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► **To cite this version:**

Adélaïde Fadhuile, Daniel Llerena, Béatrice Roussillon. Intrinsic Motivation to Promote the Development of Renewable Energy : A Field Experiment from Household Demand. 2023. hal-03977597

**HAL Id: hal-03977597**

**<https://cnrs.hal.science/hal-03977597>**

Preprint submitted on 7 Feb 2023

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**Intrinsic motivation to promote the  
development of renewable energy:  
a field experiment from household  
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Daniel Llerena  
Béatrice Roussillon**

**February 02, 2023**

**JEL: D9, C93, Q41**

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# Intrinsic Motivation to Promote the Development of Renewable Energy : A Field Experiment from Household Demand

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**Abstract:** A demand response program is a promising tool to increase the share of intermittent renewable energy in the electricity production mix. It requires that households adapt their energy consumption to the level of energy production in order to balance the grid, i.e., decrease (increase) their consumption during peak load (peak energy production) event. However, energy conservation efforts suffer from many cognitive biases that impede the optimization of electricity consumption and thus demand flexibility. This article presents a randomized field experiment aimed at introducing demand response with nonmonetary incentives coupled by a set of nudges addressing these cognitive biases. Our results are very encouraging, as demand was successfully decreased by 21% during the peak load event and increased by 17% during the peak energy production event. Our tested nudges are cheap, easy to implement and provide interesting results in demand management programs.

**Keywords:** flexibility, randomized field experiment, energy conservation, nudges.

**JEL:** D9, C93, Q41.

**Acknowledgments:** We gratefully acknowledge support from the Cross Disciplinary Program [Eco-SESA](#) funded by the French National Research Agency (ANR) in the context of the "Investissements d'avenir" program (ANR-15-IDEX-02) and from the Auvergne Rhône-Alpes Region under the "Pack Ambition Recherche 2017 - Expesigno Project" program (17 01110301). We thank the G2ELab Research Engineer Laboratory for their help and their rich discussion. We also thank participants of Eco-Sesa, "Economie Publique" and the CEE-M seminars, IAEE2021, CEA YSPOT2021, and ASFEE2022 for their comments and suggestions.

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# 1. Introduction

Energy planning programs highlight the importance of diversifying energy mixes, promoting the penetration of renewable energies (Artelys et al., 2016). Renewable energies have an intermittent production that creates a new type of peak event where the demand response program must shift household energy consumption during the peak in renewable energy production in addition to shedding it down when there is a peak load event. Demand response program has been used to balance the grid in situation of peak load event and it could now also help increase the share of renewable energies. In addition, both the urgent energy crisis at the European level and the inflation rates reinforce the need to find a valuable tool to change energy consumption behaviour with non-regressive policy tools. Hence, to increase the penetration of renewable energies, noneconomic incentives appear as an appealing solution to induce demand flexibility in a non-regressive way.

To implement demand response programs, recent research compares economic with noneconomic incentives in randomized field experiments and finds the former more efficient than the latter (Schaule and Meinzer, 2020; Burkhardt et al., 2019; Azarova et al., 2020; Ito et al., 2018). Using moral suasion as an incentive scheme, Ito et al. (2018) implement a random control trial in Japan over 18 months and find that nonmonetary incentives are less effective than economic ones and exhibit habituation (3% compared to 15% energy consumption decrease in peak events). Similarly, Burkhardt et al. (2019), comparing economic incentive and the provision information with energy conservation appeal, find a strong effect of peak pricing intervention (14% decrease) but almost no effect of their energy conservation appeal. Hence, intrinsic motivation playing on moral suasion has for now proven insufficient to induce substantial energy conservation effort. Additionally, energy conservation is difficult to achieve, as it suffers from many cognitive biases resulting in overconsumption. Nudges may help to overcome this cognitive bias and reinforce the intrinsic motivation to undertake energy conservation effort (Andor and Fels, 2018; Schubert, 2017). However, the effect of one particular nudge seems insufficient to achieve a large effect and the necessary flexibility required by the management of the grid (DellaVigna and Linos, 2020). The complementary of different nudges have been stressed in recent study on energy saving Charlier et al. (2021).

In this paper, we investigate whether noneconomic incentives coupled with nudges can induce sufficient energy conservation efforts in the long run to be a useful tool in grid management. More particularly, we focus on intrinsic motivation to induce a change in consumption and reinforce it with our intervention that comprises: i) a noneconomic incentive scheme, ii) a commitment device and iii) a feedback mechanism. Those constitute our "trilogy" of behavioral insights experimented in our field experiment. We evaluate the impact of this trilogy on the energy conservation effort and analyze the overall impact of our intervention as well as the impact of repeated interventions over time.

We conducted a field experiment on 165 households in the Grenoble area in France from June 2019 to October 2021. We implement a demand response program with a peak load event and peak energy production event. Participants were asked to lower their consumption during peak load events and increase it during peak energy production events. First, our results indicated that our incentive mechanism is an efficient tool to change electricity consumption during the peak periods. First, demand was successfully decreased by 21% during the peak load event and increased by 17% during the peak energy production event. Our results indicate that the noneconomic incentive coupled with the set of nudges succeeded

in making our participants willfully adapt their consumption to both types of peak events. Second, taking advantage of repeated interventions enables us to analyze whether the stimuli, i.e. the peak events generates habituation or dishabituation. We find no evidence of habituation or dishabituation in our analysis. We conclude that our nudge set is a promising tool for demand response programs at a very low cost for both consumers and policy makers.

The current paper is organized as follows. Section 2 reviews the literature. Section 3 describes the design and the protocol of the field experiment. Section 4 presents the empirical analysis and discusses the results. Section 5 concludes and proposes policy implications.

## 2. Literature Review

The main flexibility tools of the electrical system to ensure the balance of supply and demand are related to storage and demand management. Storage capacity seems, however, unlikely to fully compensate for supply volatility (Giulietti et al., 2019). The viability of a future green power market depends critically on a number of innovative ways to increase demand elasticity. Demand response programs that may influence consumers towards more flexibility by willfully agreeing to decrease their energy use in response to demand response programs are seen as central in this context (Palensky and Dietrich, 2011). Until recently, dynamic tariffs were considered the gold standard for demand response programs (Buckley, 2020; Faruqui and Sergici, 2010). Only a few recent studies have used noneconomic incentives to implement demand response programs with mixed results (Ito et al., 2018; Brandon et al., 2019).

Economic incentives do not appear to be sufficient to manage demand response programs Stewart (2020). They mostly concern households with electrical heating and therefore set aside a large part of the population (in France, only 35% of the population have an electrical heating). If we want to tackle all the household energy consumption we need another type of incentive scheme. Intrinsic motivation can be used to promote energy conservation effort where participants are called upon adapting their energy consumption downward and upward. Social rewards and economic rewards are incentives that have been shown to increase effort: the former calls for self- and social-image motivation, whereas the latter applies the basic principle of economic incentives (Bénabou and Tirole, 2006). The introduction of renewable energy into our production will help stop using the coal-fired power plant and thus contribute to the fight against global warming. Thus, energy conservation effort can be seen as a pro-environmental gesture. The motivation behind these pro-environmental behaviors relates to impure altruism, which is mainly driven by intrinsic motivation (Andreoni, 1989). Hence, warnings about peak day events should generate social incentives to make conservation efforts.

Social rewards have already shown promising results in other areas, such as water consumption and energy consumption (Maas et al., 2017; Asensio and Delmas, 2016), but there are only a few studies examining how noneconomic incentives can be used in demand response programs. Most of them are recent and aim to compare economic with noneconomic incentives (Schaule and Meinzer, 2020; Burkhardt et al., 2019; Azarova et al., 2020; Ito et al., 2018). Their results indicate that noneconomic incentives achieve small and not persistent effects (Ito et al., 2018; Burkhardt et al., 2019; Azarova et al., 2020). Those studies document an effect of approximately 15% for economic incentives, whereas noneconomic incentives will achieve an 8% decrease at best and suffer from habituation (Burkhardt et al., 2019; Azarova et al., 2020; Ito et al., 2018). Only, Brandon et al. (2019) find a positive effect with

no habituation when implementing a noneconomic incentive (Peak Energy Report) but they coupled it with Home Energy Report and only register 3 peak events over a one-month period.

The only study showing promising results for noneconomic incentive is the one of [Pratt and Erickson \(2020\)](#). They conduct a large-scale experiment over 16,000 households in the U.S. and find that the program achieved a substantial 13.5% decrease in energy use during the peak annual event in August 2018. However their non-economic incentive do not directly relate to moral appeal regarding energy conservation effort and was \$1,000 donation from the municipally owned utility to a local charity. Hence, noneconomic incentives produce mixed results, and we believe that they probably need to be complemented with other nudges to achieve the necessary level of reliability and flexibility.

Energy conservation efforts, and, thus, demand response programs, suffer from cognitive bias that makes energy consumption optimization difficult. First, electrical energy consumption is invisible to households because it is not consumed for its own sake but for the uses to which it is put ([Lesic et al., 2018](#); [Attari et al., 2010](#)). People have little knowledge about when they are consuming and what actions are energy intensive ([Hargreaves et al., 2010](#)). Thus, it is difficult to act upon reducing their energy consumption, as they have no real idea of what they can concretely do and when. Second, efforts in energy consumption result in delayed benefits. Thus, energy conservation behavior suffers from time inconsistency, i.e., when viewing the energy bill, the consumer would like to make an energy conservation effort, but when the day comes, he or she would rather take a bath and have comfortable heat in the house than undertake actions to reduce energy consumption ([Van Houwelingen and Van Raaij, 1989](#)). The monetary (discounted) reward from energy conservation behavior is still relatively small compared to the (immediate) cognitive and comfort cost of optimizing energy consumption. Finally, consumers may be uncertain about the expected return from their efforts and their ability to make those efforts. This distortion of one's own preferences is induced by present bias. Nudges can be used to solve those internalities ([Loewenstein and Chater, 2017](#); [Schubert, 2017](#); [Abrahamse et al., 2005](#)). However, [DellaVigna and Linos \(2020\)](#) demonstrated the limited power of the use of only one nudge. After examining 165 RCTs, 90% unpublished from the nudge units, they find an impact between 1% and 2% in RCTs when set up by the nudge unit and around 8.7% for publications in academic journals. Similarly, ([Charlier et al., 2021](#)) find that moral appeal used alone to have no effect but effective when complemented with a nudge on "social comparison" and a reminder.

To address the problem of insufficient knowledge about one's energy consumption, participants can be informed about useful actions regarding energy flexibility and these actions can be labelled according to their impact. Empirical studies suggest that informing consumers with tips on energy saving helps them decrease their energy consumption ([Andor and Fels, 2018](#); [Ruokamo et al., 2022](#)) and help choosing greener alternatives [Cardella et al. \(2022\)](#). [Ruokamo et al. \(2022\)](#), in a random control trial implemented in Finland, underline the necessity to couple a nudge (social norm) with usage feedback and energy savings tips to induce a substantial reduction in electricity consumption of 10% during wintertime. In addition, labelling the different actions according to their power impact decrease the cost of information acquisition and defeat potential biased beliefs about the value of different energy conservation actions([Andor and Fels, 2018](#)).

To overcome the present bias, people can be asked to commit to certain actions. People may sometimes exhibit time-inconsistent preferences ([O'Donoghue and Rabin, 1999](#)). Com-

mitment devices are a set of interventions that allow individuals “to lock themselves today into the action that they want to take tomorrow” (Allcott and Mullainathan, 2010). They provide a source of motivation that helps individuals to overcome such time-inconsistent preferences (Van Houwelingen and Van Raaij, 1989). When the commitment appeals to a personal norm, the individual main goal is to satisfy his or her own defined expectations. In contrast, a public commitment creates expectations by others, thereby leading to social pressure (Abrahamse et al., 2005). In our setup, no goal was defined in the sense that the participants did not commit to a particular level of energy performance. However, we asked the participants to commit to particular actions, and these actions were personalized to each person. Thus, even if the participants did not commit to a particular level of energy reduction, they committed to a number of actions that they could perform independently of one another and therefore could be understood as goals: "I have taken all the actions that I have committed to", or "I have failed to perform one or two actions". Participants did not have to advertise their commitments publicly. Thus, their commitment plays only to their own personal norms.

As consumers are imperfectly informed about the inputs required for energy conservation efforts, feedback can foster consumer learning and induce behavioral change (Carroll et al., 2014; Jessoe and Rapson, 2014; Asensio and Delmas, 2016; Houde et al., 2013). Aggregated feedback has only limited potential, but behavior-specific feedback seems promising (Tiefenbeck et al., 2019; Asensio and Delmas, 2015). As suggested by Cappa et al. (2020), feedback may also increase the engagement of the household. The recreational aspect of the scientific feedback may act as a motivational tool for our participants. We send participants feedback taking the form of a load curve so that they can learn what action is the most effective. A similar combination of nudges has already been implemented in energy saving studies with encouraging results (Abrahamse et al. (2007)). Byrne et al. (2021) document that appliance-specific feedback is a powerful tool to curb electricity consumption. They found that the treated group significantly reduced their average air conditioning usage by 17%. We choose in our case to concentrate on the person’s own performance when there is a call for flexibility. Hence, we send to the participant their load curve associated with their theoretical or business as usual consumption for the day.

The literature in psychology has documented habituation and dishabituation as potential long-term effects of particular stimuli (nudge or governmental behavioral intervention). Habituation implies that repeated presentation of a stimulus (an intervention or a nudge in our case) might cause a decrease in reaction to the stimulus (Thompson and Spencer, 1966; Groves and Thompson, 1970; Rankin et al., 2009). For example, experiments have shown a strong reaction of animals such as rats to a stimulus when it is presented for the first time, but their reaction tend to gradually decrease when the same stimuli is repeated over time. Hence, we tested whether our intervention tends to be less effective when it is repeated over time. The dishabituation is the fact that the stimulus can again create a strong reaction when it has been stopped for some time. In our case, dishabituation is that the nudge can again be effective after some period without nudges. This question is particularly relevant in our context, as peak load event alerts or messages can be seen as repeated stimuli. Therefore, our experimental design is a perfect framework to investigate this question.

## 3. Material and Methods

### 3.1. Treatments

We conducted a field experiment on households in the Grenoble area in France from June 2019 to October 2021. We have one treated and one control group. People are not well informed about the challenges associated with the introduction of renewable energy and the necessity to increase demand flexibility. In the beginning of our experiment, we present to the participants the need to introduce more renewable energy into our production mix and the challenges it creates. Particular attention was called to the gap between "production times" and "consumption times". To cope with this mismatch and to meet the need for constant balancing between electricity demand and production, the flexibility of household consumption was highlighted as one of the main solutions to avoid the use of polluting thermal installations. This first presentation was done to both control and treated groups.<sup>1</sup>

Our treatment consists of the implementation of a set of 3 coupled demand-side flexibility devices: i) a noneconomic incentive scheme, ii) a commitment device and iii) a feedback mechanism. These three devices constitute our "trptych" of behavioral insights experimented in our field experiment. We wish to compare the impact of this triptych on the treatment group to the control group and analyze the impact of our repeated intervention over time.

For the treated group, we design two types of peak events when flexibility demand will be required: the Orange period in winter from 6:00 PM to 8:00 PM, where there is a peak in energy demand with maximal use of coal-fired power plants, and the Green Period in summer from 12:00 AM to 3:00 PM, where there is a peak in renewable energy production.<sup>2</sup>

#### 3.1.1. Noneconomic incentive scheme

We inform the treated group that they will receive a text message alerts to warn them about the Orange Period and Green Period. The message will be the following for the Orange alert and the Green alert.

***Orange period:** Tomorrow, the X Day of month, from 6:00 PM to 8:00 PM; a peak load is anticipated with maximum use of coal-fired plant.*

***Green period:** Tomorrow, the X Day of month, from 12:00 AM to 3:00 PM; a peak in renewable energy production is anticipated with maximum production of solar energy.*

We told them that they would receive a maximum of 30 alerts per year in total. For each Orange or Green period on day D, we sent them i) an alert via a text message the day before (D-1) between 7:00 PM and 7:30 PM and ii) a second reminder text message on day D at 7:30 AM.

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<sup>1</sup>The whole instructions are translated and available upon request.

<sup>2</sup>The day of the Orange period corresponds to the PP1/PP2 days of the French grid management agency (<https://www.services-rte.com/en/view-data-published-by-rte/pp1-and-pp2-signals.html>). These days represent days of peak load events where the grid is particularly difficult to balance. As there is no counterpart for the Green period, the electrical engineering laboratory to which specialty is on grid balance determines which days solar energy production will be at the maximum and needs a corresponding increase in demand. You can find the details of the determination of the Green alerts and their validation in the following publication (Shahid et al., 2021).



### 3.1.2. Commitment device

We present them a list of actions that they could undertake to be more flexible, for the Orange periods (not using particular electrical equipment, not recharging particular appliances, etc.) and for the Green periods (programming the reloading of batteries, etc.). The full list of energy flexibility actions can be found in the Appendix 7.<sup>3</sup> We asked them to personalize the list of actions according to their electrical appliances and habits. For instance, if they do not have an electric vehicle, they cannot commit to not charge it during an Orange period, so they have to delete it from their list. Then, we ask them to commit to the actions they plan to undertake when there is an alert within this personalized list of actions. Finally, at each alert, they receive a text message the day before the alert to remind them of their committed actions.

*Orange period: you have committed not to [list of actions that the participants have committed at the beginning of the study].*

*Green period: you have committed to [list of actions that the participants have committed at the beginning of the study].*

### 3.1.3. Feedback mechanism

The feedback system on participants' electricity consumption for the different Orange or Green periods consists of a text message inviting the participants to consult their personal page<sup>4</sup> on the study website where they could find the consumption curves for each alert day, namely, their real load curve, made with the data from the smart meters at a step of  $\frac{1}{2}$  hour, and a "reference" consumption curve which is an estimate of the usual consumption at that time of the day.<sup>5</sup> There is an example of a feedback curve in the Appendix A, figure 6 for an Orange period.

To sum up the timeline for an alert, there is i) an alert via a text message the day (D-1) before between 7:00 PM and 7:30 PM, ii) a reminder text message on the commitments of each participant made at the beginning of the study the day before and at the same time (D-1) between 7:00 PM and 7:30 PM, iii) a final reminder text message on day D, at 7:30 AM, and iv) a few days later (usually 3 days later), a text message inviting the participants to consult their feedback curve. Households received at least four text message per alert day.

The consultation of the commitments and the feedback load, was carried out via a dedicated website with personal and secure access (see Appendix 5 for a snapshot of the website).

## 3.2. Experimental Procedures

### 3.2.1. Sample

The recruitment process was carried out between March and May 2019 via a publicity campaign using flyers placed in letterboxes and emails sent to subjects already present in the laboratory panel on the other. The people listed as students were excluded. At this stage of the recruitment process, the information given to individuals was limited to "the launch of a study on energy consumption and the development of renewable energy". Interested

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<sup>3</sup>We designed this list with the help of the electrical research engineer from G2Elab.

<sup>4</sup>See the Appendix A for details.

<sup>5</sup>Details of the design of the feedback curve and its validation in [Shahid et al. \(2021\)](#).

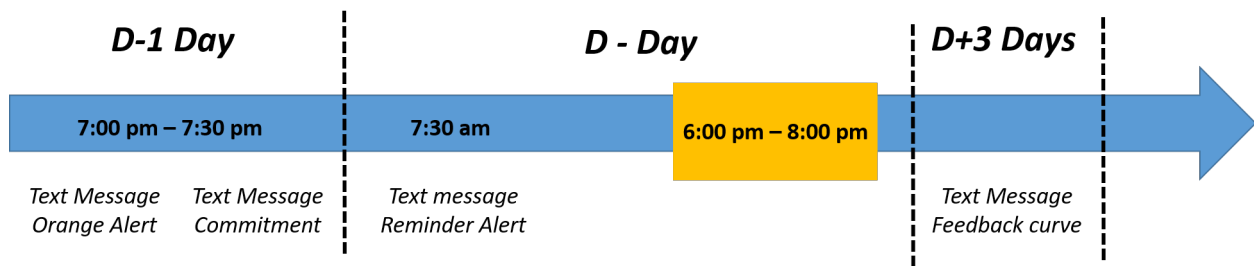


Figure 1: Timeline of the text message sending

individuals were invited to visit the laboratory’s recruitment website to complete a general questionnaire. The main information collected concerned the type of housing, the composition of the household, the socio-professional category, the presence of a smart meter for the residence, the type of heating, etc.

On the basis of this information, a selection process was carried out to respect the criteria for participation in the study: households comprising at least 2 people, with a smart meter, without a specific electricity supply contract (dynamic prices). Of the 686 people who responded to the online questionnaire, 238 participants met the criteria and were invited to participate in the study. Of these, 27 did not respond to the invitation.

Out of the 211 people invited to the sessions, 193 actually turned up. However, after processing the information collected during the session, 173 households that were finally retained (some households did not have a smart meter compatible with the collection of electricity consumption or did not follow up on our requests to register their consent).

As indicated above, the experimental design of the study was based on one treatment and a control group. The allocation of the selected participants between the two treatments was carried out on the basis of the strictest possible equivalence rule for each of the following criteria: the number of people in the household, the size of the dwelling, the presence or absence of household members in the home at least 3 days per week, and the number of household appliances in the home.

### 3.2.2. Instructions

Depending on their treatment assignment, participants were invited to attend a study presentation session. The organization of the sessions ensured that there was no communication between subjects belonging to different treatments. These sessions took place at the Faculty of Economics in late June/early July 2019.

The presentation of the instructions respected the usual conditions applied to experimental economics sessions: respect for the anonymity of the participants, no communication between the participants, reading of the instructions by the researchers, etc. To avoid any strategic behavior, especially in terms of the responses concerning the participants’ commitments, the principle of increasing information in several phases was adopted. The day of their arrival, the subjects’ only information was that it was a study on energy consumption behavior and the development of renewable energy. On arrival, each participant was given a personal code to keep them anonymous. The sessions included between 16 and 25 participants from the same treatment. The participants had to complete a very detailed questionnaire about their electrical appliances and their habits. We also asked them sociodemographic questions. These questionnaires were updated each year. We also conducted a postexperiment questionnaire asking more qualitative questions. All in all, participants stayed in the laboratory between

1h30 and 2h00.

### 3.2.3. Communication with households during the experiment

A dedicated website was constructed to communicate with and inform the participants. On the secure and private website (GPRD compliant), all the households were able to consult their profile and modify it (dwellings electrical appliances and habits). For the treated group, households were able to consult their commitments and change them when they receive the alert of the Orange or Green period, and consult their feedback curve.

### 3.2.4. Monetary compensation

Participation for the entire duration of the study was compensated at €120, paid in three installments for answering questionnaires as follows: €40 at the beginning of the experiment, €40 in the middle, and €40 at the end. This level of compensation was determined by the length of the questionnaires applied to the subjects and by the need to travel to the university site (a total of half a day devoted to our study). It was stressed that no compensation was paid for the retrieval of the data as such or for the follow-up to the actions in the treated group.

### 3.2.5. Data collection and privacy

The energy consumption data were collected thanks to the smart meter *Linky* at the 30-minutes step. During the instructions, we presented the operational conditions for data collection, storage and security provisions applied to the data (both relating to the questionnaires and to electricity consumption). This instruction ended with the collection of the participants' consent for the sharing of their data from the smart meter according to the regulations in force. This consent was collected each year from June 2019 to June 2022.

### 3.2.6. Timing

The experiment lasted slightly more than two years. Participants consent for *Linky* collection from 2019, June to 2022, June. Participants received text during winter and spring for 2020 and 2021, respectively. We chose not to send any alert during the two main holidays of the country, Christmas and the 3 first weeks of August, as well as the weekend. We also chose to stop sending alerts during the first lockdown (March 17 to mid-May 2020). Table 1 presents all the 27 alerts, and Figure 2 presents the average temperature. We have 4 waves of alerts: 2 waves of Orange alerts and 2 waves of Green alerts. As previously mentioned, the triggering of the alerts is totally exogenous, and the number of alerts depends only on weather and grid conditions.

## 4. Empirical Analysis and Results

### 4.1. Sample and observations

Our final sample was made up of 165 households: 78 for the control group and 87 for the treated group. The descriptive statistics of these two groups are presented in Table 2. Columns (1) and (2) report the descriptive statistics for our control group and treated group. The main drivers of electricity consumption are household size, size of the house measured in square meters, heating type and the date the building was constructed (see,

Wave 1	Wave 2	Wave 3	Wave 4
Orange Period	Green Period	Orange Period	Green Period
(Nov 19-March 20)	(April 20-Sept 20)	(Nov 21-March 21)	(April 20-Sept 20)
14/11/2019	27/07/2020	30/11/2020	14/06/2021
20/12/2019	25/08/2020	02/12/2020	
20/01/2020	14/09/2020	04/12/2020	
06/02/2020	17/09/2020	07/12/2020	
19/02/2020	22/09/2020	09/12/2020	
27/02/2020		18/12/2020	
02/03/2020		04/01/2021	
04/03/2020		06/01/2021	
09/03/2020		08/01/2021	
		11/01/2021	
		26/01/2021	
		11/02/2021	

Table 1: Date of load-shedding and shift-shedding periods in treatment

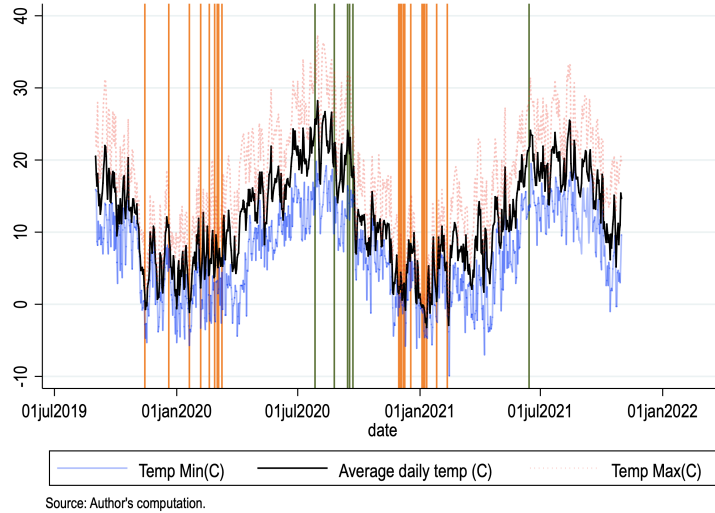


Figure 2: Minimum, average and maximum temperatures during the experiment: Orange and Green bars for alerts

among others, [Ruokamo et al. \(2022\)](#)). The two groups are statistically equivalent on the basis of these determinants; see column (3) in Table 2, except for the number of days at home per week for which the treated group is more at home. Moreover, the monthly electricity consumption is not significantly different between our two groups.

As we tested the effect of the nudge during one specific period, our analysis focuses on electricity consumption during the alerts based on two periods: 6 PM to 8 PM and 12 AM to 15 PM for Orange and Green alerts, respectively.<sup>6</sup>

## 4.2. Household consumption before the alerts

To investigate the parallel trend assumption, we start by examining the first month of our data collection. On one hand, load curves for the two groups are illustrated in Figure 3. This

<sup>6</sup>The alerts are made during weekdays, with no weekend alerts.

Table 2: Households Characteristics

	(1)		(2)		(3)	
	Control		Treated		T-test	
	Mean	S.D.	Mean	S.D.	b	p-value
Surface	102.23	45.86	98.41	41.37	3.82	(0.58)
Household Size	3.09	1.27	2.93	1.31	0.16	(0.43)
<b>Share of</b>						
At home at least 3d/w	0.46	0.50	0.62	0.49	-0.16**	(0.04)
home_owner	0.78	0.42	0.78	0.42	0.00	(0.99)
house	0.46	0.50	0.52	0.50	-0.06	(0.48)
Elec. Heat.	0.09	0.29	0.09	0.29	-0.00	(0.96)
Heat Pump	1.05	0.22	1.07	0.25	-0.02	(0.63)
Air conditioner	1.06	0.25	1.07	0.25	-0.00	(0.90)
<b>Building date</b>						
Before 1974	0.53	0.50	0.46	0.50	0.07	(0.40)
Between 1974 and 1990	0.18	0.39	0.17	0.38	0.01	(0.91)
Between 1990 to 2012	0.23	0.42	0.25	0.44	-0.02	(0.74)
After 2012	0.06	0.25	0.11	0.32	-0.05	(0.25)
Monthly electricity consumption (kWh)	255.16	240.40	247.65	211.10	7.51	(0.29)
Number of households	78		87		165	

Notes : S.D.= Standard Deviation. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Figure enables to illustrate the parallel trend assumption. Indeed, all the confidence intervals for both the treated and untreated groups overlap during all the our of the day, especially during the alter days.

On the other hand, we exploit the panel structure of our data on the pre-treatment period to confirm the parallel trend and the no-anticipation assumption. First, we regress the natural log for household  $i$  of the 30-minute electricity consumption (columns (1) and (3) in Table 3) on the control for both individual observed characteristics for the first month of the analysis, i.e., September 2019, for our two treatment periods. To control for high consumers, we added the daily consumption levels. To control for seasons, weather conditions were controlled with the average daily temperature and the amount of sun (minutes per day) during each day. Finally, we introduced a trend to control for the hour of the day.

Second, we reproduce the same approach to investigate the parallel trend assumption for the total energy consumption of the period (columns (2) and (4) in Table 3).

It is important to emphasize that there was no difference between the control and treated groups before the first alert for both the 6 PM to 8 PM and 12 AM to 15 PM time periods. This result is consistent, regardless of whether the 30-minute consumption or the total consumption is considered; see Table 3.

For columns (1) and (3), it is worth noting that the trend parameters suggest that the effect would be higher at the end of the Orange alert (+sign) and lower (-sign) at the end of

the Green alerts, respectively<sup>7</sup> Comparing the results from the total to 30 minutes enables us to emphasize that there were no significant differences between the two groups. However, it may suggest that the effort is weakened with longer periods of time, as for the Green alerts.

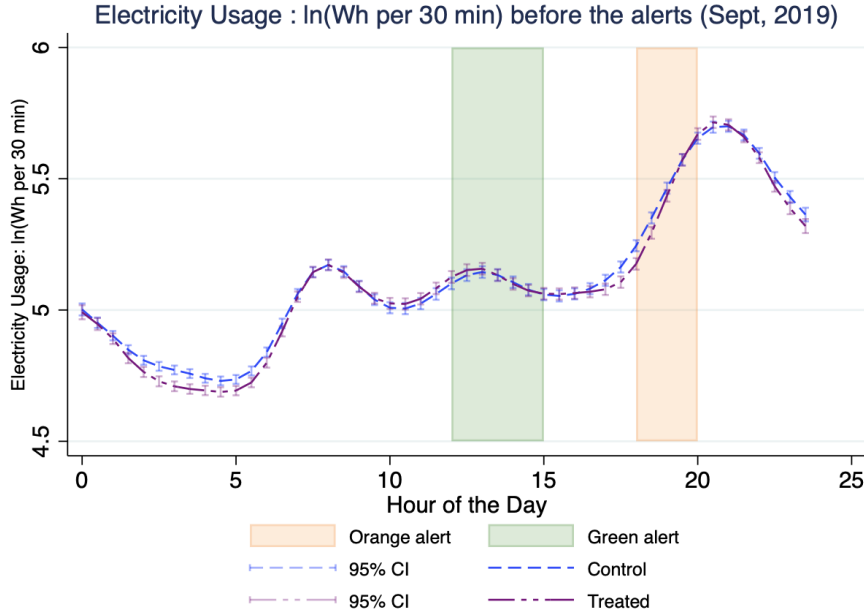


Figure 3: Electricity Consumption before treatments, 2019 September.

Table 3: Regression  $\ln(\text{kWh } 30\text{-min})$  and  $\ln(\text{Total consumption})$  (in kWh) in September during the hours of alerts

	6 PM to 8 PM		12 AM to 5 PM	
	30-min (1)	Total (2)	30-min (3)	Total (4)
Treated	-0.00470 (0.0459)	0.0124 (0.0496)	0.0230 (0.0534)	0.0252 (0.0509)
$\ln(\text{kWh})$ 24 h	1.153*** (0.0328)	1.162*** (0.0395)	0.983*** (0.0399)	1.077*** (0.0373)
Trend	0.141*** (0.0116)		-0.0319*** (0.0050)	
Constant	-3.523*** (0.0975)	-2.283*** (0.1128)	-3.344*** (0.0969)	-2.380*** (0.0948)
Observations	12624	3156	18908	3151
Controls				
days of week	Yes	Yes	Yes	Yes
weather	Yes	Yes	Yes	Yes

Standard errors between parentheses.

Note: Individual fixed effects with time dummies for day of the week and hour.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

<sup>7</sup>These results are robust whether we used only weekdays (days on which alerts can occur, see Table 3) or all the days of the week (see Table 7 in the appendix section).

### 4.3. Effect of the Nudge

To investigate the effects of the nudges, the differences-in-differences model is considered. The effect of the nudge is investigated with two objectives. First, we measure the overall effects of the nudge. Second, we take the advantage of repeated interventions to analyze the mechanism of habituation or dishabituation. The general model is written as:

$$Y_{it} = \theta_i + \lambda_t + \gamma A_{it} + \alpha \text{Treated}_{it} + \beta \text{Treated}_{it} \times A_{it} + \epsilon_{it},$$

where  $Y_{it}$  is the outcome of interest for household  $i$  and time  $t$ .  $\theta_i$  and  $\lambda_t$  are household and time fixed effects.  $\text{Treated}_{it}$  equals one if the participant is in the treated group and received the text message for the specific alert in  $t$ .  $A$  equals to one for the “alert” type investigated. The interaction terms is the treatment effect of the nudge on electricity consumption.  $\beta$ 's are the average treatment effects. Estimations are made using a fixed effect estimator with 165 households and 560 days of 30-minutes observations. Standard errors are clustered by households.

#### 4.3.1. Overall effect of the Nudge

First, we investigate the overall effects of the nudge, assumption that information on peaks would reduce consumption for Orange alerts and increase consumption for Green alerts, empirical results are reported in Table 4. Each regression is provided on the treatment hours from September 2019 to October 2021. For columns (1) and (3), the dependent variable is the natural log for household  $i$  of the 30-minute electricity consumption. For columns (2) and (4), the dependent variable is the natural log for household  $i$  of total electricity consumption during the nudge, i.e., for 2 and 3 hours for Orange and Green alerts, respectively. For the Orange alerts, the average treatment effect of the nudge during Orange periods illustrates a significant decrease<sup>8</sup> in electricity consumption, for both 30-minute and total consumption between 6 PM and 8 PM.

Table 4: Effects of the Nudge on Electricity Consumption

	6 PM to 8 PM		12 AM to 5 PM	
	30-min (1)	Total (2)	30-min (3)	Total (4)
Treated	0.0705 (0.0531)	0.0641 (0.0621)	-0.0353 (0.0503)	-0.0571 (0.0510)
Treated × Orange	-0.2140** (0.0841)	-0.1720* (0.0872)		
Treated × Green			0.1710* (0.0921)	0.1800* (0.0942)
Constant	-1.1730*** (0.0009)	-0.0744*** (0.0011)	-1.49400*** (0.0010)	-0.0697*** (0.0010)
Observations	332440	95716	498067	91393

Notes : Standard errors between parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

<sup>8</sup>at the 10% level.

Table 5: Effects of the Nudge on electricity consumption per wave

	6 PM to 8 PM		12 AM to 5 PM	
	30-min (1)	Total (2)	30-min (3)	Total (4)
Treated	0.0706 (0.0531)	0.0641 (0.0620)	-0.0353 (0.0503)	-0.0571 (0.0510)
Treated $\times$ Wave 1-Orange	-0.2360*** (0.0842)	-0.1820** (0.0884)		
Treated $\times$ Wave 3-Orange	-0.1970** (0.0937)	-0.1630* (0.0979)		
Treated $\times$ Wave 2-Green			0.1850* (0.0942)	0.1880* (0.0952)
Treated $\times$ Wave 4-Green			0.1105 (0.1235)	0.1450 (0.1461)
Constant	-1.173*** (0.0009)	-0.0744*** (0.0011)	-1.4940*** (0.0010)	-0.0698*** (0.0010)
Observations	332440	95716	498067	91393

Notes : Standard errors between parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

The time covered by the different waves are detailed in Table 1.

The magnitude of our effect is similar to that of the economic incentive found in previous studies. Ito et al. (2018) and Burkhardt et al. (2019) document the effect of economic incentives to be approximately of 15%. However, the effect of our intervention is much stronger than previous field experiments using noneconomic incentives (Brandon et al., 2019; Azarova et al., 2020; Burkhardt et al., 2019). For instance, Ito et al. (2018) in the moral suasion treatment found that moral suasion leads to a significant decrease by 3% during winter. Similarly, Brandon et al. (2019) find an effect of 2% to 4% for the treatment with energy conservation appeal and as high as 7% when energy conservation appeal (peak event report, PER) is complemented with a home energy report (HER). As can be seen, the effect of the second Orange wave is smaller than that of the first wave. This may be due to the different conditions in which the two waves took place and the different number of alerts. Unfortunately, the second wave of Orange alerts took place during the winter of 2020-21, when various contingency measures were taken in France due to COVID-19, they included curfew at 6 PM/7 PM/8 PM during the winter according to the virulent nature of the pandemic. The lockdown period related to the COVID-19 crisis in France was introduced just after the 2020 winter and did not disrupt our experimentation in the first wave of Orange periods. However, COVID-19 and different government measures during the second winter of our experiment decrease the comparability of the two winters together. We think that these different measures have increased the difficulty of acting upon energy conservation and therefore may be the reason why the effect in the second wave is smaller than that in the first wave.<sup>9</sup> Finally, we found an increase in consumption during some specific Green alerts.

#### 4.3.2. Habituation and dishabituation

The average treatment effect illustrates the heterogeneity among alerts, suggesting a staggered treatment adoption. To control for this heterogeneity, we disaggregated the effects per alert.

<sup>9</sup>The different curfews established at different times during the 2020-21 winter probably made it more difficult to decrease energy consumption as people were obliged to stay home.



The results are presented in Figure 4. Remember that we have 21 Orange and 6 Green alert days. Plot (a) of Figure 4 illustrates the treatment effect of each alert on 30-minute electricity consumption, respectively, (b) of Figure 4 for total electricity consumption.

Habituation and dishabituation are of particular interest when investigating demand flexibility, as intervention to signal peak events such as our Orange and Green alerts take the form of repeated stimuli that may or may not suffer from habituation. For instance, [Ito et al. \(2018\)](#) found that moral appeal generates a strong effect of habituation, with the effect of their peak event significantly decreasing over time and disappearing after the third event. Indeed, their average effect of 3% energy decreases hides a high heterogeneity between the different peak events, with the first peak event being very effective and generating a decrease of 8% in energy consumption, but then they observe a sharp drop of effectiveness for the rest of the peak events. Interestingly, [Burkhardt et al. \(2019\)](#) find a habituation effect even for critical peak pricing. Finally, [Brandon et al. \(2019\)](#) did not find habituation, yet they only conducted 3 peak events during a month; thus, their results may not be totally comparable.

Investigating the question of habituation, we find no evidence that our Orange and/or Green alerts resulted in habituation. In both cases, the confidence interval of each alert strongly overlapped (see Figure 4), indicating no significant differences between our coefficients. In addition, there is no clear decreasing trend; for instance, the seventh Orange alert of the first wave has the strongest effect. Comparing our results with those of [Ito et al. \(2018\)](#), who find a strong habituation when using moral suasion, we can postulate that the nudges (the commitment devices and the feedback) that complement our energy conservation appeal may have attenuated habituation in our setup.

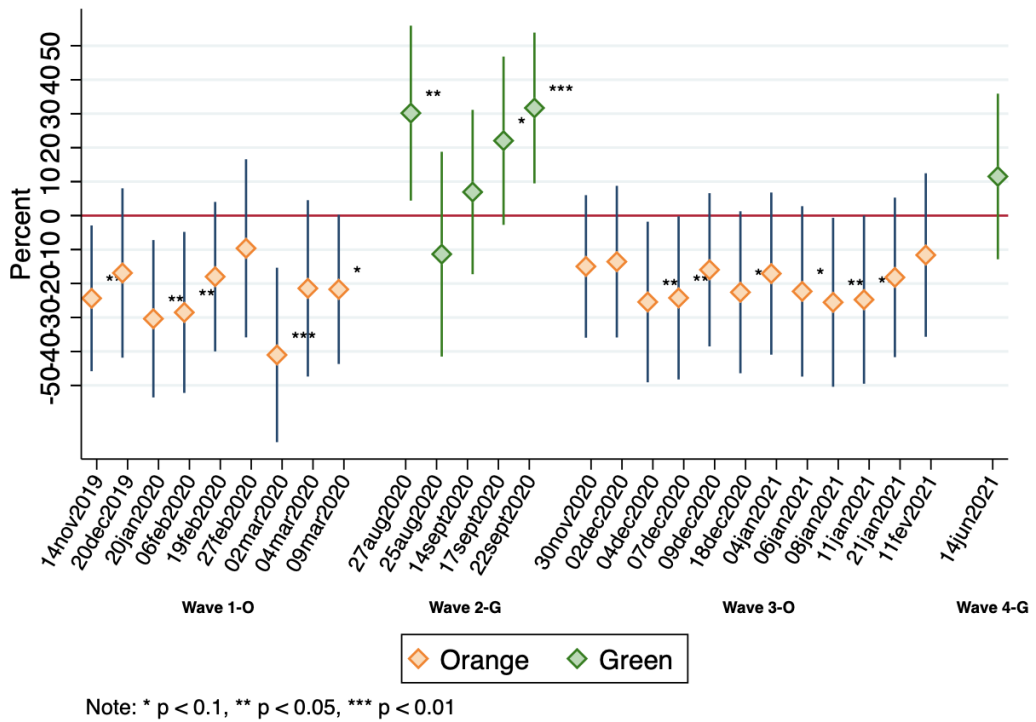
### 4.3.3. Post Analysis

Our data collection enables us to observe the electricity consumption of all participants several months after the last text message. We want to check whether our participants have similar energy consumption to that of the control group if they were not warned by our text messages during the peak event. Recall that our Orange alerts were based on PP1/PP2 days of the French grid management firm. These days are defined each year, allowing us to run a post-analysis. Similarly, the regression of electricity consumption does not exhibit a significant difference between the control and treated groups (see Table 6). This result confirms the effect of the text messages to sift electricity consumption during the winter peaks.

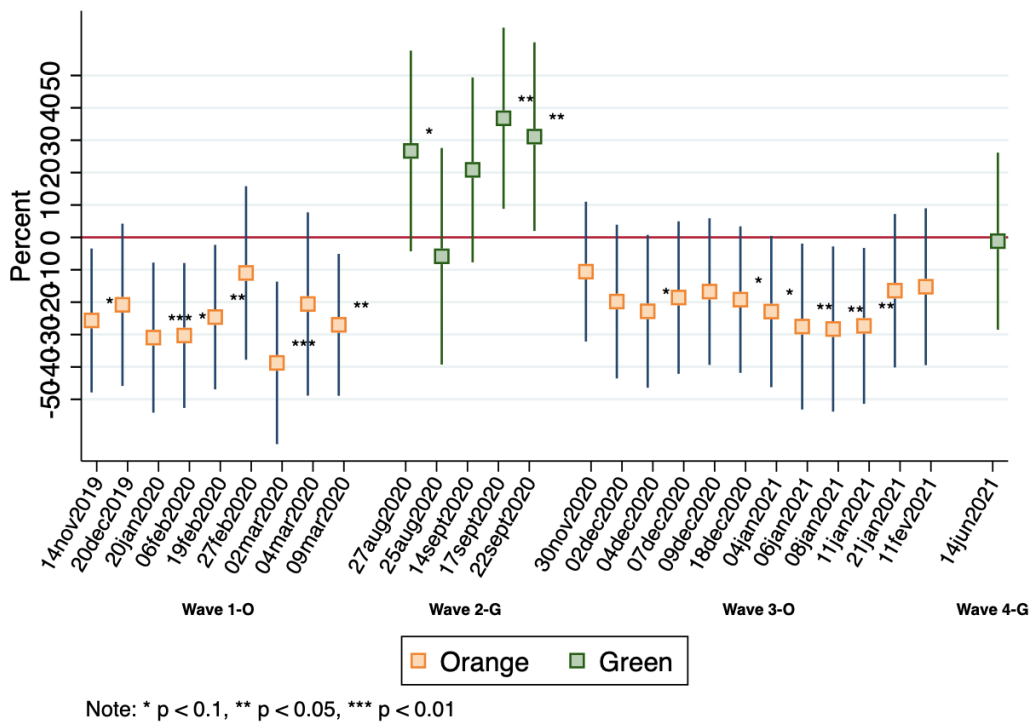
Table 6: Post-analysis period : winter 2021/2022, between 6 PM and 8 PM.

	Total	30-min
(Intercept)	-1.9982*** (0.0833)	-3.0713*** (0.0821)
Alert days	-0.0089 (0.0489)	-0.0238 (0.0492)
Num.Obs.	1837	7348
Std.Errors	Cluster by id	Cluster by id

\* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01



(a) 30-min



(b) Total

Figure 4: Effect of the nudges on electricity consumption for each alert day: Percentage change

#### 4.3.4. Policy implication

We believe that our designed intervention can be implemented on a large scale, as there is no need for monetary incentives. The difficulty of scaling up academic, laboratory or field experiments is relevant for any experimental study. In their article, [Al-Ubaydli et al. \(2021\)](#) advocate three main reasons why results published in scientific journals may be hard to apply in real life when you are implementing a tool at a large scale. The first reason is the lack of statistical power. In this experiment, we have a small sample of 165 participants observed during more than two years at the 30-minutes scale. This is enough to ascertain the internal validity of our results. The second reason is that, network effects and general equilibrium should also be considered, as they can amplify the policy intervention effect or, on the contrary, decrease its impact according to its diffusion in the network ([Tarozzi et al., 2014](#)). Finally, the third reason is the representativeness of the population and the context. Even without the classic selection bias that laboratory experiments suffer from, field experiments are only implemented in a small fraction of the population, and the result may not generalize to the entire population. This is also true in this experiment even if our sample of households resembles the population that can be targeted by this type of intervention. In addition, each field study is context dependent, and this context may not be easily replicated in everyday life (higher motivation of the participant to the program, better material condition, higher accessibility to the information, and so on). An application called [Ecowatt](#) already offers households the opportunity to subscribe to a system of alerts that intend to prevent electrical shutdown. Similarly, the [Green Monday](#) is an initiative in which households freely commit to eat a plant-based diet at a minimum on every Monday. In the US, the positive results of the study, defeat the peak([Pratt and Erickson, 2020](#)), confirm also that this behavioral instrument is promising. These different initiatives are clear evidence that a public policy in line with our intervention can be implementable with high chances of success.

## 5. Conclusion and Policy Implications

In this research, we implement a field experiment based on an original demand response program with peak load events and peak energy production events. For two years, a set of households were subjected to three coupled demand-side flexibility devices. Our results indicate that a nudge policy based on a relatively personalized system allows substantial and significant demand flexibility to be reached and could help manage the grid. We design an intervention efficient at low cost for policy-makers wishing to implement demand response programs. The designed nudge succeeded in sifting consumption downward and upward according to the grid needs and maintained the stimuli effect in the long run. Interestingly, we observed no habituation effect in behaviours. One possible explanation is that the nudges complementing the energy conservation appeal may have attenuated the habituation phenomenon usually observed when using noneconomic incentives. Indeed, our intervention had a persistent effect over the period of the experiment and continues to be positive from one wave to another with a similar effect size.

The penetration of intermittent renewable energy in the electricity production mix requires that households adapt their energy consumption to energy production to balance the grid. In addition, both the urgent energy crisis at the European level and the inflation rates reinforce the need to find a valuable tool to change energy consumption behaviour with non-regressive policy tools. The numerous social movement against taxes call for new incentive mechanisms

that don't play on prices.

Our intervention can also thoughtfully complement dynamic tariffs in two ways. First, dynamic pricing could be seen as costly and, therefore, may be unpopular if imposed on society or if it results in a low subscription rate. Consumers who are risk averse may be unwilling to subscribe to dynamic tariffs for fear that there will be an increase in bills if they fail to adapt their energy consumption according to changes in prices. Thus, some households may be willing to participate in the fight against global warming and adapt their consumption during peak usage but are not willing to subscribe to critical peak pricing. Second, the nudges complementing our noneconomic incentive can also be used to complement economic incentive, i.e. dynamic pricing. One can use the same energy flexibility tips and feedback with a critical peak pricing. Thus, our research contributes to the design of demand response programs with practical advice on how to sustain participation in the program for economic and noneconomic incentives.

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## A. Instruction Materials

Homepage

Home Energy Report

Questionnaire 2021

Your electrical appliances

Your commitments

Green Period

Orange Period

Feedback

Load curve

Guidelines

Contact

### EtudElec

This study is conducted by the Grenoble Applied Economics Laboratory (GAEL) and the Grenoble Electrical Engineering Laboratory (G2ELab), as part of a public research program funded by the [Auvergne Rhône-Alpes region](#) and the [National Research Agency](#).

This study focuses on the challenges of household electricity consumption in the context of the development of renewable energies (which currently represent only 18% of electricity production in France).

More specifically, we are interested in the conditions for greater flexibility in household consumption. This means that daily electricity consumption should be :

**Reduced:** when the production by ENR is insufficient.

**Favored:** when the production by ENR is important.

This flexibility will allow to consume green energies, to participate in the energy transition and to fight against global warming by limiting the use of thermal power plants.

Figure 5: Snapshot of the dedicated website where participants can consult their committed actions and reference curve. This is also where they can fill out the questionnaire.

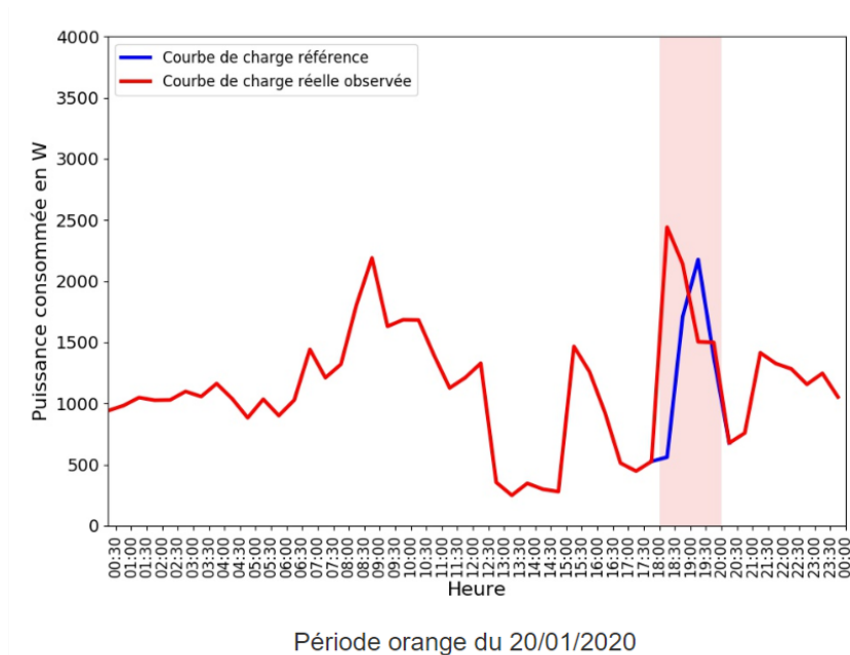


Figure 6: Example of one feedback curve for a participant in red the actual consumption of the participants, and in blue the reference load curve



Homepage

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## Your Commitments - Orange Period

Between 6pm to 8 pm, during weekdays, I commit

- not use the oven
- not use the microwave
- not use the hotplate
- not use the dishwasher
- not use heated kitchen appliances (deep fryer, food processor, kettle)
- not use electrical cooking appliances
- not use the washing machine
- not use the tumble dryer
- not iron clothes
- not use electric appliances for hair care
- not set the thermostat of the main heating system to more than 20°
- not use the space heater
- not use electronic devices that are plug on the grid (computers, ..)
- not use audio-visual devices on mains (TV, hi-fi, game console)
- not reloading the batteries of audio-visual and electronic devices (tablets, smartphones, game consoles)
- not reloading your electrical car
- not reloading your electrical scooter
- not reloading other type of electrical vehicules

Figure 7: List of energy flexibility tips that participants need to personalize and commit, with the corresponding color code.

## B. Additional result

All days of the week before the first treatment date.

Table 7: Regression ln(kWh 30-min) and Total consumption (in kWh) in September during the period of alerts

	6 pm to 8 pm		12 am to 5 pm	
	30-min	Total	30-min	Total
Treated	-0.000506 (0.0424)	0.0121 (0.0446)	0.0255 (0.0454)	0.0250 (0.0443)
Ln(kWh) 24 h	1.105*** (0.0240)	1.133*** (0.0285)	1.119*** (0.0300)	1.180*** (0.0278)
Average daily temp (C)	-0.00554 (0.0036)	-0.00826** (0.0040)	-0.00674** (0.0031)	-0.00808** (0.0033)
Sun (Minutes/day)	-0.0000941*** (0.0000)	-0.0000925** (0.0000)	0.0000516 (0.0000)	0.0000434 (0.0000)
Constant	-2.966*** (0.0807)	-2.305*** (0.0929)	-3.349*** (0.0828)	-2.233*** (0.0789)
Observations	18383	4596	27532	4589

Note: Individual fixed effects: time dummies for day of the week and hour.

Standard errors between parentheses.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$