Urgency and engagement: empirical evidence from a large-scale intervention on energy use awareness

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Abstract

We study how to foster engagement in the energy sector, where signals about consumption are opaque and infrequent. We evaluate an energy company's large-scale communication campaign for promoting natural gas self-reading. Self-readings allow utilities to bill customers on the basis of real - as opposed to estimated - consumption. Exploiting variation in campaign messages, we test the impact of imposing a sense of urgency on customers through a deadline for submitting a meter reading. We find that messages that induce a sense of urgency are twice as effective than generic messages in encouraging self-readings, consistent with recent research on the urgency effect. The increased sense of urgency moves to action customers with both high and low levels of baseline engagement; the effect is stronger on the former.

JEL classification: D12, D83, D91, Q4

PsychINFO classification: 3900, 3920

Keywords: Consumer behavior, Information, Urgency, Gas consumption, Engagement

1. Introduction

Utilities all over the world rely heavily on users to submit their energy readings to achieve billing accuracy. This is especially true in the residential natural gas market, for which smart meters - that transfer consumption data automatically and make meter reading by the customer or by the utility unnecessary - are lacking. Many European countries have rolled out smart meters for measuring electricity, but natural gas lags behind. In Europe, for instance, just five countries, among which Italy, have decided to roll out natural gas smart meters. Yet, natural gas dominates energy expenditures in many countries: in Italy, for example, the average household pays 80 per cent more for gas than for electricity. Identifying strategies to effectively encourage customers to send meter readings and improve the accuracy of energy bills is thus a widely relevant policy and marketing issue.

Increased billing accuracy is likely to improve both consumer welfare and administrative efficiency through a number of channels. First, billing accuracy reduces the likelihood of bill shocks. Bill shocks are one of the main causes of delayed and incomplete bill payments, and of complaints customers make to utilities' customer care services. Second, bills based on customers' actual consumption, rather than on their estimated consumption, send users a more precise signal of their energy usage and increase the fairness of the billing system. Third, existing evidence suggests that making information on consumption clearer, more salient or more frequent, results in expenditure reductions (Gilbert and Zivin 2014; Allcott 2011; Ferraro and Price 2013; Costa and Kahn 2013; van Houwelingen and van Raaij 1989). More specifically, feedback on consumption to residential customers, who read their own meters, has been identified a promising method for motivating them to save, when smart meters are not available (Darby 1999). Understanding how to motivate people to attend to their gas consumption is therefore both challenging and policy relevant.

We study an intervention aimed at making gas customers more attentive to their consumption. Specifically, we evaluate a communication campaign encouraging customers to submit self-readings, to be billed for their real rather than for their estimated consumption. The utility sent each targeted customer one of two versions of the campaign message. One version imposes a sense of urgency on customers through a close deadline for submitting a meter reading. In particular, this version of the campaign message informs customers that they are entering a special 4-days' time window and that they will receive a bill based exclusively on their real consumption if they send a reading before it ends. The other version of the message more generally links self-readings to having one's bill based on real consumption. We test the relative impact of the two versions of the campaign message on self-readings, and compare it to self-readings rates among customers not receiving the campaign.

The utility did not select randomly which customers should be targeted by the campaign, nor who should receive the different versions of the message. In order to obtain a clean impact evaluation of the campaign messages, we adopt tools commonly used in the evaluation of public policies, when randomization is not an option, to generate a valid control group, i.e., one with the same observable characteristics, on average, as the treated sample. Specifically, we use propensity score matching to match the sample of treated customers with untreated ones displaying similar characteristics.

Knowing that submitting a reading would result in a bill based on real consumption increases self-reading after the campaign by 12 percentage points, relative to the control group of customers excluded from the campaign; being given a deadline, by which to send a reading, leads to an additional increase in submitted readings of 16 percentage points. We explore the heterogeneous effect of the campaign, depending on customers' prior level of engagement with the utility: while effective also on previously unengaged customers, both versions of the campaign messages raise self-reading rates more among active customers, i.e. customers who were active on the utility's portal or submitted self-readings before the campaign.

Our results are consistent with recent evidence showing how agents, when made aware of time restrictions on a task, tend to prioritize it, even if secondary with respect to other tasks (Zhu, Yang, and Hsee 2018; Zhu, Bagchi, and Hock 2019). Since missing the deadline in our setting does not prevent customers from submitting a self-reading and benefitting from the improved informational content of the resulting bill (Zhu, Yang, and Hsee 2018), [1] likely explanations for the urgency effect that we observe point to the desire to meet a certain goal (Kivetz, Urminsky, and Zheng 2006), or to individuals' tendency to prefer immediate benefits over future ones (Frederick, Loewenstein, and O'Donoghue 2002; McClure et al. 2004). Urgency draws attention (Botti et al. 2008; Cialdini 2007; Pribram and McGuinness 1975; Zhu, Yang, and Hsee 2018; Zhu, Bagchi, and Hock 2019), creating enough tension to trigger action, even among those customers who are generally less reactive to informational campaigns. Indeed, we show that urgency significantly and marginally increases the response rate even among customers displaying the lowest level of attention towards the service. Still, our results confirm that urgency affects more individuals who are tuned into the time dimension (Zhu, Yang, and Hsee 2018), such as customers regularly paying bills or submitting self-readings.

We go beyond the recent literature in two main ways. First, to the best of our knowledge this among the first tests of the urgency effect in a real setting. Previous work (Zhu, Yang, and Hsee 2018; Zhu, Bagchi, and Hock 2019) has focused on small samples of either students or online workers (such as MTurkers) with hypothetical decisions. Here, we evaluate it in the field, with a large set of customers engaged in behaviours with real and relevant economic consequences. The current work is also novel in its focus on the heterogeneity of the urgency effect, namely in investigating whether urgency has the same influence on unengaged customers. We find a significant reaction from customers who displayed low attention to their own consumption before the campaign, even if not as strong as that of engaged ones.

Our results also contribute to the growing literature that puts behavioural insights to work and demonstrates their effectiveness in policy relevant domains through field studies (Andor and Fels 2018; Brandon et al. 2019; Harrison and List 2004; List and Price 2016). In the energy sector, existing studies have overwhelmingly focused on fostering efficiency in electricity consumption and used social information as behavioural lever (Allcott 2011; Allcott and Rogers

[1] Urgency effect is thus distinguished from scarcity effect (Lynn 1989; Shah, Shafir, and Mullainathan 2015; Verhallen and Robben 1994), which is strictly related to the limited availability of a commodity.

2014; Allcott and Mullainathan 2010; Andor et al. 2017; Sudarshan 2017). However, existing evidence shows the potential of enriching the behavioural policy toolbox (Abrahamse and Steg 2009; Fischer 2008) and demonstrates how even interventions not directly aimed at reducing consumption can improve efficiency, thanks to their impacts on increased awareness and attention to resource usage (Ayres, Raseman, and Shih 2013; Darby 2010; Hargreaves, Nye, and Burgess 2013; Jessoe and Rapson 2014; Wichman 2017). The current paper is one of the first attempts to use urgency as a means to increase consumers' engagement in the energy market.

The paper proceeds as follows: Section 2 briefly describes the setting of our study and provides support for its premise, Section 3 presents the design of the campaign and the data, Section 4 the empirical results, and Section 5 concludes.

2. Energy self-reading

Natural gas is used by about 95 per cent of Italian households for heating, as well as being the main energy source for hot water and cooking, and makes up about 65 per cent of energy consumption in the country ("I consumi energetici delle famiglie" 2014). Gas and electricity are responsible on average for 7 per cent of household expenditures among Italian consumers.[2]

Gas consumption is tracked through meters (see Appendix Figure A1). Traditional gas meters do not send consumption data automatically to utilities, but need to be read manually.[3] Energy distributors are obliged by law to send meter readers to collect consumption data at least once a year per household. However, distributors' readings can occur even less frequently, if users cannot be found at home. Alternatively, customers can submit self-readings.

In the absence of readings or self-readings, energy utilities estimate gas consumption through an algorithm, as a function of each household's type of use (heating, hot water, and/or cooking), geographical area, past expenditure and number of occupants. The estimate gets refined as data on the household's real consumption becomes available, thus self-readings help utilities improve bill accuracy. Once utilities get a reading or self-reading, they compute the difference between real and estimated consumption. If positive, households have to pay the difference. If negative, they get discounts on subsequent bills up to the value of the difference.

The opacity of the billing system is a widespread issue: for instance, in our sample of Italian gas users, 45 per cent of customers had received bills based on estimated consumption for more than a year. The relevance of billing accuracy as a policy issue is testified by the fact that it has come to the attention of the Italian legislator. The Budget law of 2018 contains provisions to protect consumers with outstanding debts towards utilities as a result of discrepancies between estimated and real consumption, for instance preventing utilities from billing customers for estimated consumption going back more than 24 months.[4] Among these

[2] Source: ISTAT data on Household Consumption Expenditure 2018, available at: https://www.istat.it/en/archivio/232003.
[3] As mentioned above, traditional gas meters are currently being replaced with new generation, smart meters, which will send automatically gas consumption data to the provider monthly. However, at the time of the interventions described here, the coverage of smart meters was negligible.
[4] Legge n. 205/2017, articolo 1, commi 4-10.

provisions, the legislator encourages the Italian Authority for Gas and Energy (ARERA) to design interventions aimed at encouraging self-reading among gas customers. This, in turn, has placed utilities under great pressure to enact campaigns like the one evaluated in the present study. Furthermore, energy utilities have private incentives to promote self-readings, as these typically reduce the likelihood of large shocks to bill amounts and consequently improve payment rates and timing. Within our sample, customers who submitted a self-reading before the campaign, i.e. between January and April 2016, are 50 percent less likely to be flagged by the utility as having outstanding debts ($p < 0.01$). This is consistent with infrequent readings resulting in large bill shocks, and subsequent payment issues.

More generally, policy makers are increasingly concerned with educating consumers and raising their awareness in the use of energy. The first step towards this goal consists in drawing consumers' attention towards their energy and gas use, which are typically poorly known and understood, despite representing an important expenditure items of European households. Indeed, empirical evidence shows that misperception and mis-optimization is pervasive in the energy domain, from underestimation of fuel costs (Allcott 2013; Allcott and Wozny 2014) to incorrect beliefs on the impact of energy conservation behaviors (Attari et al. 2010). Misperception, lack of information, and limited attention to operating costs are considered as primary contributors to the energy-efficiency gap (Allcott 2016; Allcott and Greenstone 2012; Caplin and Dean 2015; Gerarden, Newell, and Stavins 2015; 2017; Gillingham, Newell, and Palmer 2009; Gillingham and Palmer 2014). Such misperception may also be due to the limited attention devoted by individuals to their energy consumption: for instance, studies show that on average people spend seven minutes per year thinking about their energy use (Laskey and Syler 2013)

This evidence underlies calls for policies to make energy cost information more salient, timely and transparent. For instance, within Europe, the "EU2020 target for energy efficiency" stresses the need for greater energy efficiency, to be achieved through buildings requalification, more efficient appliances, but also through better information. To this end, EU countries have committed to rolling out smart meters for electricity and gas. Similarly, actions to increase public awareness, induce behaviour change and provide education, constitute an important element of policies and programs to support energy efficiency and energy savings supported by the JRC (Rivas, Silvia, Cuniberti, and Bertoldi 2016). Reliable, timely and accurate information to consumers are considered to be crucial to induce more awareness. The campaign that we study is an example of these policy efforts.

3. Data and design

We study an intervention conducted by a large energy company with operations in Italy and worldwide. The utility launched the campaign in May 2017, at the end of the heating season. More than 1 million customers received the campaign messages by email over the course of one week, namely a first message on May 5th, and a reminder on May 8th. We have data on the 1,083,369 customers targeted by the campaign, as well as on 1,637,002 customers that did not receive any message, who constitute our control group. The campaign targeted active residential gas customers without any repeated missing bill payments, and with no meter-readings submitted over the month before the campaign.

The utility introduced two versions of the campaign message. Customers in the No Urgency (NU) treatment received a message similar to the most effective message proposed in a pilot test, emphasizing how submitting a self-reading resulted in a bill in line with one's real gas consumption.[5] The Urgency (U) treatment augmented this message with information on a special time window to submit the self-reading. Namely, the U message told customers by what date they should submit a self-reading for it to fall within this special time window. Figure A2 shows the two campaign messages: both messages, albeit not using the exact same structure across treatments, aim to induce customers to actively submit a self-reading.

The U treatment exploits the fact that, if a self-reading is submitted between 7 and 4 days from the last day of a billing cycle, the resulting bill will be based exclusively on the submitted read, i.e., on real consumption. For ease of exposition, we will hereafter refer to the 7 to 4 days' window before the end of the billing cycle as the U window. Since most customers receive their bill bi-monthly or quarterly, submitting a reading in the U window will generate a clear signal of one's real consumption in the very short term, i.e. in the bill that will be received one week after the self-reading. On the contrary, submitting a reading outside of the U window will result in feedback on one's real consumption that is both more diluted and less timely, thus less informative. Self-readings submitted outside the U window still count, but the resulting bill will include a component based on estimated consumption, for the days between the date of the reading and the last day of the billing cycle.

Clearly the two messages differ along other attributes beside urgency. In particular, customers in the U treatment are guaranteed more informative feedback on their consumption by submitting a self-reading before the deadline. By submitting a self-reading, customers in the NU treatment instead may know that they will receive a delayed and diluted signal of their real consumption in the following bill. This, by itself, may cause different levels of engagement among customers in the two groups. The design of the campaign is such, that we cannot disentangle the effect of urgency from that of the usefulness of submitting a self-reading. However, we exploit the heterogeneity of treatment effects based on previous self-readings to argue that urgency is likely to play an important role.

[5] The intervention was anticipated by a pilot test focusing on the effectiveness of different messages on self-reading, conducted by the same utility on a subsample of clients (3,491 households). The versions of the messages piloted in this test were all broadly inspired by behavioural principles: the three messages appealed to the desire to avoid surprises in the bill, to prevent negative bill shocks and to conform to the behaviour of a growing number of customers in order to foster self-reading, respectively. Since we have no data on customers' participating in this test, assignment to treatment was not randomized, the target sample small and the test messages differed along various dimensions, beside the behavioural levers, we do not report results for it in the main text, but a description of the test and basic results are available in Appendix B. The test suggested that the desire to keep, or gain, control over one's gas expenditures was a strong motivator of customers' engagement. Consistent with this result, both versions of the campaign message that we study in this work make explicit the link between self-reading and receiving a bill with information on one's real consumption.

Bill cycles differ for each customer, and mainly depend on the contract activation date. Since campaign messages were sent over the same one-week period (May 3rd – May 8th), they could reach a customer within or outside her U window. The treatments exploit this variation: customers whose U window occurred during the campaign week received the U treatment message (24,748 customers), while other customers received the standard message (1,058,621 users). Specifically, customers received the U message if their bill was due in the week starting on May 13th.

While we may expect the U treatment to be exogenous to customers' characteristics, since it depends on the contract activation date, and thus the U and NU groups to be balanced in terms of their characteristics, this is actually not the case. Furthermore, control group customers significantly differ from treated ones across several dimensions. We assess balance using available data on customers' characteristics, such as their location, use of gas, activity on the utility's portal, type of bill received (paper or mail) and payment type (e.g. direct debit); as well as information on baseline billing and self-reading history from January 2016. Table A1 provides a description of the variables in our dataset, while Table A2 presents summary statistics for the three groups and balance tests. The three samples of customers are significantly different across all the dimensions we have data for.

We thus use propensity score matching (PSM) techniques to select the sample for our empirical analysis (Rosenbaum and Rubin 1983; Imbens 2000). PSM is commonly used in similar settings (i.e., Nikolaev 2015; Rotondi and Stanca 2015; Migali and Zucchelli 2017), where data come from (non-randomized) observational designs. Since, in these settings, an individual's treatment status depends on her choices or characteristics, any estimate of the intervention's impact may be biased by confounding factors. PSM represents a tool to solve the endogeneity problem: by constructing treatment and control groups that are similar on average along all observable characteristics, it minimizes the differences between these groups and the influence of confounding factors on treatment impact estimates (Becker and Ichino 2002).

We proceed in two stages: first, we apply PSM to construct two balanced treated samples for U and NU customers; second, we apply PSM to identify a suitable control group for our pooled sample of treated customers. We match customers on the basis of gas consumption habits and household characteristics. In terms of consumption, we consider average monthly bill amount, average consumption between January 2016 and April 2017 and the type of gas use (heating, cooking, hot water). Since our outcome variable is engagement, in the form of self-reading, we include in the matching routine customers' characteristics that are potentially related with their engagement level: total self-readings submitted between January 2016 and April 2017, past activities on the utility's website, any delays in bill payment, registered email or phone number, electronic bill, direct debit, age,[6] gender and location (North-Center-South of Italy) of the contract holder. Finally, we include controls related to customers' accounts: the type of contract they subscribed to and dual contracts (electricity and gas).

[6] We include age squared as well in the matching routine.

Having defined the independent variables for the matching algorithm, we find the common support of the propensity score, defined as the probability to be included in the U treatment given these variables, computed through a logit specification. Within the common support, we elicit the nearest neighbour (NN) matching estimator lying within the caliper (0.001), with no replacement option. This procedure produces a sub-sample of 47,535 customers. We follow the same protocol to find a suitable control group for the pooled sample of treated customers among the clients excluded from the intervention, resulting in a control sample of 29,628 customers.[7]

Table 1 shows summary statistics of the three groups: the control, NU and U. The PSM has reduced both the magnitude of the differences between the groups along all dimensions, and the number of traits where we observe significant differences between the two groups. Statistically significant differences, at the 5 per cent level or below, remain in terms of baseline consumption and bill amount, gas use and availability of email contact. However, the magnitude of these differences is small, for instance at most 6 per cent for consumption and 4.5 per cent for bills. We address the issue of unbalanced covariates by controlling for them in the regression analysis.

[7] Among the 47,535 customers exposed either to the NU or U treatments, 17,970 fall out from the common support in the second stage of the Propensity Score Matching, where we find a suitable control for the treated group. We finally end up with 14,743 customers in the NU treatment group and 14,822 in the U one.

Variable	Control Obs	Control Mean	Control Std. Dev.	NU Obs	NU Mean	NU Std. Dev.	U Obs	U Mean	U Std. Dev.	Prob > F
Baseline self-reading	29,628	2.24	2.73	14,822	2.30	2.61	14,743	2.25	2.64	0.06
Baseline consumption	29,628	89.34	154.36	14,822	88.59	101.67	14,743	94.23	78.57	0.00
Baseline bill	29,628	74.79	102.12	14,822	78.40	337.56	14,743	76.63	58.84	0.04
North	29,628	0.41	0.49	14,822	0.41	0.49	14,743	0.41	0.49	0.73
Center	29,628	0.17	0.38	14,822	0.17	0.37	14,743	0.17	0.37	0.43
South	29,628	0.37	0.48	14,822	0.38	0.48	14,743	0.37	0.48	0.72
Gas use: heating	29,628	0.86	0.35	14,822	0.87	0.34	14,743	0.88	0.32	0.00
Gas use: hot water	29,628	0.96	0.20	14,822	0.96	0.19	14,743	0.97	0.18	0.00
Gas use: cooking	29,628	0.97	0.17	14,822	0.97	0.17	14,743	0.97	0.17	0.40
Gas use: other use	29,628	0.00	0.00	14,822	0.00	0.00	14,743	0.00	0.00	.
Age	29,628	53.15	15.65	14,822	53.07	15.61	14,743	53.07	15.51	0.81
Female	29,628	0.41	0.49	14,822	0.41	0.49	14,743	0.41	0.49	0.59
Bill pay: direct debit	29,628	0.18	0.39	14,822	0.19	0.39	14,743	0.18	0.38	0.15
Late on bill	29,628	0.10	0.30	14,822	0.10	0.31	14,743	0.10	0.30	0.40
Contact: mobile	29,628	0.90	0.30	14,822	0.90	0.30	14,743	0.90	0.30	0.55
Contact: email	29,628	0.98	0.13	14,822	0.98	0.15	14,743	0.99	0.10	0.00
Electronic bill	29,628	0.23	0.42	14,822	0.23	0.42	14,743	0.23	0.42	0.28
Active on website	29,628	0.42	0.49	14,822	0.42	0.49	14,743	0.42	0.49	0.70
Contract type: free mkt 1	29,628	0.01	0.11	14,822	0.01	0.11	14,743	0.01	0.12	0.54
Contract type: free mkt 2	29,628	0.21	0.41	14,822	0.22	0.41	14,743	0.21	0.41	0.19
Contract type: free mkt 3	29,628	0.25	0.43	14,822	0.25	0.44	14,743	0.25	0.43	0.56
Contract type: regulated mkt	29,628	0.04	0.19	14,822	0.04	0.19	14,743	0.03	0.18	0.57
Dual contracts	29,628	0.09	0.29	14,822	0.09	0.29	14,743	0.09	0.29	0.83

Table 1. Summary statistics and balance across treatment samples. Summary statistics for Control, No Urgency (NU) and Urgency (U) groups. To test balance among treatments, we pool all observations across the three groups; for each variable we estimate $y_i = \beta_0 + \beta_1 NU_i + \beta_2 U_i + \epsilon_i$ and report the p-value of the joint test of the following null hypothesis $H_0: \beta_1 = \beta_2 = 0$. Variable definition: baseline self-reading, consumption and bill are computed between January 2016 and April 2017; late on bill is a dummy denoting customers who have been late in their bill payment but who did not experience any interruption in the issue of invoices; dual contract is a dummy indicating whether a customer has both a gas and an electricity contract.

4. Results

We now turn to the analysis of the campaign's impact on self-reading. All subjects in the treatment sample received the campaign email and 12,779 of them opened the email, equivalent to a 43.29 per cent average open rate. Of them, 29.17 per cent submitted self-readings in the 15 days following the campaign.

Figure 1 shows the share of customers submitting self-readings within 15 days from the campaign's start date by treatment and control groups (top panel), the share of customers opening the campaign email by treatment group among treated customers (bottom left panel), and the share of self-readings by treatment group among treated customers who opened the email.

Both campaign messages have a strong, positive and statistically significant effect on self-reading (two-sided t-test, all p's <0.01). With respect to customers in the control group, customers receiving the NU treatment are 12.5 percentage points more likely to submit a self-reading. The U treatment leads to an even larger increase: customers included in U treatment are 16 percentage points more likely to submit a self-reading than customers in the NU treatment. Similarly, among treated customers, those in the U treatment are 12 percentage points more likely to open the email, and 20 percentage points more likely to submit a reading once they opened the email. These effects are extremely large, as self-reading rates more than double under the U treatment, while open rates increase by about 33 per cent with respect to the NU treatment values.

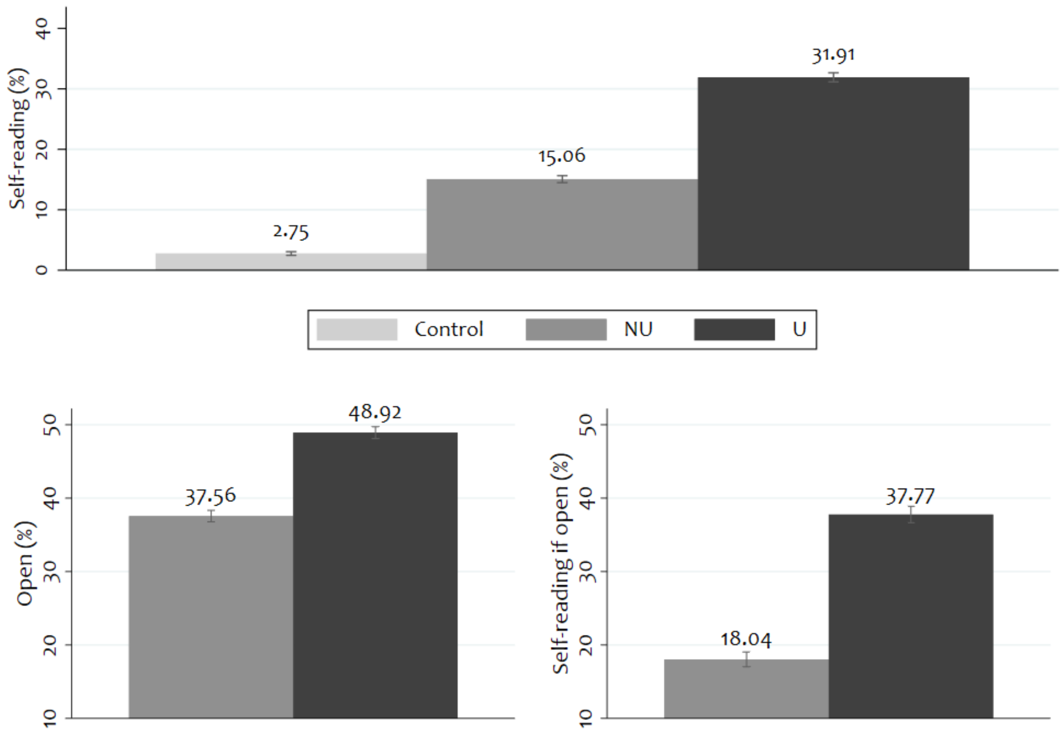

Figure 1. Rates of self-reading, email opening and self-reading if opened email. Bars indicate means, whiskers indicate 95 per cent confidence intervals. Value on bars indicates the percentage.

Since a key goal of self-reading campaigns of the type analysed here is that of engaging customers who had not submitted self-readings before, we next ask whether treatment effects vary depending on customers' baseline level of engagement.

A first indicator of prior engagement with one's own gas consumption, available in our data, is the number of self-readings submitted by a customer between January 2016 and April 2017, just before the campaign. Since customers are billed typically bi-monthly or quarterly, and do not receive any additional information by submitting more than one self-reading within each billing cycle, we would not expect customers to submit more than 8 self-readings over the 16 months' period that we observe before the campaign, if their goal is to have their bills based on real consumption.[8] Indeed, Figure A3 shows that the share of customers submitting more than 8 self-readings before the campaign is negligible. Almost 40 per cent of customers did not submit any self-readings in the 16 months prior to the campaign, confirming the need to foster customers' engagement with their gas consumption.

Figure 2 reports the share of customers submitting self-readings after the campaign and opening the campaign email, by treatment and number of self-readings submitted at baseline. The graph below the self-reading frequencies (central panel) shows the ratio of self-reading rates between subjects in the U and NU treatments (left vertical axis, dark grey line); and the absolute difference in average self-readings of customers these same two groups (right vertical axis, light grey line). The self-reading ratio and difference in averages describe the marginal and absolute effectiveness of U treatment over NU, respectively. At all levels of prior engagement, the NU and U treatments both significantly increase the share of self-readings submitted (two-sided t-test, all p's <0.01) and the U treatment is about twice as effective as the NU one. Similar results obtain when we focus on treated subjects and compare open rates and self-reading rates among customers who opened the email.

Passive customers, with no self-readings submitted at baseline (N = 10,315, with N_{NU}= 5,033 and N_{U}= 5,282), respond to the U treatment almost three times more than similar customers receiving the NU treatment ($mean_{NU}$ = 3.54 vs. $mean_{U}$ = 8.90). The middle panel of Figure 2 shows that the self-reading ratio between treatment groups is largest for customers with two self-readings at baseline (U/NU, dark grey line). The difference in self-reading rates between the two groups (U-NU, light grey line) instead becomes larger as baseline self-readings increase, peaking for customers with seven self-readings at baseline ($mean_{NU}$ = 38.65 vs. $mean_{U}$ = 75.84, with N_{U}= 546 and N_{NU}= 534). Very highly engaged customers (ten or more self-readings at the baseline), which are 1.6 per cent of the customer sample, do not show any significant difference across treatment (two-sided t-test, p =0.54). Engagement levels among these customers are, probably, independent from the utility interventions. Moreover, we lose power to detect any differences due to their low number (213 both in the NU and U conditions).

Past self-reading frequency is indicative of the information content of the bill received by a customer. A large share of customers in our sample receive bi-monthly bills: this implies that

[8] A customer may need to send frequent self-readings in case of change of contract, tariff or meter, or problems with the bill.

customers with six or more self-readings submitted at baseline, representing approximately 10 per cent of the sample, are likely to have been billed for their real consumption during the year before the campaign. Given the nature of the U treatment message, we cannot disentangle the effect of urgency from the desire of receiving a bill based on real consumption only. However, the peak in U-NU that we observe at 6-7 baseline self-readings –which should already guarantee customers an accurate consumption measurement- suggests that it is urgency, and not a desire for billing accuracy, that drives the treatment effects. This is consistent with recent experimental research confirming a mere urgency effect (Zhu, Bagchi, and Hock 2019).

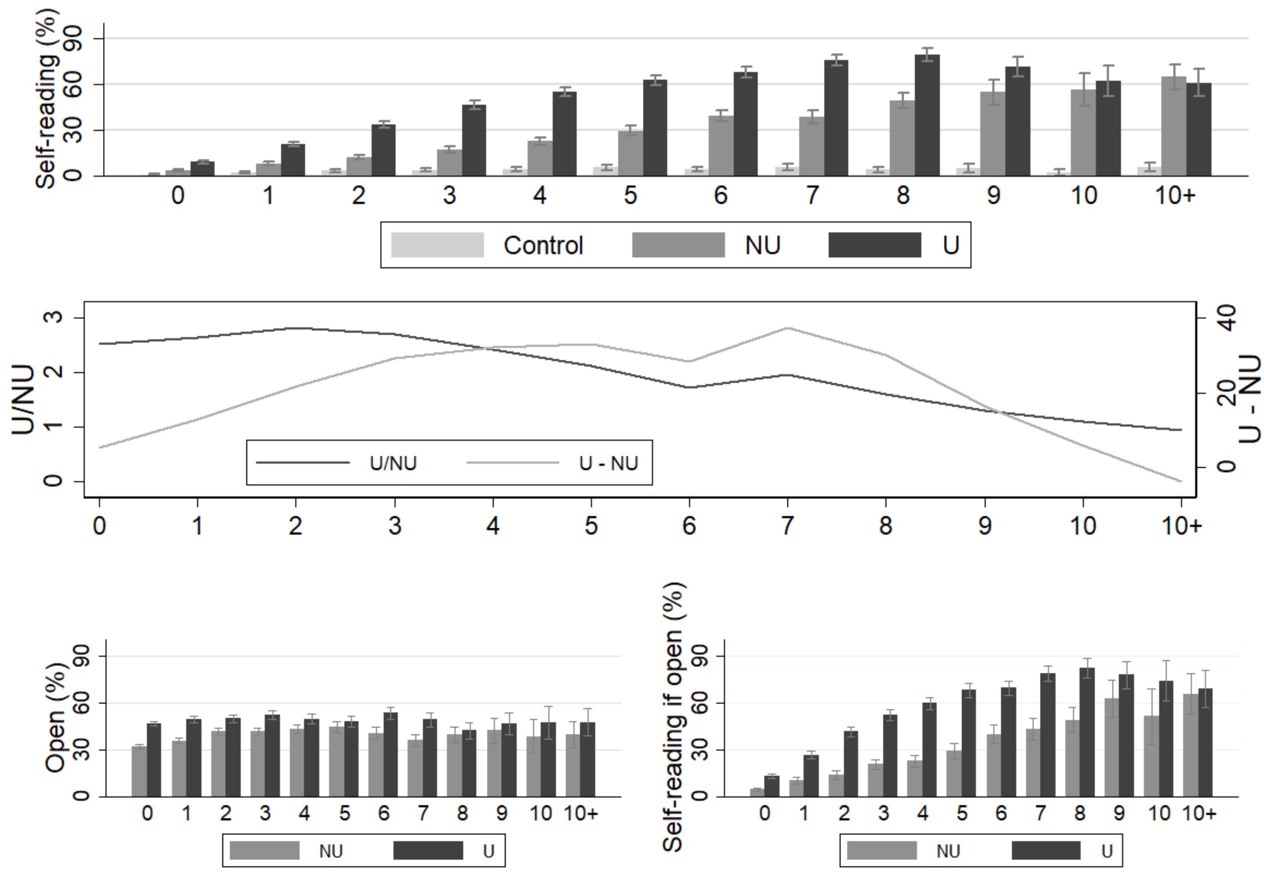

Figure 2. Rates of self-reading, email opening and self-reading if opened email, by past self-reading frequencies. Bars indicate means, whiskers indicate 95 per cent confidence intervals. The central graph represents the difference in relative terms between U and NU groups (U/NU, reported on the left vertical axis) and the absolute difference between U and NU groups (U-NU, reported on the right vertical axis).

Next, we consider activity on the utility's website as another indicator of customer engagement. On the utility's website, each customer, if registered, can access a private area with information on past bills, tariffs, an area to submit a self-reading, etc. We generate an indicator variable, equal to one if a customer made at least one operation on the utility's web portal in the 12 months before the campaign. Being active on the website is not only a signal of engagement, but also a proxy for higher digital literacy. We cannot disentangle these two dimensions, but we expect them both to impact self-reading and email opening rates for a number of reasons. First, customers, who are more digitalized, are able to submit a reading more easily through the utility's app or website and could, for this reason, respond more to the treatment. Theory and evidence from behavioural economics show how small practical barriers may have large impacts on behaviour, due to status quo bias, inertia and procrastination (Carroll et al. 2009). Second, customers, who have actively looked at their personal page on the utility's web portal, demonstrate to be more digitalized and engaged.

Figure 3 shows that, indeed, levels of engagement with the campaign are higher among customers active on the web portal, both in terms of self-readings and of email open rates. As for treatment effects, the share of passive customers submitting self-readings under the U treatment is twice as large as that under the NU treatment and 10 times larger than that of the control group. The results are qualitatively similar, but the magnitude of the differences is somewhat larger, among active customers. When comparing open rates and self-reading rates among customers who opened the email, treatment effects remain large and similar across active and inactive customers.

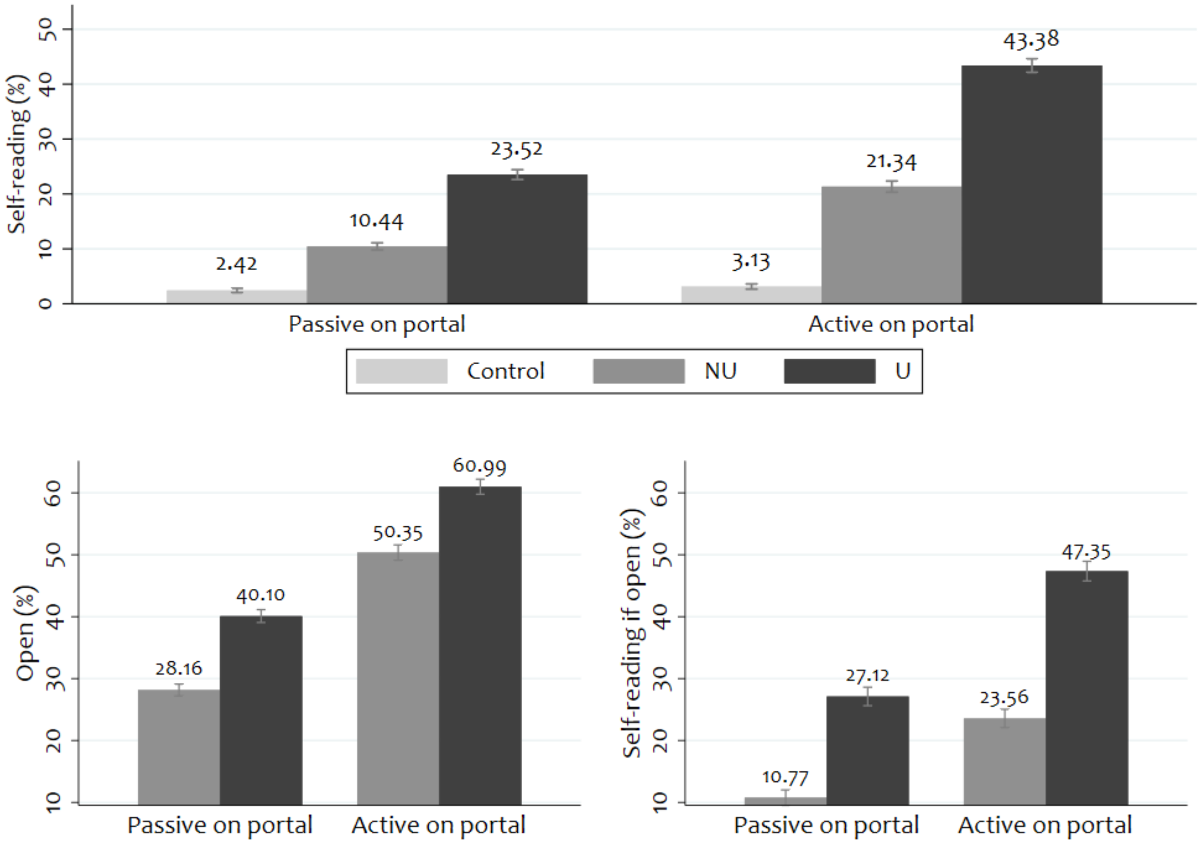

Figure 3. Rates of self-reading, email opening and self-reading if opened email, by past activity on the web portal. Bars indicate means, whiskers indicate 95 per cent confidence intervals. Value on bars indicates the percentage.

Finally, we consider a third indicator of engagement with one's gas use: timely bill payment. Although late bill payment may also signal lack of financial resources, customers who pay little attention to their bills may forget to pay them on time. We use an indicator variable, provided by the utility, of whether a customer experienced delays in paying her bills. Figure 4 shows how engagement levels, proxied by self-reading rates and email opening rates, are higher among customers who regularly pay their bills. The campaign appears to be effective in raising self-reading rates with respect to the control group, even on late-paying customers, and the two treatments show qualitatively similar and strong results among both regular and late bill payers. When focusing on treated customers, the U treatment leads to significantly higher email open rates and self-reading rates among customers who opened the email than the NU treatment, and this holds for both regular and late bill payers (two-sided t-test, all p's <0.01).

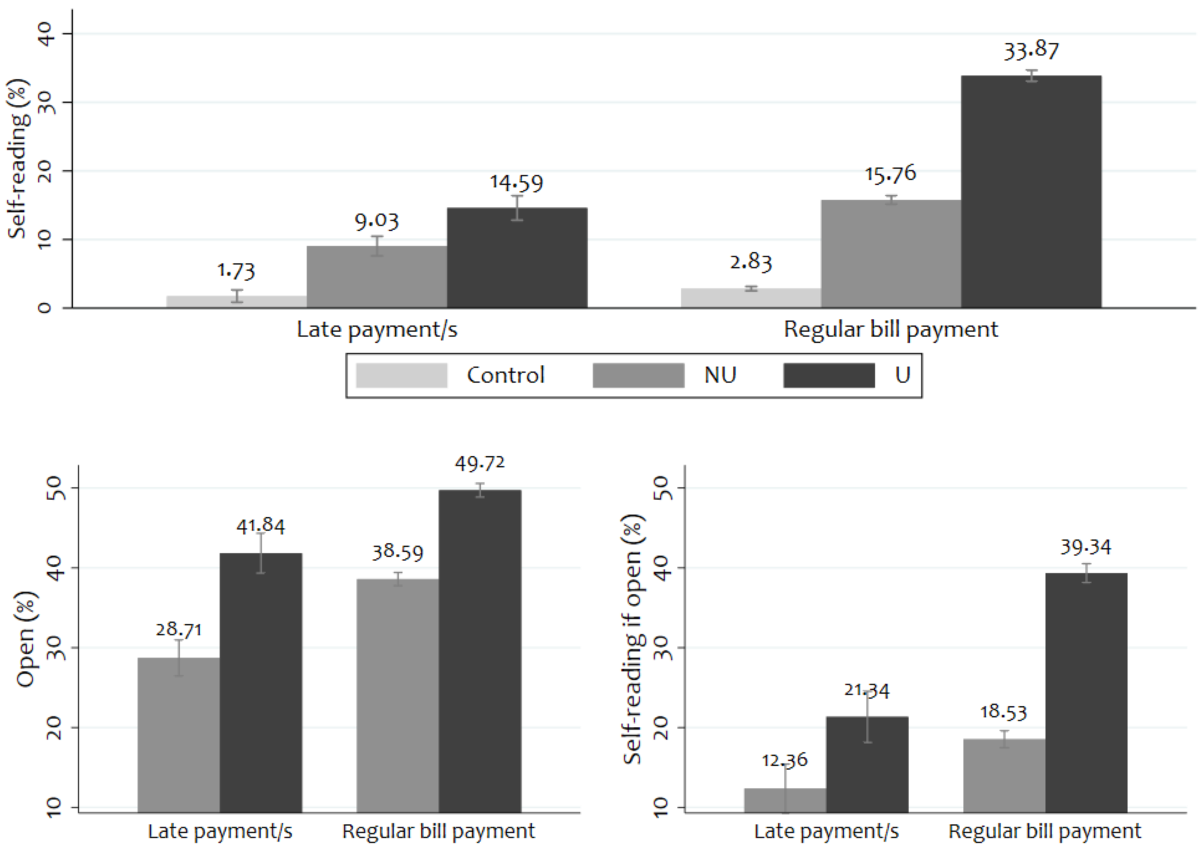

Figure 4. Rates of self-reading, email opening and self-reading if opened email, by regular bill payment. Bars indicate means, whiskers indicate 95 per cent confidence intervals. Value on bars indicates the percentage.

We test the statistical significance of these results, and in particular of differences between treatments and over each source of heterogeneity, using regression analysis. Table 2 shows results of linear regressions of self-reading on treatment indicators and their interaction with the three dimensions of engagement considered in the graphical analysis: number of baseline self-reading, being active on the web portal, and being on time with bill payment. We use the regular bill payment indicator in the regression, so that all our measures of heterogeneity are increasing in engagement. All regressions control for unbalanced covariates across treatment groups, namely baseline self-reading, baseline bill amount, baseline consumption, dummies for whether gas is used for heating or hot water, and a dummy for available customer's email address. Columns 1 to 3 consider each dimension in isolation, while Column 4 pools them in a single regression. To correct for the false discovery rate (FDR) due to multiple testing, in Column 4 we include FDR-adjusted q-values in square brackets (Anderson 2008).

The regression results confirm the basic patterns we observed in the graphical analysis. First, the likelihood of submitting a self-reading after the campaign is significantly and positively correlated with the number of self-readings submitted in the period before the campaign. However, once we control for baseline self-reading and the other covariates, neither being active on the portal nor paying bills on time is significantly or consistently correlated with self-reading after the campaign.[9]

Second, the treatments significantly increase self-reading among both unengaged and engaged customers, with the U treatment having the strongest effect. Among unengaged customers, the NU treatment increases self-reading between 1.5 and 15.5 percentage points, depending on the dimension of engagement considered, while the effect of the U treatment ranges between 12.1 and 33.6 percentage points. When we pool all dimensions of engagement together in one regression, the NU treatment does not significantly affect self-reading among unengaged customers, while the effect of the U treatment remains statistically significant. All differences between treatments are statistically significant, according to Wald tests of the equality of the U and NU coefficients (all p's < 0.01). Among engaged customers, the U treatment is also always significantly more effective than the NU one (Wald tests, all p's < 0.01). When we pool all dimensions of engagement together, the NU treatment does not significantly increase self-reading among regular bill payers.

Third, engaged customers react more strongly to the campaign. The coefficients on the interaction terms between the treatment dummies and the engagement indicators are always positive and statistically significant. When we test for the difference in coefficients between each treatment dummy in isolation and interacted with the engagement proxy, we confirm this result across all the engagement proxies that we consider, but one. Namely, both treatments are significantly more effective among engaged customers (Wald tests, all p's < 0.01), with one exception: the U treatment works equally well among customers who are active and passive on the portal (p = 0.76).

[9] The 3 proxies of engagement are correlated with each other: correlation coefficients are 0.26 between baseline self-reading and being active on portal; 0.14 between baseline self-reading and paying bills on time; and 0.10 between being active on portal and paying bills on time. All correlations are significant at the 1 per cent level (all coefficients' p's < 0.01).

Dependent variable	Self-reading after the campaign			
	(1)	(2)	(3)	(4)
NU	0.02***	0.09***	0.16***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
U	0.12***	0.22***	0.34***	0.10***
	(0.00)	(0.00)	(0.00)	(0.01)
Baseline self-reading	0.00***	0.04***	0.05***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Active on portal		-0.07***		-0.00
		(0.00)		(0.00)
Regular bill payment			-0.06***	0.00
			(0.01)	(0.00)
NU x Baseline self-reading	0.05***			0.05***
	(0.00)			(0.00)
				[0.00]
U x Baseline self-reading	0.08***			0.07***
	(0.00)			(0.00)
				[0.00]
NU x Active on portal		0.13***		0.05***
		(0.01)		(0.01)
				[0.00]
U x Active on portal		0.22***		0.11***
		(0.01)		(0.01)
				[0.00]
NU x Regular bill payment			0.08***	0.01
			(0.01)	(0.01)
				[0.12]
U x Regular bill payment			0.20***	0.08***
			(0.01)	(0.01)
				[0.00]
Constant	-0.02	-0.08***	-0.06***	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Number of Obs	40786	40786	40786	40786
R-Squared	0.26	0.22	0.21	0.27

Table 2. Treatment effect on self-reading: heterogeneity by customers' engagement level. OLS regressions, robust standard errors in parentheses, FDR-adjusted q-values in square brackets (Anderson 2008). All regressions control for: baseline self-reading, baseline bill amount, baseline consumption, dummies for whether gas is used for heating or hot water, and a dummy equal to one if the customer's email address is known to the utility. * p<0.05, ** p<0.01, *** p<0.001.

Taken together, the results of the empirical analysis suggest that the campaign, with its message emphasizing the link between self-reading and control over one's real gas expenditures, was broadly effective in fostering self-reading, among customers with both high and low levels of baseline engagement. However, adding urgency to this basic message resulted in much larger effects, among all customer segments. The larger effects that we observe among engaged customers seem to confirm that urgency best works for those people who are more attentive to the time dimension of tasks, and particularly to tasks' expiration time (Zhu, Yang, and Hsee 2018).

5. Discussion

We study the impact of messages encouraging customers of a large utility to submit gas meter readings. Treatments vary the content of the messages, in particular making salient a near deadline for submitting self-readings, which would make the upcoming bill completely based on real consumption, as opposed to estimated one. Imposing a sense of urgency is a strong motivator of engagement, especially for customers who already pay some attention to their gas consumption.

This study has implications both for business and policy. Following market liberalization and technological advancement, the energy industry has transformed from pure energy producer and distributor to provider of energy services. Engaging with customers by becoming advisors is now an integral part of energy companies' strategies. Transparency and accountability have also become key indicators in a market, which has become more complex over time. Companies seek to encourage customer feedback because of regulatory requirements, because they aim to build a reputation, as well as to ensure that payment is timely and complaints are limited – something which reducing bill fluctuations, thanks to more frequent readings, can provide.

Policymakers have pushed customer awareness and empowerment as key levers to reduce energy waste and promote a sustainable energy transition. The so called 'Energy Paradox' (Jaffe and Stavins 1994; Allcott and Wozny 2014; Attari et al. 2010) has highlighted how consumers mis-optimize their energy investments. This has a double negative impact: it affects households' welfare directly and indirectly by increasing negative externalities, such as air pollution and climate change. To help consumers make better choices, a great number of countries have legislated policies aimed at reducing the information gap (Abrahamse and Steg 2009; Sudarshan 2017; Anderson and Newell 2004). But providing information is ineffective if people do not attend to it. The advent of smart metering and real time measurements will generate a large quantity of new data, but it remains to be seen whether this will actually lead to better energy decisions by consumers (Lynham et al. 2016; Lurie 2004). The insights of this paper suggest that behavioural tools can be successfully leveraged to increase customers' engagement, even among those who are least attentive.

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