2	0.72	0.75	0.79
Number of observations	146000	160 600	159 140

Estimate is statistically significant at the 1%=***, 5%=** or 10%=* risk level.

results imply that the tested information treatments do not statistically significantly reduce household electricity consumption in the treated groups. The explanatory power of each model is high, and the results obtained are robust for different treatments of control variables. The sensitivity analysis can be found in Appendix B (Table B1, B2 and B3).

Due to large seasonal outdoor temperature fluctuation and high share of electric heated buildings (see Table 4) in the data sample, the electricity consumption is very low in the summertime and high during colder months (see Fig. 4). In other words, the energy saving potential is the highest in winter. The annual estimate does not reflect possible changes within shorter time periods. Therefore, it is important to examine whether there are differences in the treatment effects between months.

4.2. Monthly treatment effect

To determine the monthly effects, the control period indicator was divided into twelve monthly periods, where the differences in consumption between the treated and control groups were compared with the differences in the corresponding period a year ago. Figs. 5–7 present the monthly average treatment effects. The full model results are shown in Appendix C Table C1.[12]

The results for the Tip-R group are demonstrated in Fig. 5. According to the results, there is a clear variation in the treatment effects between months. The energy saving tip treatment decreases electricity consumption statistically significantly during the first months of the experiment. At the very beginning of the experiment, households in the Tip-R group consume on average 10.7% less electricity compared to November a year ago. The effect of information treatment on reducing electricity consumption is noticeable until March, when the average treatment effect is still −7.8%. Average reductions in daily electricity consumption vary between 6.4 kWh (January) and 3.7 kWh (November 2019). Between April and October, the electricity consumption increases statistically significantly in May and August about 9%. This means an average increase of 2.4 kWh per day in May and 1.8 kWh in August. Unexpected increase in consumption may, for instance, relate to the newsletter content in the summer. The newsletter in June focused on cooling, in which case households owning air source heat pumps may have increased cooling that results as a rise in electricity consumption in the hot August of 2019. In addition, possible holiday home observations remaining in the final data may explain these increases. Comparison of holiday home electricity consumption between different summer seasons is not meaningful, because the use of holiday homes varies between years. At the beginning of the heating season in November 2019, the information treatment again reduces the daily electricity consumption of households by on average 8.3% (3.7 kWh). Kažukauskas et al. (2020) found somewhat similar seasonal variation in the treatment effects for Sweden.

Additional analyses (see Supplementary material) show that households living in detached houses and households with lower income have especially reduced their consumption. Moreover, the additional analyses reveal that having electric heating is not necessarily the main determinant for the treatment effects. In other words, energy savings are not guaranteed by targeting nudges only towards electric-heated houses.

Fig. 6 presents the monthly treatment effects for the Norm-R group. The results reveal that the treatment does not induce statistically significant changes in household electricity consumption during the first 11 months. At the very end of the experiment, in November 2019, a statistically significant decrease in electricity consumption is observed. The effect of the treatment in November 2019 is −7.9%, which corresponds to an average reduction of 3.5 kWh on a daily basis. The late and desired response to the treatment can be explained, among other things, by the fact that in the beginning of experiment the Norm-R group was provided simpler energy advice than the Tip-R group. During the first eight months of the experiment, the information given for Norm-R group focused mainly on the comparison tool and electricity consumption monitoring. Later in fall 2019, the content of the newsletters largely corresponded to Tip-R group with more detailed energy saving tips. In addition, the activity of the Norm-R group to use the comparison tool was low throughout the experiment with approximately three visits per household during the one-year trial and about 40% of households not using the service at all.

Furthermore, additional analyses show (see Supplementary material) that by focusing solely on households with above-average levels of electricity consumption, treatment has statistically significantly reduced the electricity consumption of the households after September when more detailed energy advice content was added to newsletters. This implies that information nudging which combines social norm and energy saving tips works as expected: high-consumption households tend to reduce their consumption towards the average household (see also Ayres et al. (2013)).

The results of the Tip-NR group are shown in Fig. 7. Information treatment does not statistically significantly affect electricity consumption in the Tip-NR group during the entire experiment. This finding can be explained, for instance, by the observation that the opening rates of newsletters were generally lower among the unregistered than among the registered households (see Fig. 2). The Tip-NR group also included households with significantly lower electricity consumption compared to the registered households, and in turn, these households may have difficulties to reduce their electricity consumption due to the low starting level. Additional analyses do not reveal statistically significant treatment effects in the studied subsamples (e.g., households living in detached houses).

After the information nudging ends in November 2019, the treatment effect disappears relatively quickly by January 2020 in the Tip-R and Norm-R groups (see Supplementary material).[13] This implies that the permanence of the tested information nudging is important in supporting electricity savings.

[12] In addition to the DiD models estimated with OLS, the household fixed effects models were estimated to account for any unobservable household-specific effects. Overall, the fixed effects model results (see Supplementary material) are similar with the ones reported in the paper.

[13] The data for the after-treatment persistence analysis covers the period between November 23rd in 2019 and February 29th in 2020. The persistence analysis for the whole year is not reasonable due to escalating COVID-19 situation and lock down starting in March 2020.

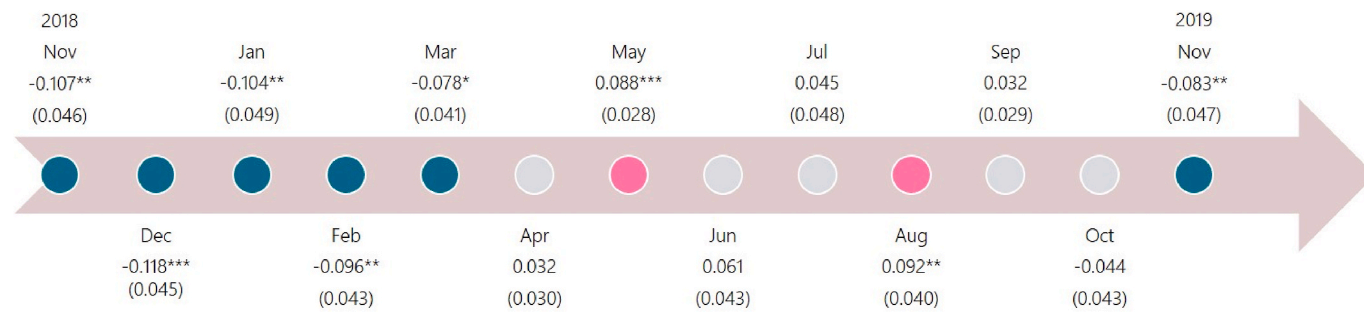

Fig. 5. Monthly average treatment effects in the Tip-R group (standard errors in parentheses). Estimate is statistically significant at the 1% = ***, 5% = ** or 10% = * risk level.

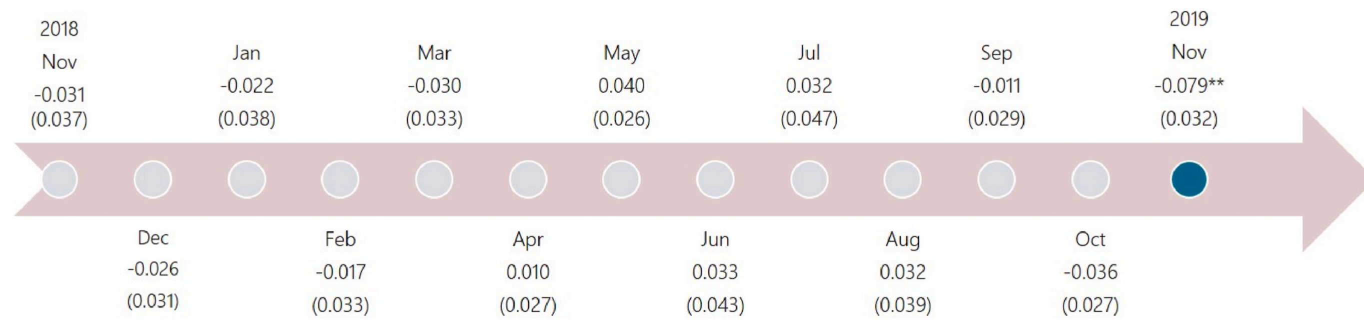

Fig. 6. Monthly average treatment effects in the Norm-R group (standard errors in parentheses). Estimate is statistically significant at the 1% = ***, 5% = ** or 10% = * risk level.

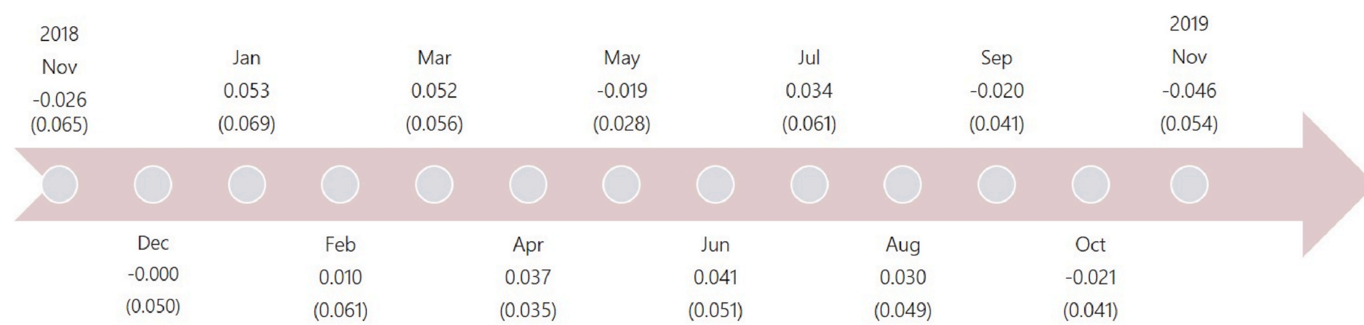

Fig. 7. Monthly average treatment effects in the Tip-NR group (standard errors in parentheses). Estimate is statistically significant at the 1% = ***, 5% = ** or 10% = * risk level.

5. Discussion

5.1. Information nudging and energy advice

This experiment gathered versatile information about household electricity consumption and energy advice, especially related to advising on digital platforms. One of the key findings is the importance of advice timing. The experiment shows that information nudging can be effective in wintertime, when energy issues are more prominent and electricity bills are highest in locations with cold climate, such as Finland. The effect of information nudging seems to decrease and the desired responses weaken with smaller electricity bills, at least among the users of the online electricity consumption following service. The effectiveness of information nudging may also be associated with initial enthusiasm. In this study, the newsletter opening percentages and reading were highest among all treated groups at the beginning of the experiment (see Fig. 2). On the other hand, Norm-R group had no noticeable treatment effects at the beginning of the experiment unlike Tip-R group. In addition, the energy saving tips worked in the Tip-R group also at the end of the experiment in November 2019.

The findings also indicate that targeting is essential. We find that users of an online energy service platform, those who are likely more interested in energy issues, are a receptive target group for information nudges. The findings demonstrate challenges to activate households who are not using such services (i.e., here the Tip-NR group) to read the monthly newsletters and reduce their electricity consumption. If the household is not interested in energy issues, the lack of interest is very likely reflected in the effectiveness of energy advice.

Furthermore, experiment results imply that information content matters. Energy advising should be up-to-date and contain suggestions and tips for each household's own needs. Households expressed a particular liking for general and seasonal energy saving tips in the end survey. Information suited for the living situation was also liked among households, and personalization was found to increase interest. For example, information about household's own level of electricity consumption increased the reading activity of the newsletters, and almost 40% of the participants said that they especially liked such content (see Figs. 2 and 3). Literature also suggests that personalization works

(Buckley, 2020).

Email proved to be a relatively efficient and cost-effective solution to deliver energy advice. The literature on the email as a delivery mode is inconclusive (Andor and Fels, 2018; Dolan and Metcalfe, 2015; Schleich et al., 2013). Although the newsletter sent by email did not necessarily reach all participants due to technical and other problems, email was perceived as a well-functioning channel to deliver energy advising among the experiment participants. The frequency of information steering with energy-saving tips once a month was reported to be appropriate among households.

In addition to email newsletters, the experiment utilized an online electricity consumption monitoring service. The experiment showed that information steering can successfully encourage households to start using online electricity consumption monitoring service. Overall, the households participating in the experiment expressed interest in monitoring electricity consumption. Well-designed and meaningful services can make the most of this existing interest.

However, activating households to make peer-to-peer comparisons in the online service proved to be challenging, and some households did not use the tool at all. This challenge was, at least partly, due to the unsatisfactory accessibility of the comparison tool. According to the results of the experiment, peer-to-peer comparisons had the desired effect when combined with more detailed energy advice. Previous research has found peer-to-peer comparisons to work, but often the information delivery mode has been easier and accessible, such as home energy report delivered by mail (Allcott, 2011; Andor et al., 2020).

5.2. Other policies and study limitations

Nudging belongs to soft policies where behavior change is motivated without forcing, restriction of choice, or large economic incentives. Hard policies include, for instance, pricing and legislation. In this experiment it was not possible to examine pricing effects, because the distributor company collaborating with the experiment did not have an hourly-based dynamic electricity pricing contract available to its customers.

Previous literature on the effectiveness of different soft and hard policies in changing household electricity consumption is relatively rich (see, e.g., Buckley, 2020; Jessoe and Rapson, 2014). In general, electricity pricing may struggle to provide sufficiently large incentives for households to change their consumption behavior (Csereklyei, 2020; Palmer, 2019). Moreover, economic incentives are often legally, socially and administratively more challenging and burdensome than information steering. On the other hand, soft and hard policies should not be seen as mutually exclusive. Indeed, information treatments can often strengthen and support pricing (Jessoe and Rapson, 2014; Sudarshan, 2017).

It was known already in the planning phase of the experiment that the participants would not be a representative sample of all Finns (see Table 4). Household electricity consumption data is in the possession of energy companies, and therefore, the study required a partner company to carry out the experiment. In addition, the study dealt with data subject to GDPR regulations, and thus, households were asked for permission to participate in the experiment. For these reasons, the experiment was conducted at the Porvoo Energia's distribution network area, and in principle, households more interested in energy issues were likelier to participate. Although the results cannot be generalized to all Finns, the experiment offers valuable new insights on the effectiveness of information nudges especially among the southernmost Finnish households and, more generally, among those who are interested in energy issues. Furthermore, if alike voluntary information steering was adopted in other areas, the participating group would likely be similar.

Even though the opening activity of the participants' newsletters was recorded, it was not possible to have full understanding on the level of engagement with the delivered information content among participants. Hence, the resulting intention to treat approach may be reflected as reduced effectiveness of the information treatment. On the other hand, the intention to treat approach captures well the characteristics of the email information delivery method: not all emails are properly read.

6. Conclusion and policy implications

This study investigates how households living in the Nordic climate conditions with a high seasonal variation in the temperature and energy consumption respond to energy saving tips and peer comparisons. To study this, a randomized field experiment is conducted to find effective ways to encourage energy saving.

The main finding of the study suggests that information nudges can reduce electricity consumption of households who are more involved in following their electricity consumption. Among such households, versatile energy saving tips can reduce average daily electricity consumption around 10% during wintertime. This is a significant reduction, particularly with winter being the critical time for power balance of power grids in cold climate conditions. On the other hand, the findings depict challenges in encouraging energy saving behavior within households for whom the energy related issues are of less interest. More research is required to identify the drivers that could help activate these households.

The study highlights that well-planned and continuing informational content sent digitally for large consumer mass could be a cost-effective way to encourage energy saving. The effort required to extend the information nudging to new households, even with some personalized content, is minimal as the cost of sending an email is very low. Encouraged by the experiment results, Motiva Ltd has launched a quarterly seasonal consumer energy advice newsletter with personalization based on house type, heating system and location. Developing a more personalized content would require cooperation between energy companies and an advising organization because the energy companies possess household-specific consumption data. The experiment has also helped to design and summarize the data content related to energy conservation, electricity consumption and consumption flexibility, taking into account various motivation factors.

The study also provides insights on the roles of different actors in energy advising. The findings indicate that online energy service and monitoring tools must be well-functioning, easy to access and to use. The development work of these services will be left to energy companies. As energy advice is associated with positive externalities, it is not desirable to decentralize energy advice and information provision to energy companies alone. In order to be effective, it is essential that general and high-quality advice is provided centrally by national actors. Energy companies can then build workable advisory concepts on top of general information guidance.

Overall, changes in electricity consumption behavior require different policies, solutions and actors to succeed. Successful change requires well-functioning structures and regulation in society, technologies that facilitate and are sufficiently affordable for behavior change, the right financial incentives, and well-designed and thoughtfully implemented energy advice.

CRediT authorship contribution statement

Enni Ruokamo: Conceptualization, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing, Project administration. **Teemu Meriläinen:** Conceptualization, Formal analysis, Investigation, Validation, Visualization, Writing – original draft, Writing – review & editing. **Santtu Karhinen:** Formal analysis, Methodology, Investigation, Data curation, Validation, Visualization, Writing – original draft, Writing – review & editing. **Jouni Räihä:** Investigation, Validation, Writing – review & editing. **Päivi Suur-Uski:** Conceptualization, Investigation, Validation, Writing – review & editing, Project administration. **Leila Timonen:** Conceptualization, Investigation, Validation, Writing – review & editing. **Rauli Svento:** Conceptualization, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing, Project administration, Funding acquisition.

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.

Acknowledgments

The authors wish to acknowledge the discussions throughout the experiment with Pekka Ripatti and Mervi Suni working at the Finnish Energy Authority. The close collaboration with Porvoon Energia is highly appreciated. The authors would especially like to thank Jukka Rouhiainen and Tomas Nordström for the cooperation. Moreover, the authors wish to thank Florian Kühnlenz, Mauricio de Castro Tomé and Ludi Wang for their help during the research work. The authors also thank the participants of the 42nd Annual Meeting of the Finnish Economic Association in Tampere and the participants of the 6th European Conference on Behavior and Energy Efficiency BEHAVE as well as the two anonymous reviewers for their constructive comments. Funding from the Strategic Research Council, operating in connection with the Academy of Finland, projects BCDC Energy (292854) and DECARBONHOME (335252) as well as the Academy of Finland project EcoRiver (323810) is gratefully acknowledged. Part of this work by the second author was carried out within the financial support from the Finnish Cultural Foundation.

Appendix A. Final sample descriptive statistics

Table A1
Descriptive statistics for treatment and control groups in the final sample.

	Non-registered		Registered		
	Tip-NR	**Control-NR**	**TiP-R**	**Control-R**	**Norm-R**
N	100	100	110	110	108
Age (average years)	54.2	56.4	52.9	53.9	53.7
Household size (average persons)	2.51	2.3	2.8	3.0	2.7
Heat floor space (average m^2)	119.5	122.7	149.2	158.3	145.5
	(%)	***(%)***	***(%)***	***(%)***	***(%)***
Female	42.0	34.0	21.8	20.0	26.9
Household monthly income <6000€	68.0	64.0	45.5	44.5	40.7
University degree	71.0	66.0	60.9	61.8	63.9
Opted for Swedish content	27.0	26.0	24.5	33.6	28.7
Detached house	60.0	64.0	82.7	83.6	81.5
Electric heating	33.0	38.0	46.4	44.5	54.6

Appendix B. Annual treatment effect results

Table B1
Annual results for Tip-NR group.

	model 1		model 2		model 3		model 4	
	Dependent variable: daily electricity consumption ln(kWh)							
	estimate	s.e.	estimate	s.e.	estimate	s.e.	estimate	s.e.
constant	2.711***	0.094	2.956***	0.102	1.151***	0.319	3.235***	0.333
treated_dummy	−0.027	0.138	−0.027	0.138	−0.033	0.096	0.013	0.052
treatmentperiod_dummy	0.007	0.014	−0.013	0.014	−0.013	0.014	−0.005	0.014
treated_dummy*treatmentperiod_dummy	0.013	0.021	0.013	0.021	0.013	0.021	0.013	0.021
temperature			−0.036***	0.002	−0.036***	0.002	−0.009***	0.002
rainfall			0.002***	0.000	0.002***	0.000	0.001***	0.000
age					−0.002	0.004	−0.002	0.003
household size					0.059	0.040	0.034	0.024
income					0.028	0.044	−0.005	0.029
high education					0.046	0.112	−0.018	0.059
Swedish language					−0.187	0.126	−0.077	0.066
energy expertise					−0.082	0.145	−0.084	0.088
floor area					0.006***	0.001	0.003***	0.001
home age					−0.001	0.002	−0.002	0.001
detached house					0.809***	0.184	0.052	0.133
semidetached house					0.909***	0.260	−0.010	0.172
terraced house					0.205	0.156	0.070	0.101
owner-occupied					0.601***	0.181	0.166	0.112
sparsely populated area					−0.015	0.168	−0.135	0.087
accumulating electric heating							0.502***	0.132
direct electric heating							0.303**	0.128
ground heating							−0.102	0.118
air-to-water heat pump							0.599***	0.111
supplementary heating							−0.077	0.092
low electricity consumption							−1.889***	0.189
average electricity consumption							−0.994***	0.113
temperature*accum. electric heating							−0.031***	0.007

(*continued on next page*)

Table B1 (*continued*)

	model 1		model 2		model 3		model 4	
	Dependent variable: daily electricity consumption ln(kWh)							
	estimate	s.e.	estimate	s.e.	estimate	s.e.	estimate	s.e.
temperature *direct electric heating							−0.029***	0.005
temperature *ground heating							−0.028***	0.004
temperature *air-to-water heat pump							−0.039***	0.007
Jan_dummy							0.043	0.031
Feb_dummy							0.021	0.031
Mar_dummy							0.011	0.021
Apr_dummy							−0.093***	0.019
May_dummy							−0.229***	0.023
Jun_dummy							−0.333***	0.028
Jul_dummy							−0.317***	0.030
Aug_dummy							−0.304***	0.027
Sep_dummy							−0.209***	0.025
Oct_dummy							−0.101***	0.012
Dec_dummy							0.063***	0.023
Observations (N)	146000		146000		146000		146000	
R2	0.000		0.080		0.461		0.718	
Adjusted R2	0.000		0.080		0.461		0.718	

Estimate is statistically significant at the 1%=***, 5%=** or 10%=* risk level.

Table B2
Annual results for Tip-R group.

	model 1		model 2		model 3		model 4	
	Dependent variable: daily electricity consumption ln(kWh)							
	estimate	s.e.	estimate	s.e.	estimate	s.e.	estimate	s.e.
constant	3.251***	0.067	3.554***	0.071	1.629***	0.316	3.075***	0.262
treated_dummy	−0.080	0.107	−0.080	0.107	−0.039	0.078	−0.027	0.043
treatmentperiod_dummy	0.021**	0.011	−0.004	0.011	−0.004	0.011	0.005	0.011
treated_dummy*treatmentperiod_dummy	−0.015	0.019	−0.015	0.019	−0.015	0.019	−0.015	0.019
temperature			−0.044***	0.002	−0.044***	0.002	−0.012***	0.003
rainfall			0.002***	0.000	0.002***	0.000	0.001***	0.000
age					−0.001	0.004	0.001	0.003
household size					0.127**	0.036	0.061***	0.018
income					0.056*	0.034	0.016	0.019
high education					−0.169**	0.084	−0.088**	0.044
Swedish language					−0.188**	0.087	−0.016	0.046
energy expertise					−0.142	0.098	0.049	0.056
floor area					0.002**	0.001	0.001***	0.000
home age					0.001	0.001	0.000	0.001
detached house					1.444***	0.203	0.590***	0.168
semidetached house					1.822***	0.279	0.662***	0.200
terraced house					0.671***	0.230	0.388**	0.170
owner-occupied					−0.041	0.182	−0.127	0.164
sparsely populated area					0.017	0.105	−0.120*	0.067
accumulating electric heating							0.341***	0.092
direct electric heating							0.379***	0.076
ground heating							−0.021	0.105
air-to-water heat pump							0.120	0.160
supplementary heating							0.047	0.079
low electricity consumption							−1.353***	0.119
average electricity consumption							−0.552***	0.051
temperature*accum. electric heating							−0.026***	0.004
temperature *direct electric heating							−0.029***	0.004
temperature *ground heating							−0.017***	0.005
temperature *air-to-water heat pump							−0.025***	0.007
Jan_dummy							0.063***	0.010
Feb_dummy							0.039***	0.010
Mar_dummy							0.010	0.012
Apr_dummy							−0.102***	0.020
May_dummy							−0.254***	0.022
Jun_dummy							−0.369***	0.027
Jul_dummy							−0.366***	0.030
Aug_dummy							−0.357***	0.028
Sep_dummy							−0.262***	0.021
Oct_dummy							−0.120***	0.008
Dec_dummy							0.073***	0.010
Observations (N)	160 600		160 600		160 600		160 600	
R2	0.002		0.17		0.499		0.752	
Adjusted R2	0.002		0.17		0.499		0.752	

Estimate is statistically significant at the 1%=***, 5%=** or 10%=* risk level.

Table B3
Annual results for Norm-R group.

	model 1		model 2		model 3		model 4	
	Dependent variable: daily electricity consumption ln(kWh)							
	estimate	s.e.	estimate	s.e.	estimate	s.e.	estimate	s.e.
constant	3.251***	0.067	3.578***	0.071	1.197***	0.241	2.452***	0.153
treated_dummy	−0.015	0.098	−0.015	0.098	0.046	0.066	0.051	0.036
treatmentperiod_dummy	0.021**	0.011	−0.006	0.011	−0.006	0.011	0.005	0.011
treated_dummy*treatmentperiod_dummy	−0.003	0.016	−0.003	0.016	−0.003	0.016	−0.005	0.016
temperature			−0.048***	0.002	−0.048***	0.002	−0.014***	0.003
rainfall			0.002***	0.000	0.002***	0.000	0.001***	0.000
age					0.003	0.003	0.004**	0.001
household size					0.103**	0.032	0.062***	0.015
income					0.103***	0.028	0.032*	0.018
high education					−0.075	0.067	−0.038	0.037
Swedish language					−0.138*	0.072	−0.033	0.033
energy expertise					−0.141*	0.082	−0.083**	0.041
floor area					0.002**	0.001	0.001***	0.000
home age					0.003	0.001	−0.001	0.001
detached house					1.595***	0.213	0.855***	0.166
semidetached house					1.826***	0.309	1.027***	0.209
terraced house					1.024***	0.232	0.701***	0.165
owner-occupied					−0.222	0.144	−0.115	0.100
sparsely populated area					0.176**	0.073	−0.001	0.041
accumulating electric heating							0.349***	0.073
direct electric heating							0.324***	0.063
ground heating							0.008	0.108
air-to-water heat pump							0.243***	0.083
supplementary heating							0.039	0.044
low electricity consumption							−1.079***	0.085
average electricity consumption							−0.478***	0.039
temperature*accum. electric heating							−0.025***	0.005
temperature *direct electric heating							−0.028***	0.003
temperature *ground heating							−0.016***	0.005
temperature *air-to-water heat pump							−0.026***	0.006
Jan_dummy							0.081***	0.008
Feb_dummy							0.057***	0.008
Mar_dummy							0.018***	0.009
Apr_dummy							−0.118***	0.012
May_dummy							−0.276***	0.015
Jun_dummy							−0.382***	0.020
Jul_dummy							−0.371***	0.023
Aug_dummy							−0.371***	0.020
Sep_dummy							−0.281***	0.014
Oct_dummy							−0.118***	0.008
Dec_dummy							0.095***	0.007
Observations (N)	159 140		159 140		159 140		159 140	
R2	0.000		0.225		0.576		0.790	
Adjusted R2	0.000		0.225		0.576		0.790	

Estimate is statistically significant at the 1%=***, 5%=** or 10%=* risk level.

Appendix C. Monthly treatment effect results

Table C1
Monthly results for Tip-R, Norm-R and Tip-NR groups.

	Tip-R		Norm-R		Tip-NR	
	Dependent variable: daily electricity consumption ln(kWh)					
	estimate	s.e.	estimate	s.e.	estimate	s.e.
constant	3.054***	0.263	2.466***	0.155	3.269***	0.317
treated_dummy	−0.026	0.043	0.054	0.036	0.010	0.051
Nov2018_treatmentperiod_dummy	0.105***	0.027	0.093***	0.023	0.071	0.052
Dec_ treatmentperiod _dummy	0.020	0.021	−0.003	0.019	−0.018	0.035
Jan_ treatmentperiod _dummy	0.019	0.025	−0.008	0.023	−0.045	0.043
Feb_ treatmentperiod _dummy	0.051**	0.022	0.034	0.022	0.013	0.039
Mar_ treatmentperiod _dummy	0.000	0.022	−0.013	0.022	−0.058	0.049
Apr_ treatmentperiod _dummy	−0.056***	0.020	−0.047***	0.018	−0.042	0.026
May_ treatmentperiod _dummy	0.010	0.018	0.028	0.018	0.060***	0.022
Jun_ treatmentperiod _dummy	−0.021	0.025	0.003	0.023	0.016	0.030
Jul_ treatmentperiod _dummy	−0.083***	0.031	−0.070**	0.029	−0.046	0.039
Aug_ treatmentperiod _dummy	−0.037	0.026	−0.030	0.025	−0.009	0.029
Sep_ treatmentperiod _dummy	0.025	0.021	0.043**	0.020	0.029	0.024

(continued on next page)

Table C1 (*continued*)

	Tip-R		Norm-R		Tip-NR	
	Dependent variable: daily electricity consumption ln(kWh)					
	estimate	s.e.	estimate	s.e.	estimate	s.e.
Oct_ treatmentperiod _dummy	0.060***	0.020	0.048***	0.019	−0.004	0.021
Nov 2019_ treatmentperiod _dummy	0.075***	0.024	0.069***	0.021	0.034	0.037
treated_dummy* Nov2018_treatmentperiod_dummy	−0.107**	0.046	−0.031	0.037	−0.026	0.065
treated_dummy* Dec_ treatmentperiod _dummy	−0.118***	0.045	−0.026	0.031	0.000	0.050
treated_dummy* Jan_ treatmentperiod _dummy	−0.104**	0.049	−0.022	0.038	0.053	0.069
treated_dummy* Feb_ treatmentperiod _dummy	−0.096**	0.043	−0.017	0.033	0.010	0.061
treated_dummy* Mar_ treatmentperiod _dummy	−0.078*	0.041	−0.030	0.033	0.052	0.056
treated_dummy* Apr_ treatmentperiod _dummy	0.032	0.030	0.010	0.027	0.037	0.035
treated_dummy* May_ treatmentperiod _dummy	0.088***	0.028	0.040	0.026	−0.019	0.028
treated_dummy* Jun_ treatmentperiod _dummy	0.061	0.043	0.033	0.043	0.041	0.051
treated_dummy* Jul_ treatmentperiod _dummy	0.045	0.048	0.032	0.047	0.034	0.061
treated_dummy* Aug_ treatmentperiod _dummy	0.092**	0.040	0.032	0.039	0.030	0.049
treated_dummy* Sep_ treatmentperiod _dummy	0.032	0.029	−0.011	0.029	−0.020	0.041
treated_dummy* Oct_ treatmentperiod _dummy	−0.044	0.043	−0.036	0.027	−0.021	0.041
treated_dummy* Nov 2019_ treatmentperiod _dummy	−0.083*	0.047	−0.079**	0.032	−0.046	0.054
temperature	−0.012***	0.003	−0.013***	0.003	−0.009***	0.002
rainfall	0.001***	0.000	0.000	0.000	0.001**	0.000
age	0.001	0.003	0.003**	0.002	−0.002	0.002
household size	0.062***	0.017	0.062***	0.016	0.033	0.024
income	0.007	0.018	0.023	0.017	−0.007	0.028
high education	−0.082*	0.044	−0.033	0.037	−0.019	0.058
Swedish language	−0.018	0.046	−0.037	0.033	−0.071	0.066
energy expertise	0.051	0.057	−0.080**	0.040	−0.093	0.088
floor area	0.001***	0.000	0.001***	0.000	0.003***	0.001
house age	0.000	0.001	−0.001	0.001	−0.002**	0.001
detached house	0.584***	0.167	0.843***	0.164	0.045	0.130
semi-detached house	0.659***	0.200	1.021***	0.208	−0.023	0.170
terraced house	0.385**	0.171	0.693***	0.165	0.060	0.099
owner-occupied	−0.116	0.164	−0.102	0.101	0.161	0.109
sparsely populated area	−0.123*	0.067	−0.005	0.041	−0.130	0.088
accum. electric heating	0.339***	0.092	0.354***	0.072	0.482***	0.133
direct electric heating	0.379***	0.076	0.330***	0.063	0.300**	0.127
ground heating	−0.021	0.106	0.004	0.108	−0.113	0.166
air-to-water heat pump	0.117	0.159	0.241***	0.082	0.595***	0.111
supplementary heating	−0.047	0.079	0.036	0.044	−0.075	0.091
low electricity consumption	−1.358***	0.118	−1.086***	0.083	−1.890***	0.189
average electricity consumption	−0.554***	0.052	−0.477***	0.040	−0.997***	0.112
temperature*accum. electric heating	−0.025***	0.004	−0.025***	0.005	−0.031***	0.007
temperature*direct electric heating	−0.029***	0.004	−0.028***	0.003	−0.029***	0.005
temperature*ground heating	−0.017***	0.005	−0.016***	0.005	−0.028***	0.004
temperature*air-to-water heat pump	−0.024***	0.007	−0.026***	0.005	−0.039***	0.007
Jan_dummy	0.101***	0.014	0.113***	0.011	0.065***	0.023
Feb_dummy	0.059***	0.016	0.067***	0.014	0.025	0.023
Mar_dummy	0.050***	0.019	0.054***	0.015	0.039*	0.021
Apr_dummy	−0.064***	0.023	−0.077***	0.013	−0.070***	0.015
May_dummy	−0.266***	0.022	−0.282***	0.017	−0.244***	0.026
Jun_dummy	−0.360***	0.027	−0.374***	0.021	−0.341***	0.029
Jul_dummy	−0.323***	0.030	−0.326***	0.026	−0.293***	0.031
Aug_dummy	−0.348***	0.027	−0.346***	0.023	−0.298***	0.027
Sep_dummy	−0.267***	0.021	−0.280***	0.016	−0.208***	0.025
Oct_dummy	−0.121***	0.010	−0.112***	0.010	−0.083***	0.012
Dec_dummy	0.113***	0.014	0.124***	0.012	0.085***	0.023
Observations (N)	160 600		159 140		146000	
R2	0.753		0.789		0.721	
Adjusted R2	0.753		0.789		0.721	

Estimate is statistically significant at the 1%=***, 5%=** or 10%=* risk level.

Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2021.112731.

References

Allcott, H., 2011. Social norms and energy conservation. J. Publ. Econ. 95, 1082–1095. https://doi.org/10.1016/j.jpubeco.2011.03.003.

Allcott, H., Rogers, T., 2014. The short-run and long-run effects of behavioral interventions: experimental evidence from energy conservation. Am. Econ. Rev. 104 (10), 3003–3037. https://doi.org/10.1257/aer.104.10.3003.

Andor, M.A., Fels, K.M., 2018. Behavioral economics and energy conservation–a systematic review of non-price interventions and their causal effects. Ecol. Econ. 148, 178–210. https://doi.org/10.1016/j.ecolecon.2018.01.018.

Andor, M.A., Gerster, A., Peters, J., Schmidt, C.M., 2020. Social norms and energy conservation beyond the US. J. Environ. Econ. Manag. 103, 102351 https://doi.org/10.1016/j.jeem.2020.102351.

Angrist, J.D., Pischke, J.S., 2014. Mastering'metrics: the Path from Cause to Effect. Princeton University Press.

Asensio, O.I., Delmas, M.A., 2016. The dynamics of behavior change: evidence from energy conservation. J. Econ. Behav. Organ. 126, 196–212. https://doi.org/10.1016/j.jebo.2016.03.012.

Aydin, E., Brounen, D., Kok, N., 2018. Information provision and energy consumption: evidence from a field experiment. Energy Econ. 71, 403–410. https://doi.org/10.1016/j.eneco.2018.03.008.

Ayres, I., Raseman, S., Shih, A., 2013. Evidence from two large field experiments that peer comparison feedback can reduce residential energy usage. J. Law Econ. Organ. 29 (5), 992–1022.

Bird, S., Legault, L., 2018. Feedback and behavioral intervention in residential energy and resource use: a review. Curr. Sustain. Renew. Energy Rep. 5 (1), 116–126. https://doi.org/10.1007/s40518-018-0106-8.

Brandon, A., Ferraro, P.J., Metcalfe, R.D., Price, M.K., Rundhammer, F., 2017. Do the Effects of Social Nudges Persist? Theory and Evidence from 38 Natural Field Experiments. National Bureau of Economic Research, Cambridge, MA. Available at: www.nber.org/papers/w23277.

Brounen, D., Kok, N., Quigley, J.M., 2013. Energy literacy, awareness, and conservation behavior of residential households. Energy Econ. 38, 42–50. https://doi.org/10.1016/j.eneco.2013.02.008.

Buckley, P., 2020. Prices, information and nudges for residential electricity conservation: a meta-analysis. Ecol. Econ. 172, 106635 https://doi.org/10.1016/j.ecolecon.2020.106635.

Byrne, D.P., La Nauze, A., Martin, L.A., 2018. Tell me something I don't already know: informedness and the impact of information programs. Rev. Econ. Stat. 100 (3), 510–527. https://doi.org/10.1162/rest_a_00695.

Carroll, J., Lyons, S., Denny, E., 2014. Reducing household electricity demand through smart metering: the role of improved information about energy saving. Energy Econ. 45, 234–243. https://doi.org/10.1016/j.eneco.2014.07.007.

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.

Csereklyei, Z., 2020. Price and income elasticities of residential and industrial electricity demand in the European Union. Energy Pol. 137, 111079 https://doi.org/10.1016/j.enpol.2019.111079.

De Dominicis, S., Sokoloski, R., Jaeger, C.M., Schultz, P.W., 2019. Making the smart meter social promotes long-term energy conservation. Palgrave Commun. 5 (1), 51. https://doi.org/10.1057/s41599-019-0254-5.

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 Pol. 61, 729–739. https://doi.org/10.1016/j.enpol.2013.05.109.

Dolan, P., Metcalfe, R., 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 (2589269).

Finnish Meteorological Institute, 2021. Seasons in Finland. Available at: https://en.ilmatieteenlaitos.fi/seasons-in-finland.

Frölich, M., Sperlich, S., 2019. Impact Evaluation. Cambridge University Press.

Gans, W., Alberini, A., Longo, A., 2013. Smart meter devices and the effect of feedback on residential electricity consumption: evidence from a natural experiment in Northern Ireland. Energy Econ. 36, 729–743. https://doi.org/10.1016/j.eneco.2012.11.022.

Gleerup, M., Larsen, A., Leth-Petersen, S., Togeby, M., 2010. The effect of feedback by text message (SMS) and email on household electricity consumption: experimental evidence. Energy J. 31 (3), 113–132.

Houde, S., Todd, A., Sudarshan, A., Flora, J.A., Armel, K.C., 2013. Real-time feedback and electricity consumption: a field experiment assessing the potential for savings and persistence. Energy J. 34 (1), 87–102.

Jessoe, K., Rapson, D., 2014. Knowledge is (less) power: experimental evidence from residential energy use. Am. Econ. Rev. 104 (4), 1417–1438. https://doi.org/10.1257/aer.104.4.1417.

Každukauskas, A., Broberg, T., Jaraitė, J., 2020. Social comparisons in real time: a field experi-ment of residential electricity and water use. Scand. J. Econ. https://doi.org/10.1111/sjoe.12422.

Kua, H.W., Wong, S.E., 2012. Lessons for integrated household energy conservation policies from an intervention study in Singapore. Energy Pol. 7, 49–56. https://doi.org/10.1016/j.enpol.2012.04.009.

Lesic, V., de Bruin, W.B., Davis, M.C., Krishnamurti, T., Azevedo, I.M., 2018. Consumers' perceptions of energy use and energy savings: a literature review. Environ. Res. Lett. 13 (3), 033004.

Official Statistics of Finland (OSF), 2020a. Asumisen Energiankulutus [verkkojulkaisu]. ISSN=2323-3273. 2018. Helsinki: Tilastokeskus. Available from: http://www.stat.fi/til/asen/2018/asen_2018_2019-11-21_tie_001_fi.html. (Accessed 10 October 2020).

Official Statistics of Finland (OSF), 2020b. Energian Hankinta Ja Kulutus [verkkojulkaisu]. ISSN=1799-795X. Helsinki: Tilastokeskus. Available from: http://www.stat.fi/til/ehk/tau.html. (Accessed 19 October 2020).

Official Statistics of Finland (OSF), 2020c. 11ra – Key Figures on Population by Region, 1990-2019. Population Structure. Statistics Finland, Helsinki. Available from: https://www.stat.fi/til/vaerak/tau_en.html. (Accessed 14 May 2020).

Official Statistics of Finland (OSF), 2019a. 12c1 – Key Figures on Families by Family Type and Area, 2006-2018. Families. Statistics Finland, Helsinki. Available from: https://www.stat.fi/til/perh/tau_en.html. (Accessed 14 May 2020).

Official Statistics of Finland (OSF), 2019b. 11s3 – Population According to Urban-Rural Classification by Age and Sex, 2000-2018. Population Structure. Statistics Finland, Helsinki. Available from: https://www.stat.fi/til/vaerak/tau_en.html. (Accessed 14 May 2020).

Official Statistics of Finland (OSF), 2019c. 12bs – Population Aged 15 or over by Level of Education, Municipality, Region, Gender and Age, 2007-2018. Educational Structure of Population. Statistics Finland, Helsinki. Available from: https://www.stat.fi/til/vkour/index_en.html. (Accessed 19 May 2020).

Official Statistics of Finland (OSF), 2017a. Buildings and Free-Time Residences. Appendix Table 1. Number of Buildings, Dwellings and Persons by Type of Building and Number of Storeys 31 Dec. 2017. Statistics Finland, Helsinki. Available from: https://www.stat.fi/til/rakke/2017/rakke_2017_2018-05-25_tau_001_en.html. (Accessed 19 May 2020).

Official Statistics of Finland (OSF), 2017b. Buildings and Free-Time Residences. Appendix Table 3. Number of Buildings by Heating Fuel 1970-2017. Statistics Finland, Helsinki. Available from: https://www.stat.fi/til/rakke/2017/rakke_2017_2018-05-25_tau_003_en.html. (Accessed 19 May 2020).

Palmer, D., 2019. Estimating the LES Demand System Using Finnish Household Budget Survey Data. Thesis. University of Uppsala.

Ruokamo, E., Kopsakangas-Savolainen, M., Meriläinen, T., Svento, R., 2019. Towards flexible energy demand – preferences for dynamic contracts, services and emissions reductions. Energy Econ. 84, 104522 https://doi.org/10.1016/j.eneco.2019.104522.

Schleich, J., Klobasa, M., Gölz, S., Brunner, M., 2013. Effects of feedback on residential electricity demand—findings from a field trial in Austria. Energy Pol. 61, 1097–1106. https://doi.org/10.1016/j.enpol.2013.05.012.

Schultz, P.W., Estrada, M., Schmitt, J., Sokoloski, R., Silva-Send, N., 2015. Using in-home displays to provide smart meter feedback about household electricity consumption: a randomized control trial comparing kilowatts, cost, and social norms. Energy 90, 351–358. https://doi.org/10.1016/j.energy.2015.06.130.

Schultz, P.W., Nolan, J.M., Cialdini, R.B., Goldstein, N.J., Griskevicius, V., 2007. The constructive, destructive, and reconstructive power of social norms. Psychol. Sci. 18 (5), 429–434.

Sudarshan, A., 2017. Nudges in the marketplace: the response of household electricity consumption to information and monetary incentives. J. Econ. Behav. Organ. 134, 320–335. https://doi.org/10.1016/j.jebo.2016.12.015.

Thaler, R., Sunstein, C., 2008. Nudge: Improving Decisions about Health, Wealth, and Happiness. Yale University Press, New Haven, CT, US.

Vassileva, I., Odlare, M., Wallin, F., Dahlquist, E., 2012. The impact of consumers' feedback preferences on domestic electricity consumption. Appl. Energy 93, 575–582. https://doi.org/10.1016/j.apenergy.2011.12.067.