Energy Economics 104 (2021) 105687

Contents lists available at ScienceDirect

Energy Economics

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

The effect of descriptive information provision on electricity consumption: Experimental evidence from Lithuania

Fissha Asmare, Jūratė Jaraitė, Andrius Kažukauskas *

Faculty of Economics and Business Administration, Vilnius University, Sauletekio 9, II rumai, Vilnius, Lithuania

ARTICLE INFO

JEL classification:
D12
D83
L94
Q41

Keywords:
Electricity
Field experiment
Descriptive information
Smart meters
Household data
Lithuania

ABSTRACT

Studies on the effects of information provision on residential energy use conclude that such information can promote households' energy-saving investments and conservation behavior. However, most of these studies are conducted in the U.S. or in other OECD countries, where households, on average, are richer and consume more electricity. This study evaluates the effect of descriptive information provision on residential electricity consumption in a less wealthy OECD country – Lithuania. By using a randomized experiment, we find that the availability of descriptive hourly electricity information provided on web portals reduces electricity consumption by about 8.6%. This effect is equivalent to an annual energy saving of 241 kWh per household. The effect is more pronounced for households with high energy consumption, living in rural areas and detached houses.

1. Introduction

Information tends to be not only imperfect but also costly to access (Caplin and Dean, 2015; Stiglitz, 2000). Studies that sought to ascertain this confirm that filling an information gap affects the individual's decision making and behavior (Dolls et al., 2018; Duflo and Saez, 2003; Jalan and Somanathan, 2008). The residential energy sector is one of the energy sectors where imperfect information is highly prevalent as households typically receive utility bills based on the total monthly amount of electricity usage. This lack of more granular information about households' electricity use potentially leads to imperfect decisions that households might not make given sufficient information.

Several literature reviews synthesize the earlier studies on the effects of information provision in various forms on residential energy use (see, e.g., Abrahamse et al., 2005; Buckley, 2020; Darby, 2006; Ehrhardt-Martinez et al., 2010; Faruqui et al., 2010; Fischer, 2008). These studies conclude that provision of personalized information can promote households' energy-saving investments and influence consumption behavior, at least in the short run. However, these studies are usually conducted in the U.S. or other rich OECD countries, where households consume more electricity, tend to have stronger environmental concerns, and care more about the environmental footprints of their activities (Hunter, 2000; MacInnis and Krosnick, 2020; OECD, 2014). Furthermore, most of these studies analyze interventions in the form of social comparisons combined with energy saving tips and other information. To the best of our knowledge, there are only a few studies that aim to estimate the effect of *purely descriptive* personalized information provision on households' electricity use (Gans et al., 2013; Gleerup et al., 2010; Nilsson et al., 2014).

The present analysis aims to expand the existing literature in the field of behavioral and energy economics in the following two unexplored directions. First, our field experiment is based in Lithuania, a recent OECD member country, which is different from other older OECD countries in terms of income and energy intensity. For instance, in 2019, Lithuania's gross domestic product per capita stood at 83% of the OECD's average, and Lithuania's overall electricity consumption per capita (4.4 MWh/capita) was only about half as high as the OECD's average (8 MWh/capita). Furthermore, in Lithuania, a high share of households is experiencing energy poverty (Eurostat, 2021).

Second, our experiment aims to estimate the effect of *pure* descriptive information provision on households' electricity use without combining it with other normative type of information, such as social comparisons, energy saving tips or goal setting. Our focus on descriptive information is important from a welfare enhancing perspective. Households facing

* Corresponding author.
E-mail address: andrius.kazukauskas@evaf.vu.lt (A. Kažukauskas).

https://doi.org/10.1016/j.eneco.2021.105687
Received 25 March 2021; Received in revised form 29 October 2021; Accepted 30 October 2021
Available online 3 November 2021

normative type of information might experience disutility. For instance, Allcott and Kessler (2019) show that a large share of households who were exposed to normative information in the form of injunctive social comparisons preferred not to receive such reports. Broberg and Kažukauskas (2021) show that households prefer more descriptive type of information about their own energy use than information that compares their electricity consumption with others. This might suggest that households would experience less disutility if they received feedback about their electricity use in a more descriptive manner.

Our one-year country-wide field experiment started in July 2016, and was implemented by a national Lithuanian electricity and gas distribution company, AB ESO. The overall objective of this pilot was to test the impact and viability of smart metering technology in Lithuania, and to explore the effect of a descriptive information provision enabled by the installation of smart meters.[1] Specifically, we analyze how an enhanced web portal with additional information on hourly electricity use would influence households' energy use. Compared to dedicated in-home displays, web portals provide a low-cost and simple design solution for making energy feedback available. Given the fast development of smart meters and other information-delivering technologies, our research provides an example of whether the demand-side management of resources through the provision of continuous real-time hourly electricity use information can stimulate resource conservation in poorer OECD economies.

First, we find that, on average, descriptive information provision reduces electricity consumption by 0.661 kWh (or 8.6%) per day in Lithuanian households. This is equivalent to an annual energy saving of 241 kWh per household. Second, we measure the effect of our intervention beyond the mean using quantile treatment effects (QTEs). Our results reveal that a large reduction effect of descriptive information provision is observed at the highest percentiles of electricity consumption. The higher the percentile, the higher the impact. Much higher reduction effects are observed for consumption levels above the 75th percentile. The implication of this result is vital for policy makers, as it explicitly suggests which group of consumers policy makers should target to achieve energy conservation objectives.

The remainder of the paper is organized as follows. In Section 2, we review the related literature. We describe our experimental setting and randomization of the treatment and control groups in Section 3. The experimental data is presented, and the results are discussed in Section 4. Section 5 concludes the paper.

2. Related literature review

The effect of personalized information provision on energy conservation has received considerable attention in the behavioral and environmental economics literature. In this section, we review some results of previous studies conducted under the randomized/field experiment framework in the OECD countries that aimed to analyze the effect of non-price information provision on household electricity conservation. Our review only covers those studies that are in line with the scope of our study and are relevant to highlight the contribution of our analysis. Table 1 summarizes the studies in terms of their treatment object, type of treatment, mode of treatment provision, duration of the treatment, frequency of measurement, average treatment effect (ATE), geographic location of the experiment, and sample size of the control and treatment groups.

Almost all considered studies find negative ATEs of personalized information provision on households' electricity use (see column 7 in Table 1). These effects range from 20% (see, e.g., Aydin et al., 2018) to almost none (Delmas and Lessem, 2014). The selected studies evaluate the effect of information provision presented in two different forms: in the form of social comparisons (with or without saving tips) and monetary incentives (Harries et al., 2013; Mizobuchi and Takeuchi, 2013), or in the form of descriptive feedback about their own resource consumption with or without saving tips (Benders et al., 2006).

In the United States, information presented in the form of social comparisons reduces households' electricity consumption by about 2.0–2.9% (Allcott, 2011; Allcott and Rogers, 2014; Costa and Kahn, 2013; Henry et al., 2019). Interestingly, Delmas and Lessem (2014) evaluate the effectiveness of detailed private and public information on electricity conservation of students residing in the resident halls at the University of California. Their results reveal that private feedback in the form of social comparisons alone is ineffective. But a 20% average energy saving is attained when private feedback is combined with publicly visible information. The ATEs of social comparisons implemented in other OECD countries range from −0.7% (Andor et al., 2020) to about −20% (Aydin et al., 2018). However, Andor et al. (2020) note that the cost-effectiveness of letter-based intervention depends not on the size of ATEs, but on the baseline consumption levels and the carbon intensity of electricity generation. Higher average consumption levels translate a given ATE (in terms of percentage reduction of electricity consumption) into the higher absolute electricity saving in terms of kWh. Similarly, higher carbon intensity of electricity generation implies that a given ATE translates into higher reductions in greenhouse gas emissions. In the case of letter-based home energy report interventions that include social comparisons, Andor et al. (2020) use "back-of-the-envelope" calculations to show that, once these dimensions are taken into account, the cost effectiveness of social comparisons is highest for the U.S. and Canada but not so much for other OECD countries.

The other studies considered in our literature review measure the effect of descriptive personalized information provisions on households' electricity use. This type of intervention does not allude to social norms, since households are only exposed to their private information and they are not compared to other similar households as in the case of home energy reports (see, e.g., Allcott, 2011). In other words, we might think that households who are exposed to descriptive information might have less unpleasant pressure to conserve energy than those households who receive social comparisons. Furthermore, the latter households might experience higher disutility. For instance, Allcott and Kessler (2019) show that 43% of customers who received home energy reports with social comparisons preferred not to receive such reports. This might suggest that households would experience less disutility if they received feedback about their electricity use in a descriptive manner (Broberg and Kažukauskas, 2021).

Results of the selected studies show that the descriptive personalized feedback could be as effective as social comparisons. For instance, Houde et al. (2013) and Schleich et al. (2013) find that the provision of descriptive information reduced households' electricity use by about 5.7% and 4.5%, respectively. However, these studies (as well as those with social comparisons) combined descriptive feedback with advice on how to conserve electricity, and thus they were not able to disentangle the effect of information from that of electricity-saving tips. In this respect, the study of Gleerup et al. (2010) is different as it tested the effect of *pure* descriptive information provision. They find that such feedback resulted in an electricity saving of about 3% among Danish households.

Thus, unlike the previous studies summarized above, the present analysis aims to expand the existing literature in the field of behavioral and energy economics in the following two unexplored directions. First, our field experiment is based in Lithuania, where a relatively high share of households is experiencing energy poverty (Eurostat, 2021). On the one hand, it could mean that these households might be already consuming low electricity levels and might have no room to reduce

[1] The EU Member States are required to ensure the implementation of smart metering under EU energy market legislation. This implementation may be subject to cost-benefit analysis (CBA). The state-owned Lithuanian national electricity distribution company AB ESO was asked to implement such CBA. A pilot experiment that is assessed in this study was designed as part of AB ESO's CBA.

Table 1
Summary of selected field experiment studies on the effects of information provision on household's electricity use.

Study[1]	Treatment object	Treatment type	Mode of treatment provision	Duration of treatment	Data frequency in measuring ATE	ATE	Location	Sample size[3]
1	2	3	4	5	6	7	8	9
Our study	**Electricity**	**Descriptive feedback**	**Web portal (continuous)**	**12 months**	**Daily**	**−8.60%**	**Lithuania**	**419 (T), 632 (C)**
Benders et al. (2006)	Electricity	Descriptive feedback with tips	Web portal	5 months	Once in 5 months	−8.50%	Groningen, the Netherlands	137 (T), 53 (C)
Gleerup et al. (2010)	Electricity	Descriptive feedback	Text messages and email	12 months	Daily	Between 0 and −3.00%	Denmark	92–105 (T), 183–196 (C)
Allcott (2011)	Electricity	Social comparisons with tips[2]	Letters (monthly, bimonthly, quarterly or mixed)	2 years	Daily	−2.03%	U.S. (OPOWER clients in 17 regions)	306,670 (T), 281,776 (C)
Ayres et al. (2012)	Electricity	Social comparisons with tips	Letters (quarterly or monthly)	12 months	Daily	−2.02%	U.S. (OPOWER clients in the Sacramento Municipal Utility District)	34,557 (T), 49,570 (C)
Harries et al. (2013)	Electricity	Descriptive feedback with social comparison	Web portal	16 weeks	Daily	−3.00%	Residential areas of Bristol, UK	214 (T), 102 (C)
Mizobuchi and Takeuchi (2013)	Electricity	Monetary Incentive	–	8 weeks	Monthly	−5.90%	Matsuyama, Western Japan	103 (T), 52 (C)
		Monetary incentive with social comparison	Web portal			−8.20%		53 (T), 52 (C)
Costa and Kahn (2013)	Electricity	Social comparisons with tips	Letters (quarterly or monthly)	8–10 months	Daily	−2.10%	U.S. (OPOWER clients in California)	33,664(T), 48,058 (C)
Houde et al. (2013)	Electricity	Descriptive feedback with tips	Web portal	9 months	Hourly	−5.70%	U.S., California	752 (T), 313 (C)
Schleich et al. (2013)	Electricity	Descriptive feedback with tips	Web portal and letter	11 months	Yearly data	−4.50%	Linz, Austria	601 (T), 469 (C)
Allcott and Rogers (2014)	Electricity	Social comparisons with tips	Letters (monthly, bimonthly, quarterly or mixed)	4–5 years	Daily, monthly	−2.50%	U.S. (OPOWER clients in 3 sites in upper Midwest and on the West coast)	26,262 (Continued T), 12,368 (Dropped T), 33,524 (C)
Delmas and Lessem (2014)	Electricity	Social comparisons (private)	Web portal and email (weekly)	5 weeks	Daily	No effect	U.S.	43 (T), 23 (C)
		Social comparisons (public)	Email and public poster (weekly)	7 weeks		−20.00%		
Aydin et al. (2018)	Electricity	Social comparison with tips and goal setting	In home display (every 15 min)	8 months	Monthly	Between −20.00% & -23.00%	Texel, Netherlands,	104 (T), 54 (C)
Burkhardt et al. (2019)	Electricity	Social comparison	Web portal	19 months	Minute level	No effect	Austin, U.S.	44 (T), 57 (C)
Henry et al. (2019)	Electricity	Social comparisons with tips	Email (monthly, quarterly, semi-annually, once a year or mixed)	12 months	Monthly	(−2.88%)	U.S.	7667 (T), 1275 (C)
Andor et al. (2020)	Electricity	Social comparisons with tips	Letters (quarterly)	12 months	Yearly	−0.70%	Kassel, Germany	5808 (T), 5812 (C)
Kažukauskas et al. (2021)	Electricity	Social comparisons	In home display (continuous)	12 months	Daily	−6.70%	Umeå, Sweden	100 (T), 315 (C)

[1] The studies are listed in chronological order.
[2] By tips, we mean that the treatment also includes general or customized advice on how to conserve electricity.
[3] (T) refers to the number of households (subjects) in the treatment group. (C) stands for the number of households (subjects) in the control group.

electricity use any further. On the other hand, households subject to energy poverty might be relatively more responsive to relevant information provision. So far, most experiments directed towards electricity conservation have been implemented in the U.S. and other wealthy OECD countries, where people on average consume more electricity and tend to be more concerned about environmental footprint of their electricity consumption (see, Section 1). Second, our experiment aims to estimate the effect of *pure* descriptive information provision through a web portal on households' electricity use without combining it with other normative types of information, such as energy saving tips or goal setting. To the best of our knowledge, not many field experiments have tested this type of intervention.

3. Design of the experiment

3.1. General context

Lithuania is a small open economy, a member of the European Union (EU)'s and a new OECD's member state. Since 2010, after the complete closure of the Soviet-era Ignalina Nuclear Power Plant, which had made

Lithuania a net electricity exporter, it has been relying on electricity imports from its neighboring countries. For instance, the amount of imported electricity accounted for about 70% of Lithuania's total electricity demand in 2019. Lithuania has implemented several national and EU-wide policies aiming to reduce reliance on energy imports, energy-related pollution, and improve energy efficiency in the residential sector and in the economy as a whole. For instance, in June 2018, the Lithuanian Parliament approved the National Energy Independence Strategy, which reflects the key focus areas for Lithuanian energy policy – namely to achieve energy independence, energy security and deep decarbonization at an affordable cost (LME, 2018). Regarding energy efficiency, Lithuania has committed to contribute to the EU's 2030 energy efficiency target by ensuring that primary and final energy intensity is 1.5 times below the 2017 level by 2030 (NECP, 2019).

The timely achievement of those targets would be difficult without the completion of the energy sector's liberalization, and a nation-wide rollout of smart electricity meters. From January 2021, household's retail electricity price deregulation was started and the mass installation of smart meters will commence in the first quarter of 2022. It should be also added that Lithuania is one of the most affected EU member states by energy poverty. According to the EU Survey on Income and Living Conditions (Eurostat, 2021), in 2019, 26.7% of its people could not afford to keep their houses adequately warm, that is the second highest percentage among the EU countries after Bulgaria. This context might suggest that the provision of personalized information about electricity use might not encourage households experiencing energy poverty to reduce their electricity consumption as these households might use electricity below the subsistence consumption level.

3.2. Formation of the treatment and control groups

The experiment was implemented and financed by a national electricity and gas distribution company, AB ESO, which is based in Lithuania. The formation of the treatment and control groups was done in the following steps. First, the sample of households living in apartments or detached houses and urban or rural areas in Lithuania was selected. Second, by using a simple randomization, from each block, a group of households was selected to receive the treatment in the form of personalized hourly electricity consumption data on their personal ESO web portals. The provision of hourly electricity consumption information for the treatment group was enabled by replacing old household electricity meters with new smart meters.[2]

In total, 2927 households were selected to form a treatment group. Prior to the start of experiment, as in general population, the randomly selected households were already equipped with mainly two types of electricity meters: electromechanical and analogue electricity meters. Some of electromechanical electricity meters had an internal memory for storing hourly electricity consumption data. However, most of the selected households had electricity meters that did not have internal memory for storing historical hourly electricity consumption. After dropping households without available historical electricity consumption data or with inaccurate and missing data due to faulty old meters, we were left with 419 households in the treatment group. Hourly electricity consumption data from old electricity meters were retrieved by AB ESO after these meters were replaced by new smart meters. A control group of 702 households equipped with electromechanical electricity meters with internal data storage capacity was randomly selected from the same blocks as the treatment group (households living in apartments/detached houses and urban/rural areas). Again, after dropping households without any available historical electricity consumption data for the pre-treatment period or with inaccurate and missing data due to faulty old meters, 632 households formed our control group. Hourly electricity consumption data from these meters were retrieved after the treatment ended.

3.3. The treatment

Hourly electricity consumption of participating households was observed for 24 months – 12 months before (1 June 2015–31 May 2016) and 12 months after the start of the treatment (1 July 2016–30 June 2017). The length of the experiment was decided to be based on the objective to study the persistence of the treatment effect, and the need to control for the seasonal variation in electricity consumption. Most of the smart meters for households in the treatment group were installed in one month (June 2016). We do not take this month in our analysis, as it caused many missing or inaccurate observations.

The main difference between the treatment group and the control group is that households in the treatment group have received additional information available on their personal ESO web portals (see Fig. 1). This additional information includes information about a particular household's hourly electricity consumption patterns, highlights electricity use in the morning, day, evening and night hours, and shows the expected electricity consumption for the current month. About a half of households in both groups logged into their personal ESO accounts. Unfortunately, we were not provided with data on who from experiment participants checked their personalized electricity consumption information.[3]

3.4. Estimation of ATEs

Our key objective of household randomization to the treatment and control groups is to identify the causal effect of the descriptive information provided by the personal web portals on the average consumption of electricity. Ideally, we would have liked to have as “clean” as possible a randomized controlled trial (RCT) setting. However, due to technical difficulties to retrieve historical electricity consumption from the old meters for the control group in the beginning of experiment we were left with uneven daily observations across time for the treatment and control groups. The unbalanced number of observations across the pre- and post-treatment periods does not allow to claim that we analyze an ideal RCT.[4] However, our experiment arguably resembles RCT, which is why we consider it to be more a “natural field experiment,” in line with the taxonomy provided by Harrison and List (2004). In the absence of a completely “clean” RCT, we must turn to natural experimental methods that try to mimic the randomized allocation setting under reasonable conditions. A major concern is that the control and treatment groups might be different in observable and unobservable variables, and these differences may be correlated with the outcome variable (electricity). A common method of controlling for observable and time-invariant unobserved heterogeneity is to use difference-in-differences (DID) models. The main advantage of DID method is that it is an intuitive and flexible way to measure the impact of an intervention, which has been widely used in studies based on natural field experiments. Moreover, it also relaxes the assumption of selection only on observables and provides a tracible way to account for biases from time invariant

[2] The explicit consent for replacing old meters with the new ones from participating households was not needed as AB ESO owns these meters. However, households had an option to opt-out from this experiment if they wanted (just few cases of opt-outs were reported).

[3] We asked AB ESO to provide us with such information, but the company refused to do it on the grounds of personal data protection laws and due to lack of resources to retrieve such data.

[4] See Figure A2 in the Appendix for the number of observations available for each month for both the treatment and control groups before and after the treatment.

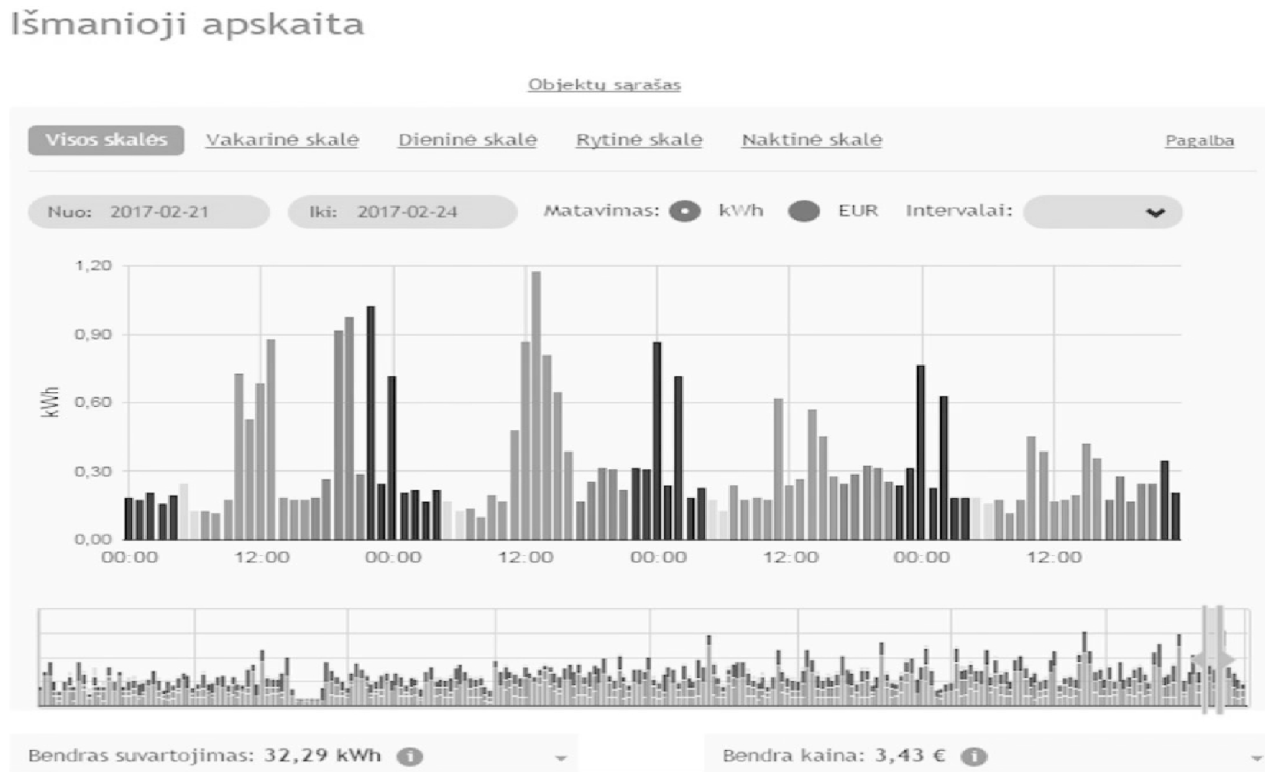

Fig. 1. Additional information on the personal web portal available for the household in the treatment group.

unobserved factors (Abadie and Cattaneo, 2018; Angrist and Pischke, 2009; Imbens and Wooldridge, 2009).

To estimate the ATEs, we run the following difference-in-differences regression model:

$$y_{it} = \beta_1 TREAT_i + \beta_2 POST_{it} + \beta_3 TREAT_i * POST_{it} + \boldsymbol{\mu} X_t^{'} + \alpha_i + \varepsilon_{it}, \quad (1)$$

where y_{it} is the daily electricity use (in kWh) in household i at time t, $TREAT_i$ is a dummy variable indicating whether household i is in the treatment group or the control group, $POST_{it}$ is a dummy variable indicating the pre- and post-treatment periods, X_t' is a set of the time-varying covariates[5] (year-monthly fixed effects, daily temperature, and cloudiness), α_i are household fixed effects, and ε_{it} is an idiosyncratic error term (unobserved household-specific shocks). This model is estimated in OLS by using the standard fixed-effects estimator with Huber-White standard errors, which are clustered at the household level to account for serial correlation (Bertrand et al., 2004). The estimated coefficient β_3 measures the ATE of provision of personalized information about hourly electricity use.

4. Results and discussion

4.1. Variable description and summary statistics

Table 2 presents the average daily electricity consumption for households in the treatment and control groups along with the other control variables one year before and one year after the delivery of the treatment. In our main analysis, we exclude all observations with zero values of electricity consumption. We have strong reasons to believe that most of these observations are mistakes; hence, we think it is unreasonable to consider them as truthful observations.[6]

Panel A of Table 2 shows that the average daily electricity use in the treatment group increased by 0.095 kWh (from 7.575 kWh to 7.670 kWh), while in the control group it decreased by 0.359 kWh. We can observe that our sample is imbalanced in terms of the temperature variable across the treatment and control groups before the start of the treatment.[7] This could be explained by the fact that in the control group we have more observations in the cold-season months (see Fig. A2 in the Appendix). The DID approach will help us to control for the seasonal variation, and changes in weather conditions. In panel B of Table 2, we present the average daily electricity consumption across the housing types (houses vs. apartments) and geographical locations (urban vs. rural). We observe that households living in the rural parts of the country, and those who are living in detached houses consume twice as much electricity than households living in apartments and urban areas.

Fig. 2 plots the dynamics of the monthly daily average electricity consumption before and after the treatment for the treatment and

[5] At the time of experiment, retail electricity market was not yet liberalized and all households were subject to the same regulated electricity prices. Unfortunately, we do not observe household characteristics such as income.

[6] We identified 15–25% of total monthly observations with zero electricity consumption values for the treatment group one month before and two months after the major installations of smart meters in June 2016. In other months, we observe only 1–2% of observations with zero values for both the treatment and control groups (see Figure A1 in the Appendix). It seems that the replacement of old meters temporarily disrupted the collection of electricity consumption data for some households. Furthermore, zero value observations suggest that all appliances, including the fridge and freezer, must have been switched off for the entire day. Smart meters themselves consume a small amount of electricity, which should be visible in our data.

[7] We have conducted the parametric t-test, a non-parametric test based on K-sample test on the equality of medians, and the Mann-Whitney two-sample test to test the equality of sample characteristics between the treated and control groups before the treatment period started. All test results suggest that we cannot reject the hypothesis of no differences between the treatment and control groups in terms of electricity use. However, we find significant differences in terms of house type, location and weather variables.

Table 2
Descriptive statistics before and after the treatment.

	Panel A: Definition and summary statistics of variables							
	Pre treatment				Post treatment			
	Treated		Control		Treated		Control	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Daily electricity (kWh)	7.575	6.364	7.687	8.91	7.670	7.033	7.328	8.473
House type (1 = Detached house)	0.266	0.442	0.254	0.435	0.291	0.454	0.214	0.410
Daily temp. (C°)	6.808	8.402	5.825	8.290	7.010	8.222	7.164	8.235
Daily cloudiness (%)	67.07	30.62	68.14	30.37	73.87	26.89	73.75	26.70
Location (1 = Rural)	0.204	0.403	0.164	0.370	0.224	0.417	0.136	0.343
No. of non-zero daily obs.	103,547		185,613		150,709		230,249	
	Panel B: Average daily electricity consumption by location and housing type, kWh							
	Mean		S.D.		No. of daily obs.			
Rural	12.530		14.300		113,495			
Urban	6.495		5.360		541,408			
Detached house	12.170		12.850		162,723			
Apartment	6.012		4.655		492,180			

control groups. It is evident that the residential consumption of electricity is seasonal – the electricity tends to be used less in summer months than in winter months. Both the treatment and control groups have very similar pre-treatment and post-treatment trends. However, in May–August 2016, the average daily electricity consumption of the treatment group is below that of the control group. A possible explanation of this discrepancy is the disruption caused by the installation of new smart meters for households in the treatment group. In addition, during this time period, the number of valid observations for the control group is much higher than for the treatment group (see Fig. A2 in the Appendix). Overall, we can conclude that, from the visual inspection of the raw average electricity consumption data across the treatment and control groups, it is not clear whether the treatment had any effect at all.

4.2. Average treatment effects (ATEs)

To estimate the ATE of descriptive information provision on electricity consumption, we employ the fixed-effects DID model as described in Eq. (1). The estimation results summarized in Table 3 reveal a significant treatment effect, namely an average daily reduction of 0.661 kWh (or about 8.6%). This effect is equivalent to an annual electricity saving of 241 kWh per average household.[8]

We would like to highlight that our estimated ATE of information provision on electricity use is much higher than ATEs found in other similar studies that use data from Western countries, such as the U.S. or Germany. For instance, our ATE estimate is higher than ATE estimates of Allcott (2011), Costa and Kahn (2013), and Ayres et al. (2012) who document ATEs of around −2% in the U.S, or Schleich et al. (2013) (−4.5% in Linz, Austria) and Andor et al. (2020) (−0.7% in Germany). The difference between our estimated ATE and ATEs of the above-mentioned studies could be explained not only by geographical and methodological differences, but also by the nature and intensity of interventions implemented. Unlike our study, these studies use informational interventions mixed with either energy saving tips, social comparisons or social norms. Interestingly, our ATE estimate is still higher than the ones from scant studies that employ a purely descriptive type of information provision. For example, Gleerup et al. (2010) find an ATE of between 0 and − 0.3% in Denmark. The only exception is the study by Gans et al. (2013) who find a relatively higher ATE (a reduction in energy use between 11 and 17% in Northern Ireland). However, to understand whether descriptive information provision is more or less superior than other types of informational interventions require more studies that investigate the *isolated* effect of descriptive information provision.

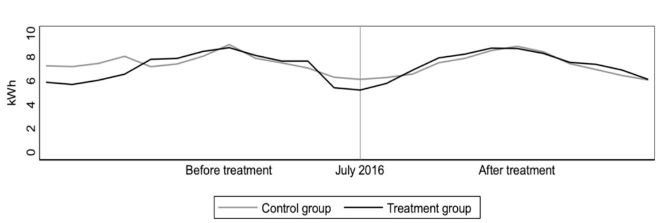

Fig. 2. Daily average electricity use 12 months before and after the treatment

Table 3
ATE on daily electricity consumption (in kWh).

Variables	Electricity
TREAT*POST	−0.661***
	(0.139)
POST	0.292
	(0.177)
Temperature	−0.066***
	(0.007)
Cloudiness	0.004***
	(0.000)
Year-month fixed effects	Yes
Household fixed effects	Yes
No. of daily observations	654,903
No. of households	1051

Notes: The standard errors clustered at the household level are in parenthesis. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

4.3. Quantile treatment effects

Recent developments in the impact evaluation literature stresses the importance of measuring the distributional effects of a treatment (see, e.g., Bedoya et al., 2018; Byrne et al., 2018; Havnes and Mogstad, 2015). To fully understand how personalized information provision affects households with different levels of electricity consumption, we estimate the quantile treatment effects (QTEs) following the specification of Firpo et al. (2009).[9]

Fig. 3 presents the estimated QTEs together with 95% confidence intervals. For comparison, we also plot in the same figure the ATE

[8] We multiply the coefficient of daily ATE (0.661 kWh/day) by the total number of days in a year (365 days) to find the annual electricity saving.

[9] To estimate the QTEs, we use STATA command developed by Rios-Avila (2019).

estimated using Eq. (1). Fig. 3 reveals that the treatment effects are largest at the highest percentiles of the electricity consumption distribution. Compared to the ATE, a significant and higher reduction in electricity use is observed for households with electricity consumption levels above the 75th percentile. Contrariwise, for electricity consumption levels above the 40th percentile and below the 75th percentile, the QTEs are smaller than the ATE. We do not find significant QTEs for electricity consumption level below the 40th percentile. These results show the importance of addressing distributional effects of informational interventions, and that these types of interventions are more effective among higher electricity users. Similar findings were shown by Schleich et al. (2013) who reported the heterogenous ATEs of feedback information provision on electricity consumption in Austria.

4.4. Persistency of treatment effects

Next, we investigate whether the treatment effect is persistent. Answering this question is crucial for understanding whether non-price instruments like behavioral interventions in the form of information provision could bring a long-lasting option for energy conservation. To examine the persistency of the treatment effect, we plot the ATEs for each month of the experiment for both treatment groups (see Fig. 4). The monthly ATE's are estimated by using the following DID model:

$$y_{it} = \gamma_0 TREAT_i + \gamma_1 POST_{it} + \sum_{m=1}^{12} \beta_m (MONTH_m * TREAT_i) + \boldsymbol{\mu} X_t^{'} + \alpha_i + \varepsilon_{it}, \tag{2}$$

where $MONTH_m$ are the dummy variables representing a specific month ($m = 1, …,12$) in the post-treatment year. The remaining variables are the same as in the main model described above. The estimated coefficients of the interaction terms between the monthly dummies and the treatment variable, β_m, give the monthly ATEs. As before, the model is estimated by using OLS with household fixed effects, and clustered standard errors.

Fig. 4 shows that the treatment reduces electricity consumption significantly in all months after the intervention. In line with similar studies, this result suggests that continuous treatment in the form of the provision of descriptive information could encourage persistent electricity saving choices. For instance, Schleich et al. (2017) for Austria, Allcott and Rogers (2014) and Brandon et al. (2017) for the U.S. find similar results by using other types of informational interventions. Interestingly, Byrne et al. (2018) argue that the persistency effect of information provision in the form of social comparison depends on household's beliefs in pre-treatment energy use and the actual level of consumption before the treatment. They find a persistent treatment effect only after accounting for pre-treatment energy use.

At this juncture, it is worth raising the question of what drives these persistent electricity savings? The literature suggests two explanations. First, a continuous provision of information could induce electricity conservation by influencing an individual's behavior. One example of such permanent behavioral change is the formation of a habits, which means that some actions, like switching off lights, or turning off appliances when they are not in use become automatic. Second, the provision of information could encourage households to invest in more energy efficient housing equipment (see, e.g., Allcott and Rogers, 2014). Both of these drivers could explain the persistent ATE on electricity consumption. We might think that providing continuous descriptive information about the household's hourly electricity consumption might enable the household to better understand its electricity consumption patterns, and to identify times of relatively high electricity consumption, caused by either inefficient appliances or sub-optimal behavior. This information would encourage the household to alter its electricity consumption patterns either by changing its habits or by changing its in-home capital stock, or both.

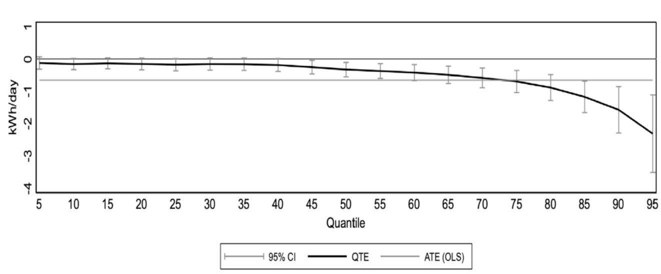

Fig. 3. Quantile treatment effects.

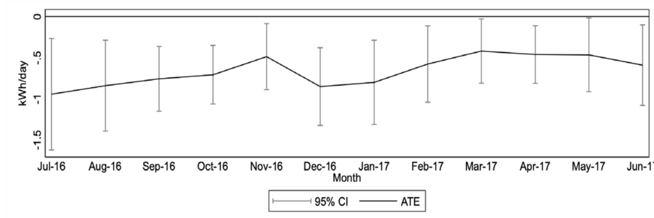

Fig. 4. Persistency of the treatment, monthly ATEs over the period of the treatment.

5. Heterogeneity analysis

An effective policy intervention requires identifying a particular segment of users or a geographical area, where the intervention effect could be more pronounced, and could bring a substantial change. For this purpose, we examine whether the ATEs vary among households (rural vs. urban households, households living in houses vs. apartments). Below we present and discuss the results of estimating models and exploring heterogeneity.

5.1. Rural vs. urban households

First, we estimate the ATEs in rural and urban households. From the estimation results reported in column 1 of Table 4, it is evident that information provision significantly reduces energy consumption in both groups of households. However, the treatment-induced electricity conservation in rural households is higher by a factor of three: in rural households, electricity consumption decreased by 1.423 kWh/day, while in urban households, only by 0.465 kWh/day. We might think that rural households have more options available at hand to reduce their electricity consumption as, on average, they consume twice as much electricity as urban households (see Table 2).

5.2. Houses vs. apartments

Then, we explore heterogeneity of the ATEs across households' housing types. Column 2 in Table 4 shows that descriptive information provision significantly reduces electricity consumption for households living in detached houses and apartments, but the treatment effect is much larger for households living in detached houses (1.078 kWh/day) compared to households living in multi-unit apartments (0.515 kWh/day). As in the case of rural versus urban households, users living in detached houses consume twice as much electricity as households living in apartments. Again, this might suggest that households living in detached houses have more choice when it comes to electricity

Table 4
ATE on daily electricity use by location and housing type.

	Location (1)		House type (2)	
	Rural	Urban	House	Apartment
TREAT*POST	−1.423**	−0.465***	−1.078**	−0.515***
	(0.542)	(0.124)	(0.403)	(0.123)
POST	1.006	0.184	1.072*	0.0638
	(0.782)	(0.138)	(0.534)	(0.139)
Controls	Yes	Yes	Yes	Yes
Year-month f.e.	Yes	Yes	Yes	Yes
Household f.e.	Yes	Yes	Yes	Yes
No. of daily obsv.	113,495	541,408	162,723	492,180
No. of households	181	870	258	793

Notes: 1. The standard errors clustered at the household level are in parenthesis. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. 2. "f.e." stands for fixed effects.

conservation.[10]

5.3. Robustness tests

5.3.1. Hourly analysis

Granularity in our data gives us an opportunity to estimate the intervention effect by using hourly data. We estimate the hourly ATE by using the same empirical model as in Eq. (1); we only add hourly fixed effects to it. We also exclude all observations with a zero level of hourly electricity consumption. The results presented in Table 5 show that descriptive information provision reduces electricity consumption by 0.027 kWh per hour. The estimated effect can be translated to a daily reduction of 0.648 kWh (8.4%), which is comparable to the ATE estimated with daily data (0.661 kWh or 8.6%).

5.3.2. Randomized inference

As a robustness test, we repeat our analysis by using randomization inference (RI). Since the assignment of households to the treatment group and the control group was not entirely random (see Section 4.2), and since we rely on a relatively small household sample, we think it is important to test for the causal effect of our treatment by using an RI approach. Originally developed by Fisher (1953) and later developed by Rosenbaum (2002), RI places no distributional assumptions on the errors and is valid even in small samples. This method is being increasingly applied to experimental data (Hess, 2017).

RI is a simulation method that computes the empirical distribution of the difference-in-differences estimate for a large number of randomly generated placebo treatments under the null hypothesis of no effect. From a large number of simulations, the critical value of the treatment effect can be determined for the inference test.[11] We randomize the assignment of households to the treatment and control groups and use the difference-in-differences coefficient (interaction term in Eq. (1)) as the test statistic. Our null hypothesis is that the provision of personalized descriptive information on web portals had no effect on electricity consumption, or $\beta_3 = 0$ in Eq. (1). We use 1000 replications in the "ritest" command developed by Hess (2017) to conduct the RI test in

Table 5
ATE on hourly electricity consumption (in kWh/h).

Variables	Electricity
TREAT*POST	−0.027***
	(0.006)
POST	0.009
	(0.007)
Temperature	−0.003***
	(0.003)
Cloudiness	0.000048***
	(0.000)
Year-month fixed effects	Yes
Household fixed effects	Yes
Hour fixed effects	Yes
No. of hourly obsv.	15,470,564
No. of households	1038

Notes: The standard errors clustered at the household level are in parenthesis. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

STATA. The estimated p-value (0.000) using the RI test confirms that the treatment effect on electricity consumption is significant. We report this result by including the p-value in square brackets in Table 6.[12]

6. Conclusion and policy implications

Our daily energy consumption decisions are highly vulnerable to imperfect information problems. Households typically receive utility bills where all electricity use during a fixed period is lumped together. The lack of direct feedback potentially leads to mistakes in households' decision-making. In this study, we tested whether the provision of personalized information about hourly electricity use encouraged households to conserve electricity. Our analysis contributes to the existing literature in the two following ways. First, unlike previous studies, our field experiment was based in Lithuania, where a high share of households has been experiencing energy poverty. On the one hand, it could mean that these households might be already consuming low electricity levels and might have no room to reduce electricity use any further. On the other hand, households subject to energy poverty might be relatively more responsive to relevant information provision. So far, most experiments directed towards electricity conservation have been implemented in the U.S. and other rich OECD countries, where people on average consume more electricity. Second, our experiment aimed to

Table 6
ATE on daily electricity consumption (in kWh), RI method.

Variables	Electricity
TREAT*POST	−0.661★★★/☆☆☆
	(0.139) **[0.000]**
Controls	Yes
Year-month fixed effects	Yes
Household fixed effects	Yes
No. of daily obsv.	654,903
No. of households	1051

Notes: Randomization inference and clustered error methods were conducted to obtain alternative p-values. ★★★/☆☆☆ $p < 0.01$, ★★/☆☆ $p < 0.05$ and ★/☆ $p < 0.1$ indicate significance levels, where filled stars ★ indicate significance levels preserved under randomization inference, while empty stars ☆ indicate significance levels that are sustained by the cluster-robust standard errors. The standard error clustered at the household level is in parentheses, and p-value obtained using randomization inference is provided in squared brackets.

[10] We have investigated the interaction treatment effects in the case for households living in apartments but in rural area and in the case of households living in detached houses but in urban areas. Unfortunately, there are not so many households in our sample for this zooming-in analysis. There are only 22 households in our sample living in apartments in the rural areas and 98 in detached houses in the urban areas. Still, we run our triple interaction DID models to see if the treatment effects are different between apartments and detached houses given that they are located in rural or urban areas. We found no statistically significant different treatment effects between these groups.

[11] See Rosenbaum (2002) or Imbens and Rubin (2015) for more information.

[12] We also conducted the RI test for all the other models we estimated, and we did not find any different results. The computed p-values using the RI approach are consistent with the p-values generated using the cluster-robust method.

estimate the effect of *pure* descriptive information provisions on households' electricity use without combining it with other normative types of information, such as energy saving tips or goal setting. To the best of our knowledge, only few experiments have tested this type of intervention. These studies used different modes for treatments, such as sending letters to the energy consumers or using expensive in-house displays. The postal, technological, administrative and psychological costs of such policy interventions are substantial (Allcott and Kessler, 2019; Andor et al., 2020). Digitalization of energy use information through smart metering does change the customer interface of utilities and extends the spectrum of possibilities for energy saving interventions. Clearly, more research is needed to gauge the potential of such information digitalization. Our study aims to fill this gap in the literature by showing how a *purely* descriptive type of information provision through web portals can be an effective way to achieve energy savings in the residential sector.

We found that, on average, descriptive information provision reduced electricity consumption by 0.661 kWh (or 8.6%) per day in Lithuanian households. This is equivalent to an annual energy savings of 241 kWh per household. Furthermore, our results revealed that most reductions in electricity use occurred among households at the highest percentiles of electricity consumption. On the other hand, the intervention had no effect in low-consumption households. This result confirmed our initial expectations: low electricity users are not able to reduce electricity even if they are exposed to more detailed information about their electricity consumption. The implication of this result is vital for policy makers, as it explicitly suggests which group of consumers policy makers should target to achieve energy conservation objectives. In similar vein, our heterogeneity analysis also shed some light on the effect of our intervention based on the type of house where the household lives in, and the location of the living place. We found that the treatment effect was more pronounced for households located in rural areas and living in detached type of houses than for household located in urban areas and living in apartment houses. Finally, our persistency analysis revealed that, on average, the treatment effect was persistent for the duration of the experiment. This finding supports the claim that non-price interventions in the form of descriptive information provision could serve as an effective tool for energy conservation even in less wealthy OECD countries.

Even though our study provides insightful policy implications and fills a clear gap in the literature, we cannot rule out some of its limitations. First, as we do not have information about the frequency of logging into the web portal, the estimated treatment effects are contingent upon the intensity of viewing the provided information. Second, our study does not delve into the channels through which the ATE is derived. Finally, our informational intervention is purely descriptive, and we did not consider other types of interventions, such as energy saving tips or social comparisons, that would allow us to evaluate the additional potential to decrease electricity consumption. The recent meta-analysis by Buckley (2020) offers some insights about what we could expect by adding such information to our treatment. Buckley (2020) finds that providing households with generic advice or social comparison information did not have desired effect on energy conservation. Most studies analyzed by Buckley (2020) come from the U.S. and Western European countries. The future research could uncover how different modes and types of information provision alter energy consumption patterns among households in other less wealthy countries.

Acknowledgments

This research is funded by the European Regional Development Fund (project No 01.2.2-LMT-K-718-02-0007) under grant agreement with the Research Council of Lithuania (LMTLT). The authors would like to thank professor Vincentas Giedraitis (Vilnius University, Faculty of Economics and Business Administration) for language editing, two anonymous reviewers, and participants at the 26th Annual Conference of the European Association of Environmental and Resource Economists, 3rd Baltic Economics Conference (University of Tartu, Estonia), Winter Metting of the Annual Lithuanian Conference on Economic Research (2020), and 15th Conference on Energy Economics and Technology (ENERDAY 2021) for many useful comments that led to the improvement of this study.

Appendix

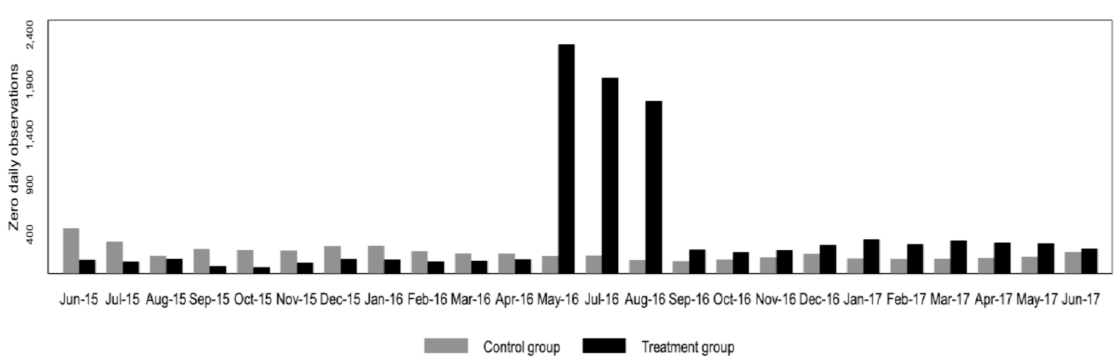

Fig. A1. Number of zero daily observations by treatment status for each month of the experiment.

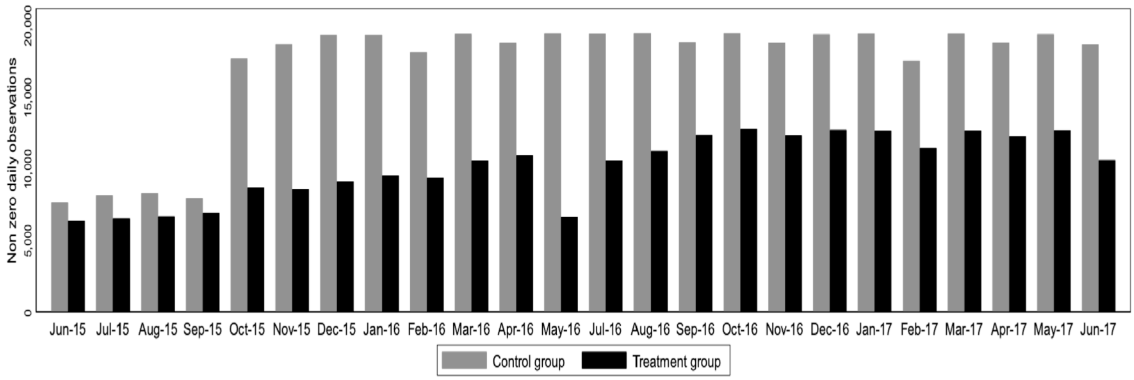

Fig. A2. Number of non-zero daily observations by treatment status for each month of the experiment.

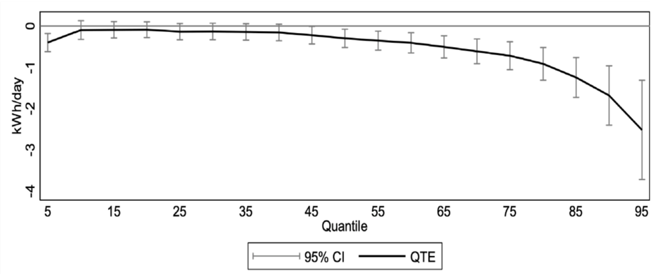

Fig. A3. Quantile Treatment effects including zero consumption levels

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105687.

References

Abadie, A., Cattaneo, M.D., 2018. Econometric methods for program evaluation. Ann. Rev. Econom. 10 (1), 465–503.

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

Allcott, H., 2011. Social norms and energy conservation. J. Public Econ. 95 (9–10), 1082–1095.

Allcott, H., Kessler, J.B., 2019. The welfare effects of nudges: a case study of energy use social comparisons. Am. Econ. J. Appl. Econ. 11 (1), 236–276.

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.

Andor, M.A., Gerster, A., Peters, J., Schmidt, C.M., 2020. Social norms and energy conservation beyond the US. J. Environ. Econ. Manag. 103.

Angrist, J.D., Pischke, J.S., 2009. Mostly Harmless Econometrics: An Empiricist's Companion. Princeton University Press.

Aydin, E., Brounen, D., Kok, N., 2018. Information provision and energy consumption: evidence from a field experiment. Energy Econ. 71, 403–410.

Ayres, I., Raseman, S., Shih, A., 2012. Evidence from two large field experiments that peer comparison feedback can reduce residential energy usage. J. Law Econ. Org. 29 (5), 992–1022.

Bedoya, G.B., Luca Davis, J., Mittag, N., 2018. Distributional Impact Analysis: Toolkit and Illustrations of Impacts beyond the Average Treatment Effect. IZA Discussion Papers, No. 11863, Institute of Labor Economics (IZA), Bonn.

Benders, R.M.J., Kok, R., Moll, H.C., Wiersma, G., Noorman, K.J., 2006. New approaches for household energy conservation—in search of personal household energy budgets and energy reduction options. Energy Policy 34 (18), 3612–3622.

Bertrand, M., Duflo, E., Mullainathan, S., 2004. How much should we trust differences-in-differences estimates? Q. J. Econ. 119 (1), 249–275.

Brandon, A., Ferraro, P.J., List, J.A., Metcalfe, R.D., Price, M.K., Rundhammer, F., 2017. Do the Effect of Social Nudges Persist? Theory and Evidence from 38 Natural Field Experiments (23277) [Working Paper].

Broberg, T., Kažukauskas, A., 2021. Information policies and biased cost perceptions-the case of Swedish residential energy consumption. Energy Policy 149 (112095).

Buckley, P., 2020. Prices, information and nudges for residential electricity conservation: a meta-analysis. Ecol. Econ. 172.

Burkhardt, J., Gillingham, K., Kopalle, P.K., 2019. Experimental evidence on the effect of information and pricing on residential electricity consumption. National Bureau of Economic Research. No. w25576.

Byrne, D.P., Nauze, A.L., 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.

Caplin, A., Dean, M., 2015. Revealed preference, rational inattention, and costly information acquisition. Am. Econ. Rev. 105 (7), 2183–2203.

Costa, D.L., Kahn, M.E., 2013. Energy conservation "nudges" and environmentalist ideology: evidence from a randomized residential electricity field experiment. J. Eur. Econ. Assoc. 11 (3), 680–702.

Darby, S., 2006. The Effectivness of feedback on energy consumption. In: A Review for DEFRA of the Literature on Metering, Billing and Direct Displays.

Delmas, M.A., Lessem, N., 2014. Saving power to conserve your reputation? The effectiveness of private versus public information. J. Environ. Econ. Manag. 67 (3), 353–370.

Dolls, M., Doerrenberg, P., Peichl, A., Stichnoth, H., 2018. Do retirement savings increase in response to information about retirement and expected pensions? J. Public Econ. 158, 168–179.

Duflo, E., Saez, E., 2003. The role of information and social interactions in retirement plan decisions: evidence from a randomized experiment. Q. J. Econ. 118 (3), 815–842.

Ehrhardt-Martinez, K., Donnelly, K.A., Laitner, J.A., 2010. Advanced Metering Initiatives and Residential Feedback Programs: A Meta-Review for Household Electricity-Saving Opportunities. American Council for an Energy-Efficient Economy, Washington, D.C.

Eurostat, 2021. Can You Afford to Heat Your Home? Available at. Accessed: 11 February 2021.

Faruqui, A., Sergici, S., Sharif, A., 2010. The impact of informational feedback on energy consumption—a survey of the experimental evidence. Energy 35 (4), 1598–1608.

Firpo, S., Fortin, N.M., Lemieux, T., 2009. Unconditional quantile regressions. Econometrica 77 (3), 953–973.

Fischer, C., 2008. Feedback on household electricity consumption: a tool for saving energy? Energy Efficiency 1 (1), 79–104.

Fisher, R.A., 1953. The Design of Experiments. Oliver & Boyd, Oxford, England.

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.

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).

Harries, T., Dibb Marylyn Carrigan, S., Rettie, R., Studley, M., Burchell, K., Chambers, S., 2013. Is social norms marketing effective? Eur. J. Mark. 47 (9), 1458–1475.

Harrison, G.W., List, J.A., 2004. Field experiments. J. Econ. Lit. 42 (4), 1009–1055.

Havnes, T., Mogstad, M., 2015. Is universal child care leveling the playing field? J. Public Econ. 127, 100–114.

Henry, M.L., Ferraro, P.J., Kontoleon, A., 2019. The behavioural effect of electronic home energy reports: evidence from a randomised field trial in the United States. Energy Policy 132, 1256–1261.

Hess, S., 2017. Randomization inference with Stata: a guide and software. Stata J. Promot. Commun. Stat. Stata 17 (3), 630–651.

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.

Hunter, L.M., 2000. A comparison of the environmental attitudes, concern, and behaviors of native-born and foreign-born US residents. Popul. Environ. 21 (6), 565–580.

Imbens, G.W., Rubin, D.B., 2015. Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction. Cambridge University Press, Cambridge, UK.

Imbens, G.W., Wooldridge, J.M., 2009. Recent developments in the econometrics of program evaluation. J. Econ. Lit. 47 (1), 5–86.

Jalan, J., Somanathan, E., 2008. The importance of being informed: experimental evidence on demand for environmental quality. J. Dev. Econ. 87 (1), 14–28.

Kažukauskas, A., Broberg, T., Jaraitė, J., 2021. Social comparisons in real time: a field experiment of residential electricity and water use. Scand. J. Econ. 123 (2), 558–592.

LME, 2018. National Energy Independence Strategy of the Republic of Lithuania.

Maclnnis, B., Krosnick, J.A., 2020. Climate Insights 2020: Surveying American Public Opinion on Climate Change and the Environment.

Mizobuchi, K., Takeuchi, K., 2013. The influences of financial and non-financial factors on energy-saving behaviour: a field experiment in Japan. Energy Policy 63, 775–787.

NECP, 2019. National Energy and Climate Action Plan of the Republic of Lithuania for 2021–2030. Accessed: 11 February 2021.

Nilsson, A., Bergstad, C.J., Thuvander, L., Andersson, D., 2014. Effects of continuous feedback on households' electricity consumption. Appl. Energy 122, 17–23.

OECD, 2014. Greening Household Behaviour: Overview from the 2011 Survey, revised edition. OECD Publishing, Paris.

Rios-Avila, F., 2019. Recentered influence functions in stata: methods for analyzing the determinants of poverty and inequality. In: Working Paper, No. 927. Levy Economics Institute of Bard College, Annandale-on-Hudson, NY.

Rosenbaum, P.R., 2002. Covariance adjustment in randomized experiments and observational studies. Stat. Sci. 17, 286–327.

Schleich, J., Klobasa, M., Gölz, S., Brunner, M., 2013. Effects of feedback on residential electricity demand—findings from a field trial in Austria. Energy Policy 61, 1097–1106.

Schleich, J., Faure, C., Klobasa, M., 2017. Persistence of the effects of providing feedback alongside smart metering devices on household electricity demand. Energy Policy 107, 225–233.

Stiglitz, J.E., 2000. The contributions of the economics of information to twentieth century economics. Q. J. Econ. 115 (4), 1441–1478.