FAERE
French Association
of Environmental and Resource Economists

Working papers

Behavioral intervention to conserve energy in the workplace

Valeria Fanghella, Giovanna D'Adda, Massimo Tavoni

WP 2020.21

Suggested citation:

V. Fanghella, G. D'Adda, M. Tavoni (2020). Behavioral intervention to conserve energy in the workplace *FAERE Working Paper, 2020.21.*

ISSN number: **2274-5556**

www.faere.fr

Behavioral intervention to conserve energy in the workplace

Valeria Fanghella, Giovanna D'Adda, Massimo Tavoni*

Abstract

This study investigates the effect of a large-scale behavioral intervention to conserve energy in the workplace, consisting of an energy-saving competition among a bank's branches. More than 500 branches were involved for a period of one year. Using a difference-in-difference estimation, we find that the competition significantly reduces monthly electricity consumption outside the work schedule (by 7 percent), but that overall energy use does not change significantly (reduction of 2.5 percent). Branch characteristics do not lead to differentiated program response, in stark contrast with the residential sector. In the same setting, we also evaluate a technological intervention automating building energy management. The retrofit leads to significant energy savings (of 18 percent), also concentrated outside the main work schedule. Our results stress the importance of considering contextual characteristics when implementing behavioral programs and show potential overlaps with smart technology investments.

Keywords: Behavioral intervention; Energy conservation; Workplace; Difference-in-difference; Energy efficiency

JEL codes: C93, D91, H32, Q41

* Corresponding author: Valeria Fanghella (valeria.fanghella@grenoble-em.com), Grenoble Ecole de Management and University of Trento. Giovanna d'Adda, University of Milan, EIEE and Fondazione Pesenti. Massimo Tavoni, Politecnico di Milano, EIEE and CMCC.

1 Introduction

In the last years residential energy use has reduced in Europe whereas commercial consumption has increased (ODYSSEE-MURE, 2018). Commercial buildings are therefore a critical lever to achieving global sustainability goals (Güneralp et al., 2017). Human behavior is one of the primary sources of energy waste in buildings (Allcott, Mullainathan, & Taubinsky, 2014; Gillingham & Palmery, 2014), especially in the workplace, where market failures lead to the inefficient use of appliances (Giraudet, 2020). The most relevant market failures are principal-agent problems –namely, the misplaced incentive between those who consume energy (the employees) and those who pay for it (the company)– and imperfect information –i.e., the lack of knowledge about one's energy consumption and the related operating costs.

There are different strategies to reduce energy consumption in the workplace. Based on traditional economic theory, employees act as rational and selfish agents who, in the presence of market failures, do not make any effort to save energy. They save energy if the company incentivizes them to do so, for instance by introducing bonuses and gifts. Alternatively, the company can take it upon itself to control its employees' energy consumption (Karjalainen, 2016), such as by installing smart appliances or automating the peak load management. In this case, no effort is required from employees to reduce their consumption, and their passive compliance with the installed technology will generate energy savings for the company.

Other possibilities are offered by the growing body of research in behavioral economics. Behavioral economics shows that people systematically deviate from traditional economic predictions and that such deviations can be harnessed to promote resource conservation (Thaler & Sunstein, 2008). For example, individuals tend to reduce their energy consumption if they discover that they consume more than others do (Allcott & Rogers, 2012) or that their actions have negative environmental and health consequences (Asensio & Delmas, 2015). With this type of intervention, a company can foster its employees' active engagement in energy-saving practices while leaving the incentive structure or the physical environment unchanged.

This study investigates the impact of a large-scale behavioral intervention implemented by an Italian bank to reduce its branches' energy consumption. The intervention centers on an energy-saving competition among the bank's branches. Every month, the top three branches in terms of energy conservation are announced through the company's newsletter. Winners gain social recognition along with a small material reward in the form of an eco-gadget. The competition is reinforced by additional incentives, such as informational materials and individual challenges. The program involves more than 500 branches and lasts one year (January-December 2019).

We assess the impact of the behavioral intervention on branches' monthly electricity consumption using a difference-in-difference (DID) approach from mid-2017 to the end of 2019. As control, we use a subset of branches that are not directly involved in the competition as they are part of a precedent retrofitting program. Our dataset's long time coverage enables us to determine whether the parallel trend assumption holds in the pre-intervention period, proving the reliability of our empirical investigation.

We find that the behavioral intervention reduces average monthly energy consumption by 2.5 percent, but this effect is not statistically significant. This effect size is at the lower end of results achieved in the residential sector (Buckley, 2020; Delmas, Fischlein, & Asensio, 2013). However, energy consumption outside the main work schedule significantly reduces by around 7 percent. This result confirms previous evidence (Orland et al., 2014), and it is easy to explain: while at work, employees need to use appliances for work-related activities and may not be willing to sacrifice their comfort to conserve energy (Buchanan, Russo, & Anderson, 2015). On the other hand, keeping appliances and lights switched off overnight only requires employees to switch them off when leaving the office.

The reason for the overall insignificant effect of the behavioral intervention is likely attributable to the characteristics of consumption in the workplace. First, employees are not charged for their energy consumption. Environments in which users do not pay their bills have shown mixed responsiveness to behavioral interventions (Myers & Souza, 2020; Tiefenbeck, Wörner, Schöb, Fleisch, & Staake, 2019). The absence of bills also reduces the salience of energy consumption, which is usually relegated to the background relative to work-related tasks. Moreover, the company may consider employees' energy consumption as a proxy of their productivity, thereby creating a barrier for conservation efforts. Second, the workplace's energy consumption is the product of many people's actions, and disentangling personal contribution is almost impossible. Employees may experience that their personal efforts to save energy have little effect on the company's final consumption (Carrico & Riemer, 2011), thereby renouncing to change their behavior. The energy-saving competition fails to address this issue, because it targets branches' rather than individuals' consumption and does not clarify the link between one's efforts and the corresponding savings achieved by the company. Finally, even if employees want to save energy, they can do so only by changing their behavior, whereas in the domestic setting landlords can also invest in energy efficiency improvement (Brandon et al., 2017). Considering the foregoing, our study claims for caution when generalizing behavioral interventions results from a specific context to another (in this case, from home to work).

We use branches' characteristics to explore possible sources of heterogeneity in program effect and inform similar future efforts. Contrary to our expectations, we find that none of the characteristics investigated (pre-treatment energy consumption, electric air conditioning system, number of employees, and surface) influence the behavioral intervention. This result is striking for two reasons. First, the residential sector findings show that households with higher pre-treatment consumption save more in response to behavioral interventions than those with lower pre-treatment levels (Allcott, 2011; Bonan, Cattaneo, D'Adda, & Tavoni, 2019; Byrne, Nauze, & Martin, 2018; List, Metcalfe, Price, & Rundhammer, 2017; Tiefenbeck et al., 2018). This result is not replicated for the branches that consumed more energy. Second, prior research suggests that the workplace is a good environment for implementing behavioral interventions because employees are subject to peer effects (Deline, 2015; Staddon, Cycil, Goulden, Leygue, & Spence, 2016). Peer effects should be prominent when energy consumption is apportioned to existing small to medium-sized groups that the employees identify with (Bedwell et al., 2014). We therefore expected a stronger treatment effect among smaller branches. However, no interaction is observed between the number of employees (or surface) and the behavioral intervention. Ex-post survey data show that employees did not speak about the competition, suggesting that the targeted unit (i.e., the branch) is too large and heterogeneous to trigger any peer effect.

Our study makes two main contributions to the literature on energy conservation. First, to the best of our knowledge, this is one of the first economic studies that evaluate the impact of a behavioral intervention in the workplace. While psychological and engineering research provides early insights into the topic (see Staddon et al. (2016) for a review), economists to date have paid more attention to the residential sector (Andor & Fels, 2018; Ramos, Gago, Labandeira, & Linares, 2015). A few notable exceptions exist, though. Brown et al. (2013) show that changing the default settings on office thermostats significantly reduces internal temperature. Handgraaf et al. (2013) and Ornaghi et al. (2018) find that social influence effectively prompts behavioral change when it is tailored to an employee and addresses a specific source of inefficiency, such as office windows left open overnights (Ornaghi et al., 2018). This type of feedback is generally the most effective because it highlights the link between one's action and a given outcome (Tiefenbeck et al., 2018). Finally, Charlier et al. (2021) find that only combinations of nudges prompt employees' conservation efforts. We extend this literature by investigating whether an intervention targeted at a group level reduces total buildings' consumption.

Second, there is growing interest in the interactions between behavioral and traditional policy instruments (e.g., Hagmann, Ho, & Loewenstein, 2019; Panzone, Ulph, Zizzo, Hilton, & Clear, 2018). This study explores the interplay between a behavioral intervention and a smart technology retrofit program, which took place before the energy-saving competition and involved a subset of highly consuming branches. Even if we cannot directly quantify the joint impact of behavioral and technological interventions, our results suggest that the two programs may overlap, rather than complement each other. Both the behavioral and automation interventions prompt conservation behaviors that save energy outside working hours. Combining these two types of intervention may fail to trigger positive synergies because they affect similar inefficiency drivers.

The remainder of the paper is organized as follows. In Section 2 we provide a detailed description of the behavioral intervention. Section 3 discusses the data and results, while Section 4 concludes.

2 Intervention design

The bank implemented a behavioral intervention to promote energy conservation among its employees. The company relied on external consultants specialized in nudges for the design of the program. The core of the intervention was an energy-saving competition among branches, which was reinforced by additional incentives. All the materials were communicated through the company's newsletter and the program webpage. Every month, the bank published the ranking on the program webpage in three versions: a podium with the first three ranked, a list with the first ten, and a list with all the branches. The ranking was computed internally by the firm, considering the year-to-date savings compared to the consumption in the two previous years.[2] Due to billing constraints, rankings were published with two months of delay compared to the reference period.

The energy-saving competition appeals to people's desire to be perceived as good and pro-social by others (Ariely, Bracha, & Meier, 2009; Zhang & Zhu, 2011), as the monthly public ranking ensures social recognition to the best performers (Handgraaf et al., 2013). Besides, employees of the top three branches received prizes in the form of eco-gadgets.[3] This added a small material incentive to conserve energy. At the end of the intervention period, the three branches that saved the most were publicly awarded bigger prizes than monthly rewards (e.g., planting a tree with the certification of the winning branch).

Additional materials were published on the program newsletter on an ongoing basis. First, tips on conserving energy and reducing waste were provided, both through fliers and videos. As people are more likely to comply with social norms that refer to a relevant reference group (Goldstein, Cialdini, & Griskevicius, 2008), videos were filmed in the bank buildings. They told the stories of employees seeking to conserve energy to improve their position in the monthly ranking. Second, employees were tasked with "missions," also posted on the program webpage. Such missions mostly had engagement rather than conservation purposes. Some examples of these are the best picture showing how to save energy at home or the best suggestion for reducing waste in the branch. For each mission, the company selected a winner, who was rewarded with an eco-gadget. The different contents were posted simultaneously to

[2] The company used the following formula to compute the rankings: $y_i = \frac{\sum_{i=1}^{12} \overline{x_i} - x_i}{\sum_{i=1}^{12} \overline{x_i}}$, where y_i is the energy savings from January 2019 to month i; $\overline{x_i}$ is the total energy consumption from January to month i, averaged between the years 2017 and 2018; and x_i is the total energy consumption from January to month i for the year 2019. As a check, we recalculated the rankings and compared them with those computed by the firm. The two overlap, as shown in Figure A1.

[3] Each branch could receive the prize only once. Notably, if a firm that had already received the gadget was again ranked among the first three in another month, the prize would be given to the next highest-ranked firm that had not received it yet.

enhance the program (e.g., the rankings for the month plus a video on how to reduce lighting consumption).

The project ran from January to December 2019. A total of 553 branches were assigned to the energy-saving competition (henceforth, *behavioral group*). As control, we used 70 branches that were not directly involved in the contest and that instead received a technological renovation (henceforth, a*utomation group*). The retrofit program took place before (from 2016 to 2017) and consisted of the installation of a building energy management system (BEMS), an integrated software–hardware system that controls the indoor climatic conditions in buildings. Branches allocation to the interventions was not random. Those who received the technological renovation were selected to reduce the investment payback time: they had higher baseline energy consumption and higher consumption outside peak working hours, the latter being an indicator of energy waste.

We exploit the different timings of the interventions to assess the saving competition's impact on branches' monthly consumption. We use a DID approach from July 2017, after completing all the retrofitting interventions,[4] to December 2019, when the implementation of the behavioral intervention ended. This setting allows us to have a more-than-one-year pre-intervention period to assess whether the parallel trend assumption holds, which is required for DID estimation (Angrist & Pischke, 2008). A priori, there are no theoretical explanations for this assumption not to hold: the two groups are composed of branches located in the Italian territory and issues of attrition, self-selection, and partial compliance (Levitt & List, 2009) are ruled out because the bank managers administered the project with a top-down approach; that is, they assigned the branches to either of the two interventions, with no possibility of opting out.

Among the assumptions required for a DID estimation, our setting may not completely satisfy the lack of spillovers between treated and non-treated subjects. In the behavioral intervention design, the bank partially involved the non-treated employees to maximize their engagement with the company's initiative and possibly the overall energy savings. The online materials were available to all branches, including those that received the technological renovation. Moreover, the ranking was extended to all branches three times during the competition. This notwithstanding, we believe that the estimation bias is limited in our setting. The non-treated group did not have direct contact with the treated units, and mere information disclosure is often not enough to prompt behavioral change (Madrian, 2014). This is especially true for infrequent information. For example, Carroll et al. (2014) find that the same feedback significantly reduced energy consumption when provided monthly, but not when provided bimonthly.

[4] The installation actually ended in May 2017. We left one month free to prevent possible transition effects from affecting our empirical analysis.

Finally, if even any bias occurred in the estimation, it is downward, leading to a conservative assessment of the behavioral intervention's impact.

3 Results

3.1 Data and descriptive statistics

Our empirical analysis dataset combines the bank's administrative data, including branches' characteristics, and electricity consumption data. Electricity consumption was measured monthly through the meter installed in each branch. We have access to monthly billing records at branch level from January 2015 to December 2019. However, as already explained in Section 2, we use only the readings after July 2017 to assess the behavioral intervention's impact. Before that date, branches in the automation group were receiving the retrofit (we estimate the retrofit effect in Section 3.4). Monthly billing records are divided by time of use (TOU). In Italy, TOUs correspond to the following hours:

- F1: from Monday to Friday, from 8.00 a.m. to 7 p.m., excluding national holidays;
- F2: from Monday to Friday, from 7.00 a.m. to 8.00 a.m. and from 7 p.m. to 11 p.m., and on Saturday, from 7 a.m. to 11 p.m., excluding national holidays;
- F3: from Monday to Saturday, from 11 p.m. to 7.00 a.m., and on Sundays and national holidays.

Distinct drivers contribute to energy consumption in different TOUs. The standard work schedule of the bank's branches is from 8.25 a.m. to 4.55 p.m. Hence, F1 represents peak working hours and captures the consumption from employees' activities. F2 represents the energy consumption outside the main work schedule, partly due to human activities as some branches are open on Saturdays and some employees may work overtime, partly due to the passive consumption of buildings. F3 represents the outside working hours, and consumption here results only from buildings' passive consumption. We derive the total consumption of each branch by summing up the consumption in the three TOUs.

The initial sample size is 553 for the behavioral group and 70 for the automation group.[5] We drop two branches from the automation group because their meter is not uniquely identified. We also drop 39 branches from the behavioral group because their meter is likewise not uniquely identified or excluded from the monthly rankings. They do not have enough historical data to compute their energy savings. We further exclude the branches that have less than two successful readings per year so that the sample composition is not excessively unbalanced across the years. As non-successful readings, we consider those that are estimated, those non-positive or very close to zero, or those inconsistent across TOUs (i.e., very low in one while very high in another). We identify them as readings that are 95 percent lower or

[5] The bank has a higher number of branches than those considered in the study. To be eligible to one of these two groups, the branch should not be an office, should have an uniquely identified meter and should not be assigned to receiving other retrofit interventions in the next years.

higher than the branch's mean energy consumption. Such values are likely due to temporary closing of branches or to data errors, which we cannot control for given the available data. The final sample size is 570 branches, 503 for the behavioral group and 67 for the automation group.

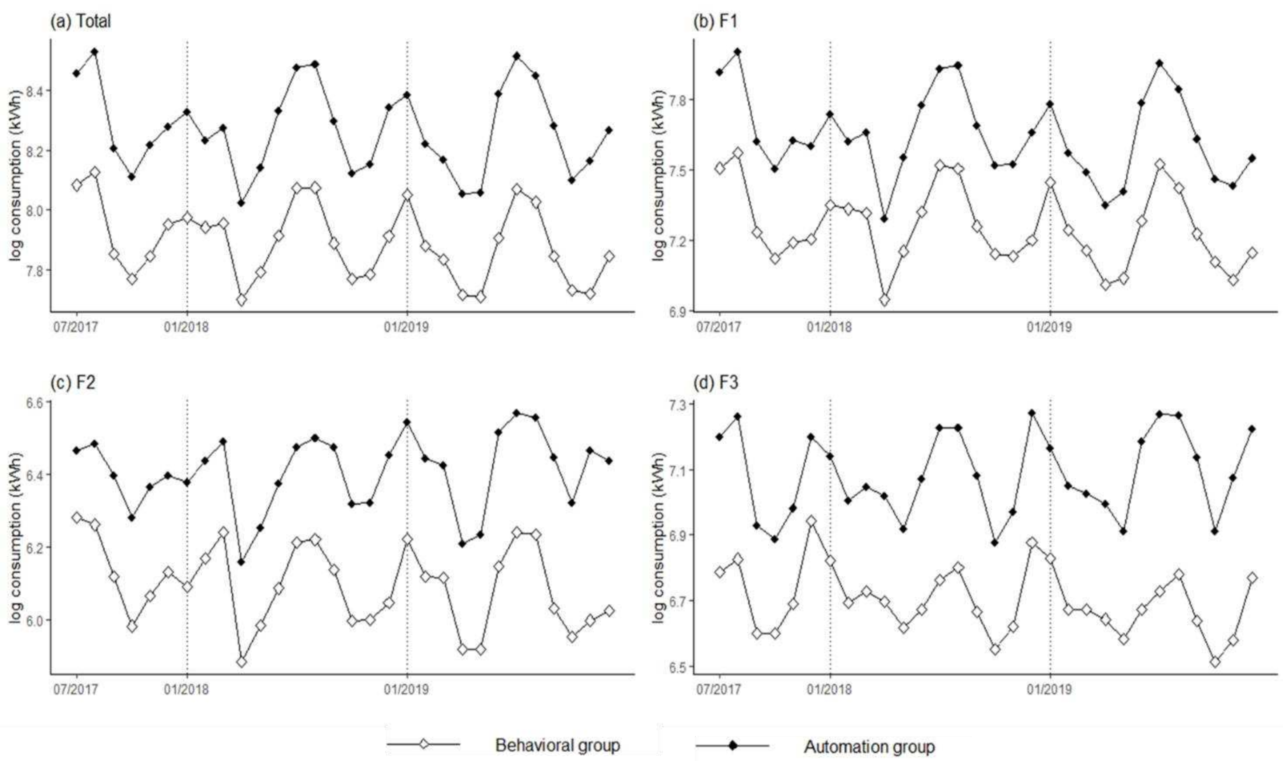
Table 1. Descriptive statistics

	Behavioral	Automation
N. of branches	503	67
Panel A: Controls		
Average number of employees	5.485	9.627
	(3.151)	(5.113)
Average surface (m2)	312.41	534.53
	(352.43)	(270.44)
Electric air conditioning (%)	58.8	50.7
Area: Center (%)	9.15	6.0
Area: North (%)	40.6	79.1
Area: South and islands (%)	50.3	14.9
Pre-treat usage: TOT	2710	3921
	(1448)	(1884)
Pre-treat usage: F1	1447	2146
	(936)	(1243)
Pre-treat usage: F2	443	594
	(238)	(282)
Pre-treat usage: F3	820	1180
	(423)	(514)
Panel B: Outcomes		
Post-treat usage: TOT	2610	3872
	(1419)	(1894)
Post-treat usage: F1	1381	2031
	(894)	(1189)
Post-treat usage: F2	437	622
	(244)	(292)
Post-treat usage: F3	793	1219
	(428)	(574)

Note: The average number of employees is computed considering the number of employees in December 2018. *Pre-treat usage* is calculated as average monthly energy consumption in 2018 (in kWh). *Post-treat usage* is calculated as average monthly energy consumption in 2019 (in kWh). Standard deviations in parentheses when applicable.

Table 1 reports sample descriptive statistics. As branches are not randomly assigned to the two programs, they have different characteristics. Consistent with the retrofit intervention's targeting criteria, the branches in the automation group are larger in terms of number of employees and surface than those in the behavioral group. The behavioral group branches are more likely to be located in the South and islands and less in the North than the automation group branches. As branches in the behavioral group are smaller, they also consume less energy than those in the automation group. Total baseline consumption, computed as the average pre-treatment monthly consumption in the year preceding the launch of the energy-saving competition (2018), is around 2,700 and 3,900 kWh for the two groups, respectively. In both conditions, more than half of the total energy consumption is generated during peak working hours (F1). The use of DID specification with fixed effects in the empirical analysis should control for group differences and prevent them from affecting the results.

Figure 1. Electricity consumption per TOU and group from mid-2017 to 2019



Log monthly electricity consumption for the behavioral and automation group. Vertical dotted lines represent the beginnings of the years. The behavioral intervention was launched in January 2019.

Figure 1 graphically illustrates the monthly energy consumption divided by TOU and program assignment. The months from July 2017 to December 2018 represent the pre-intervention period as the energy-saving competition was launched in January 2019 and was ongoing until December 2019. A first graphical inspection of the data supports the parallel trend assumption, with the two groups following the same pattern in the pre-consumption period. This shows the validity of our DID specification. The (generally) small effect of behavioral interventions makes it difficult to visually detect changes in energy consumption after the competition launch.

3.1 Empirical analysis and results

3.1.1 Impact on energy use

We test the effect of the behavioral intervention on electricity consumption. To this aim, we estimate the following specification for the full sample for the period ranging from July 2017 to December 2019:

(1) $y_{it} = \beta_0 + \beta_1 * T_i * post_t + t_{pt} + \alpha_i + \lambda_t + \varepsilon_{it}$

where y_{it} is the monthly electricity consumption of branch i in period t; as we assess treatment effect on the different time of use (TOU), y_{it} denotes the total energy consumption, and the consumption subdivided in F1 (peak working hours, weekdays from 8 a.m. to 7 p.m.), F2 (low working hours, weekdays from 7 to 8 a.m. and from 7 to 11 p.m., and Saturday from 7 a.m. to 11 p.m.), F3 (non-working hours, weekdays and Saturday from 11 p.m. to 7 a.m., Sunday and holidays).

T_i is the indicator for the behavioral intervention and is equal to one for the branches assigned to the program and zero otherwise. $post_t$ is the post-treatment dummy and takes the value zero before January 2019 and one for all the periods thereafter. The regression also includes the monthly temperature of the main Italian provinces where branches are located, t_{pt},[6] and branch and month-by-year fixed effects, respectively denoted as α_i and λ_t. We allowed for arbitrary within-branch correlation by clustering the standard errors at the branch level (Bertrand, Duflo, & Mullainathan, 2004).

Results are reported in Table 2. The behavioral intervention's effect on total monthly electricity consumption is negative, but it is not statistically significant (Column 1). Such effect, equal to 2.5 percent, is at the lower end of the effect of behavioral programs in the residential sector (Buckley, 2020). Different mechanisms can explain this outcome. First, the program may have failed to engage the employees. However, survey and engagement data suggest that this is not a likely explanation (see Section 3.3 for further discussion). Second, the possible spillover to non-treated branches may reduce our estimate of the behavioral intervention's effect. Yet, we believe that the spillover is not strong enough to fully explain the lack of significance. We therefore rule out this explanation, or at least that it is the only one. Most likely, the characteristics of energy conservation in the workplace cause the small effect observed in this study.

[6] The temperature data are retrieved from the archives of the National Oceanic and Atmospheric Administration (source: https://www.ncdc.noaa.gov/, accessed 1 July 2020).

Table 2. Impact of the behavioral intervention on electricity usage

	(1)	(2)	(3)	(4)
	TOT	F1	F2	F3
DID	-0.025	0.011	-0.075***	-0.067**
	(0.018)	(0.019)	(0.023)	(0.025)
N. branches	570	570	570	570
Observations	16,501	16,501	16,501	16,501

Regression of log monthly electricity consumption on treatment indicator. All the models include branch and time fixed effects and temperature of the province. *DID* is the difference-in-difference estimator for the behavioral intervention. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the peak working hours, *F2* during the low working hours, and *F3* during the non-working hours. Standard errors clustered at the branch level reported in parentheses. *p < .05, **p < .01, ***p < .001.

Despite the behavioral intervention's insignificant effect on total consumption, we find it generates significant energy savings outside the main working hours. The effect is negative and significant for both F2 (Column 3) and F3 (Column 4), resulting in 7 and 6 percent savings, respectively. This value is quite high compared to the average effect of behavioral interventions and shows how non-price interventions can help firms reducing inefficiencies outside the work schedule. That energy savings are concentrated when employees are not at work is also found by Orland et al. (2014), who show that a serious game in the office mostly reduced energy consumption outside working days. Going beyond a certain amount of energy savings is indeed difficult when people need to perform energy-consuming activities (Buchanan et al., 2015). Moreover, even in the housing sector, where people have a financial incentive to reduce their energy consumption, people are reluctant to sacrifice their comfort to conserve energy (Buchanan, Russo, & Anderson, 2014).

3.1.2 Robustness checks

We test for sensitivity to our DID specification by varying the outcome, panel length, and sample used to estimate Equation (1). First, Column 1 to 4 of Table B1 show similar results if we estimate the regression in levels rather than logs. The only difference is that F1 turns out to be positively statistically significant, probably due to the presence of outliers in the untransformed dependent variable. Second, we restrict the analysis to the years 2018-2019 so that the lengths of the pre- and post-intervention periods are the same, and we replicate the results in Table 2 (Column 5 to 8). For the same period, we also estimate treatment effects on yearly rather than monthly energy consumption as this is another way to eliminate the serial correlation in the data (Bertrand et al., 2004). Results in Column 9 to 12 show that the significance levels are the same as in the main specification. Third, the behavioral intervention's impact is similar when we keep all the real meter readings in the database (Column 13 to 16). The higher noise in the data causes larger point estimates and standard errors than in the main specification, making the impact on F3 only marginally significant ($p < .10$).

Finally, we test whether our main specification is robust to an in-time placebo test. To this aim, we eliminate year 2019, during which the behavioral intervention was ongoing, and we check if our specification detects as significant a fictitious treatment starting in January 2018. Table B2 shows that our specification does not detect significant treatment effects when no intervention occurred. Hence, we rule out the possibility that the pre-existing differences between the two groups cause our main results.

3.1.3 Heterogeneous program effects

We assess heterogeneous effects of the behavioral intervention according to the different branches' characteristics (i.e., pre-treatment energy consumption, whether air conditioning is electric or gas, and size) by adding to Equation 1 interactions between treatment and post-intervention dummies with the relevant variable. We report in Table 3 the results for total energy consumption. Results for the other TOUs, which are similar to those for total consumption, are reported in Table C1.

The first source of heterogeneity that we examine is the pre-treatment energy consumption. We include it because a higher initial energy consumption generally means a higher "slack" in resource usage (Tiefenbeck et al., 2018). Accordingly, households that have high pre-consumption levels are more responsive to non-pecuniary interventions (Allcott, 2011; Bonan et al., 2019; Byrne et al., 2018; List et al., 2017). However, evidence of whether this also applies in the non-domestic setting is still scattered as previous studies do not investigate this dimension (Brown et al., 2013; Charlier et al., 2021; Handgraaf et al., 2013; Ornaghi et al., 2018). We thus estimate Equation 1, interacting intervention and post-intervention dummies with a continuous measure of consumption in the year preceding the implementation of the energy-saving competition (January-December 2018). The sign of the interaction goes in the expected direction, but it is not statistically significant (Column 1).

Although this is surprising, we identify one mechanism that may explain why we fail to reproduce this result. In the domestic setting, non-pecuniary interventions prompt energy efficiency investments (Brandon et al., 2017). Heterogeneity in pre-consumption levels is partly explained by the fact that low energy users have already adopted energy efficiency measures and are less likely to do so again in response to the intervention (Tiefenbeck et al., 2018). In contrast, employees cannot invest in building renovations to conserve energy; they can only change their behavior to reduce their consumption. This constraint probably causes the high-energy-usage branches to respond to the behavioral intervention to the same extent as the low-energy usage branches do.

Next, we investigate heterogeneous effects based on other observable branch characteristics: whether the heating and cooling systems are electric, and size in terms of number of employees and surface. These characteristics influence energy consumption and may indirectly affect interventions' impacts because they contribute to the pre-consumption levels. However, they may also have a direct impact, which we isolate using our empirical analysis's fixed effects specification. That is, we assess how a specific characteristic interacts with the behavioral intervention net of all the other branch characteristics.

Table 3. Heterogeneous effect of the behavioral intervention

	(1) TOT	(2) TOT	(3) TOT	(4) TOT
DID	0.308	-0.040*	-0.024	-0.002
	(0.390)	(0.018)	(0.048)	(0.037)
DID x pre-treat	-0.042			
	(0.047)			
DID x heating		0.028		
		(0.035)		
DID x employees			0.001	
			(0.004)	
DID x surface				-0.001
				(0.001)
N. branches	570	570	570	570
Observations	16,501	16,501	16,501	16,501

Regression of log monthly total electricity consumption on treatment indicator. All models include branch and time fixed effects, temperature of the province and the post-treatment indicator interacted with the heterogeneity variables. *DID* is the difference-in-difference estimator for the behavioral intervention. *Pre-treat* is a continuous variable for average consumption before the launch of the competition (2018). *Heating* is a dummy equal to 1 if the branch has an electric air conditioning, 0 otherwise. *Employees* is a continuous variable for the number of employees at December 2018. *Surface* is a continuous variable for the squared meters. Standard errors clustered at the branch level reported in parentheses. *p < .05, ** p < .01, ***p < .001.

We expect the behavioral intervention to be more effective for the branches with electric heating and cooling systems. There, the employees have more energy-saving opportunities because they can optimize their use of appliances, lighting, and heating and cooling. In contrast with our expectations, Column 2 shows a non-significant interaction. On the other hand, the behavioral intervention coefficient becomes statistically significant for branches without electric heating and cooling systems, showing that employees change their use of appliances and lighting but not of heating and cooling devices. The lack of interaction outside working hours (Table C1) also suggests that the employees do not optimize the climatic conditions (e.g., closing the windows and reducing the air conditioning) when leaving the office.

This is consistent with the residential sector finding that tenants who do not pay their bills are significantly less likely to change heating settings at night (Gillingham, Harding, & Rapson, 2012).

Finally, social norms and group dynamics within the workplace significantly influence employees' energy-saving behaviors (Deline, 2015; Staddon et al., 2016). Engineering studies also show that the effects of social influence programs depend on the characteristics of the network (Jain, Gulbinas, Taylor, & Culligan, 2013; Peschiera & Taylor, 2012). Smaller groups generate stronger peer effects (Boucher, Bramoullé, Djebbari, & Fortin, 2012). These, in turn, trigger conservation behaviors (Wolske, Gillingham, & Schultz, 2020). Moreover, feedback is more effective when it is possible to monitor how energy is related to individuals' behavior (Grønhøj & Thøgersen, 2011), which is easier to do in smaller groups. Accordingly, we expect the behavioral intervention to have a higher impact on smaller rather than larger branches. However, Column 3 and 4 show no interaction between the behavioral intervention and the branch size in terms of number of employees and surface. Smaller branches are therefore not more responsive to the energy-saving competition. While surprising, this result is in line with the fact that the rate of contributions to public goods (Zhang & Zhu, 2011) and the rate of peer sanctions (Carpenter, 2007) do not depend on the group size. Survey data also suggest another explanation: other employees' engagement with the program does not affect individuals' engagement with it (see Section 3.2 for further details). Hence, peer effects may not have occurred regardless of the branch size.

3.2 Engagement with the behavioral intervention

This section analyzes employees' engagement with the behavioral intervention using survey data and the statistics of the interaction with the program webpage. The goal is to complement the quantitative analysis by exploring how and how much employees interacted with the initiative.

The survey, conducted at the end of the behavioral intervention (February-March 2020), was designed in collaboration with the managers of the program. The bank administered it to a subsample of its employees on the occasion of a broader questionnaire on corporate social responsibility. Overall, 1,152 employees participated in the survey. Respondents are predominantly male (61.1%), with ages ranging from 18 to more than 50, and with 43.8% of them working in branches and the rest in offices. In accordance with the company's privacy policy, responses were collected anonymously from all branches, with no possibility of linking the response to the branch where it came from. We therefore cannot discern whether respondents work in a branch belonging to the behavioral or the automation group. We can isolate whether they work in offices, which are not directly involved in the energy-saving competition.

Concerning the interaction with the program webpage, we have data regarding the number of accesses made to the platform. The data also illustrate the number and types of contents posted online every month, and how many times each of them was viewed. As for the survey, we cannot distinguish whether an employee makes the access from a branch belonging to the behavioral group. Although our data are not suitable for estimating any treatment effect, we believe that they still provide insights into which parts of the behavioral intervention were more appreciated and what motivated employees to participate in the competition.

The results of the survey reveal that the initiative was known and welcomed by the employees. Overall, 74.7% of the respondents are aware of the behavioral intervention. Of these, most accessed the program's informative materials sometimes over the year (53.7%) or at least once per month (35.2%). Only 5.3% of the respondents declare that they had never accessed the platform. These figures are consistent with the data of engagement with the online platform. The platform was visited 31,444 times during the intervention. Considering that the total number of employees in the branches belonging to the behavioral group is 2,825,[7] the average number of accesses per targeted employee is 11.1 per year or 0.9 per month. Even if this is an overestimation as it also includes the visits from non-targeted employees, it shows a good level of engagement with the intervention. The core of the program, i.e., the ranking, was published 11 times over the course of the intervention (the June and July rankings were combined due to the summer break).

Survey results also reveal that employees had a positive attitude toward the intervention, with 87% considering it useful, 58% considering it interesting, 84% agreeing that it prompts good behavior, and 86% saying that it gives tips on how to save energy. Most respondents also state that the intervention changed their behavior, with 77% applying some conservation tips in the workplace and 72% doing so at home. This last figure highlights the possibility of creating a positive spillover (Maki et al., 2019): prompting good behaviors in the workplace may also improve energy-saving practices at home (Yuriev, Boiral, Francoeur, & Paillé, 2018).

We then focus on which parts of the behavioral intervention the employees perceived as more engaging. As in Senbel et al. (2014), participants were asked to indicate the three most important drivers of program's participation. Table 4, Panel A summarizes the answers of respondents working in branches and aware of the project (N = 368). Overall, the most relevant driver of engagement is the concern for environmental issues (96.7%), followed by the willingness to save energy more than the other branches do (18.5%). Peer pressure (i.e., colleagues and bosses' interest in the initiative) is not cited as an important driver of participation. This outcome may explain the absence of interaction between the number of employees and the behavioral intervention in our heterogeneity analysis. We expected smaller branches to react more to the intervention as smaller groups usually trigger more decisive social influence. However, survey data suggest that peer pressure did not happen in general. By targeting the

[7] Sum of the employees working in the branches belonging to the behavioral group in December 2018.

branches rather than the smaller and more homogeneous units within them, the company may have failed to trigger this important dynamic.

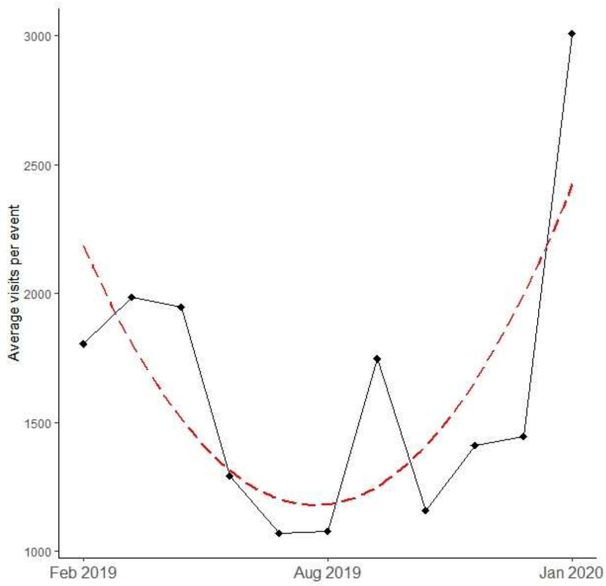
Employees' engagement with the different parts of the initiative corresponds to the reported drivers of participation. Survey responses illustrate that news and informative materials were the most accessed contents, followed by the monthly rankings (Table 4, Panel B). Missions and videos were less relevant. Engagement data with the program webpage partially support survey answers. The intervention's main page was accessed 8,100 times, that of the monthly rankings 8,582 times, and that of missions 4,505 times. Videos with conservation tips were seen 4,524 times, and the rules of the game and the informative materials were seen 2,248 and 1,530 times, respectively. Taken together, survey and engagement data show that the additional incentives (i.e., missions, videos, and prizes) engaged employees less than the competition did. However, one main difference emerges between survey and interaction data. The former indicates that news was accessed more times than the rankings whereas the latter shows the opposite. This contrast is consistent with the fact that people tend to underestimate the effect of social influence on their behavior (Nolan, Schultz, Cialdini, Goldstein, & Griskevicius, 2008).

Table 4. Survey results

Panel (A): Which are the main drivers that made you participate in the initiative?	%
Concern for environmental issues	0.967
Willingness to save more energy than the other branches	0.185
My colleagues' interest in the initiative	0.049
My bosses' interest in the initiative	0.043
Presence of incentives and prizes	0.038
Panel (B): Which contents have you accessed?	%
News on the program platform	0.660
Informative materials	0.497
Monthly rankings	0.402
Missions	0.144
Videos with tips	0.136
None	0.046

Finally, we use interaction data to monitor the employees' engagement over time. The number of contents posted varied by month because the company alternated news, missions, and videos. As a standardized proxy of engagement, we use the average number of views per content posted in that month. Figure 2 shows the engagement with the program from January 2019 to January 2020. The relation between time and engagement follows a U shape: it starts high and reaches its minimum during the summer break. It then increases again and achieves a peak at the end of the intervention. This shape is probably explained by the fact that the initial enthusiasm subsided over time but was ultimately rekindled by the final ranking.

Figure 2. Monthly average number of visits to the program webpage



Average number of views per content posted per month. The data from June and July 2019 were pooled together because only one ranking was published for the energy savings achieved in the two months. The dashed line represents the fitted quadratic curve.

3.3 The retrofit program

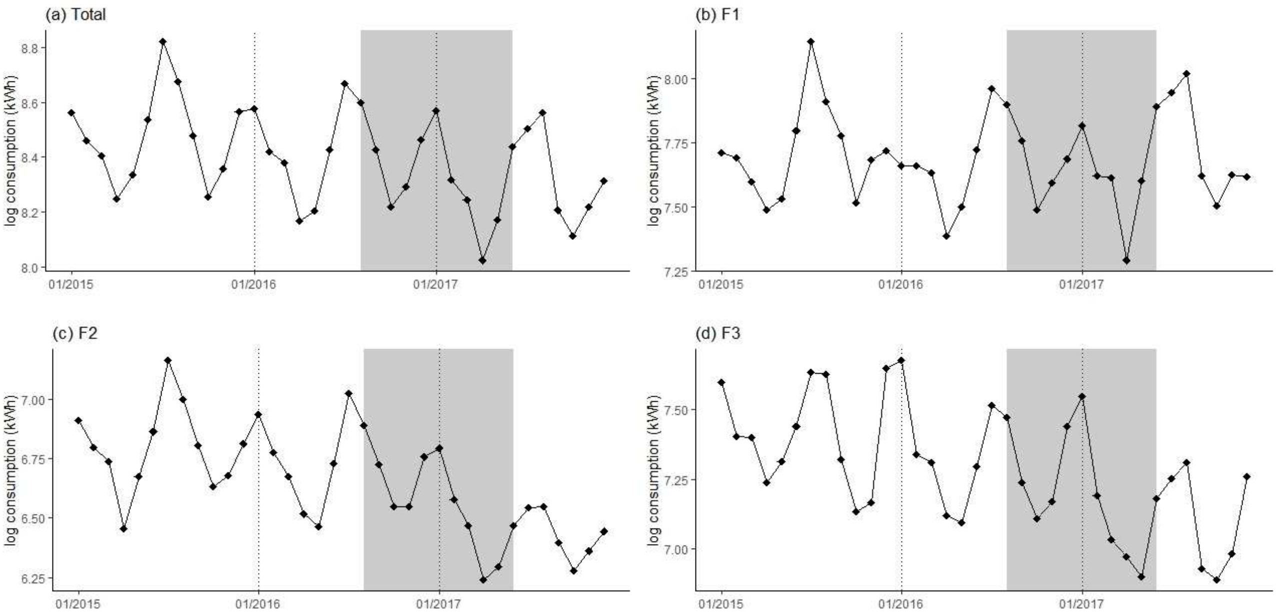
We now assess the impact of the technological intervention, which consisted of a building energy management system (BEMS) implemented in the 67 branches belonging to the automation group. Each branch received the renovation on a date within the period from August 2016 to May 2017. The impact of the retrofit is clearly visible in Figure 3. During the installation period (gray area), energy consumption gradually reduces in all TOUs, especially outside the main working hours (Panel (c) and (d)), and remains low after the installation is completed. We empirically estimate the effect of BEMS using the following staggered DID specification from 2015 to 2017:

(2) $y_{it} = \beta_2 + \beta_3 * post_{it} + t_{pt} + \alpha_i + \lambda_t + \varepsilon_{it}$

where all the terms are the same as those in Equation (1), except that the analysis includes only the branches in the automation group[8] and that the variable for the post-intervention period, $post_{it}$, is branch-specific and takes the value zero before the retrofit month and one for all the periods thereafter.

[8] We attempted to perform a DID similar to that used to assess the energy-saving competition, using the behavioral group as a control. However, the specification fails the placebo test for the parallel trend in the pre-intervention period. The retrofitted branches had very high baseline energy consumption and potential problems in the parametrization before the BEMS installation, which may have caused the differences in trend.

Figure 3. Electricity consumption of the automation group per TOU from 2015 to 2017



Log monthly electricity consumption for the branches in the automation group. Vertical dotted lines represent the beginnings of the years. Gray area represents the BEMS installation period.

Results are reported in Table 5. We estimate that the technological renovation curbs total monthly consumption by 18 percent (Column 1). This amount is in line with the other BEMS implementations, which achieve average energy savings of 16-17 percent (Lee & Cheng, 2016). The reduction in consumption is statistically significant in all TOUs, but its magnitude varies across them: it is around 9 percent during the main work schedule (Column 2) and reaches a maximum in F2 of 28 percent in the evenings (Column 3).

Table 5. Impact of the retrofit on electricity usage

	(1) TOT	(2) F1	(3) F2	(4) F3
DID	-0.193***	-0.095*	-0.329***	-0.281***
	(0.047)	(0.047)	(0.064)	(0.069)
N. branches	67	67	67	67
Observations	2,275	2,275	2,275	2,275

Regression of log monthly electricity consumption on treatment indicator. All models include branch and time fixed effects and temperature of the province. *DID* is the staggered difference-in-difference estimator for the retrofit. *TOT* denotes total electricity consumption, *F1* electricity consumption during peak working hours, *F2* during low working hours and F3 during non-working hours. Standard errors clustered at the branch level reported in parentheses. *p < .05, ** p < .01, ***p < .001

Although we cannot directly compare the effects of the behavioral and technological interventions, our setting allows us to make two points. First, the retrofit's high effect size shows the efficacy of the smart management of buildings, in comparison to the energy-saving competition. From a behavioral perspective, the effectiveness of automation is explained by people's tendency to stick to the status quo (Kahneman, Knetsch, & Thaler, 1991), which makes them accept the indoor conditions they are provided with (Brown et al., 2013). This type of intervention is particularly suitable in the workplace, where market failures reduce employees' willingness to make an effort to save energy and responsiveness to behavioral interventions. Needless to say, technological retrofits are much more expensive than behavioral campaigns. Second, the retrofit, like the energy-saving competition, has a stronger effect outside the main work schedule. The two interventions act upon similar inefficiency sources, such as the appliances and lights left switched on overnight. Therefore, they may overlap rather than reinforce each other if they are implemented together.

4 Conclusion

This study assesses the impact of a large-scale behavioral intervention implemented by an Italian bank to reduce its branches' energy consumption. The intervention consists of an energy-saving competition among the branches aimed at triggering employees' conservation efforts. It was launched in January 2019 and continued for the whole year and involved more than 500 branches. Employees participated in and engaged with the intervention, generating significant savings outside the main work schedule (by around 7 percent). However, this effect is not strong enough to significantly affect total electricity consumption.

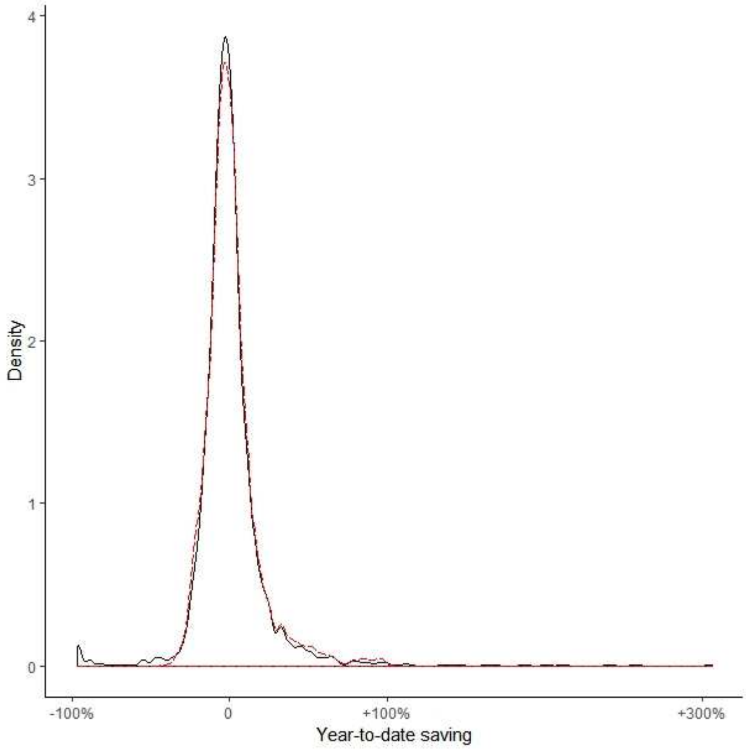
We also study the effect of a retrofit program consisting of installing a building energy management system (BEMS). The intervention was applied to a subsample of branches with high baseline energy consumption from 2016 to 2017. Branches receiving this intervention reduced their energy consumption by 18 percent. The highest amount of energy savings is registered outside working hours, reaching more than 25 percent.

This study has policy implications. Our results question the applicability of behavioral policies in the workplace or at least underscore the importance of considering the characteristics of the context in the policy's design. An intervention targeting the total energy consumption of a branch does not seem effective. On the other hand, timely and behavior-specific interventions may have stronger effects because they highlight the link between employees' efforts and energy savings. Also, peer effects may reinforce the effect of non-pecuniary interventions, but insofar the programs target pre-existing groups, where social ties are strong and mutual influence is likely to occur. Finally, the inefficiencies outside the working hours are the first to be cut because they do not require any comfort-consumption compromise. A company needs to consider this when combining different energy-saving programs, comprising investment and engagement ones. An important implication of this paper is that even when energy-efficiency programs have different natures, the interventions may overlap if they address the same energy waste drivers.

Appendix

Appendix A. Saving calculation of monthly ranking

Figure A1. Calculation of the saving by the company (black line) and by the authors (red line)



Appendix B. Robustness checks

Table B1. Impact of the behavioral intervention on electricity usage, robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	TOT	F1	F2	F3	TOT	F1	F2	F3	TOT	F1	F2	F3	TOT	F1	F2	F3
DID	-40.14	70.89*	-38.67**	-72.37*	-0.024	0.003	-0.065**	-0.057*	-51.07	51.64	-36.02**	-66.69*	-0.034	-0.022	-0.114**	-0.072
	(49.20)	(28.35)	(12.28)	(28.49)	(0.017)	(0.017)	(0.023)	(0.025)	(50.49)	(27.552)	(13.91)	(30.01)	(0.040)	(0.045)	(0.043)	(0.043)
N	570	570	570	570	570	570	570	570	570	570	570	570	570	584	584	584
Obs	16,501	16,501	16,501	16,501	13,253	13,253	13,253	13,253	1,140	1,140	1,140	1,140	17,182	17,182	17,182	17,182

Column 1 to 4: Regression of monthly electricity consumption on treatment indicator. Column 5 to 8: Regression of log monthly electricity consumption on treatment indicator, excluding year 2017. Column 9 to 12: Regression of yearly electricity consumption on treatment indicator, excluding year 2017. Column 13 to 16: Regression of log monthly electricity consumption on treatment indicator, including all real meters. All models include branch and time fixed effects and temperature of the province (temperature is not included in Column 9 to 12). DID is the staggered difference-in-difference estimator for the behavioral intervention. *TOT* denotes total electricity consumption, *F1* electricity consumption during peak working hours, *F2* during low working hours and *F3* during non-working hours. Standard errors clustered at the branch level reported in parentheses. *N* represents the number of branches, *Obs* the number of periods. *p < .05, ** p < .01, ***p < .001

Table B2. Placebo test for the main specification

	(1) TOT	(2) F1	(3) F2	(4) F3
DID	-0.003	0.024	-0.032	-0.029
	(0.013)	(0.013)	(0.020)	(0.021)
N. branches	570	570	570	570
Observations	9,871	9,871	9,871	9,871

Regression of log monthly electricity consumption on treatment indicator, excluding year 2019. All models include branch and time fixed effects and temperature of the province. *DID* is the difference-in-difference estimator for the fictious behavioral intervention, which is 0 before January 2018 and 1 after. *TOT* denotes total electricity consumption, *F1* consumption during peak working hours, *F2* during low working hours and *F3* during non-working hours. Standard errors clustered at the branch level reported in parentheses. *p < .05, ** p < .01, ***p < .001.

Appendix C. Heterogeneous effect of the behavioral intervention

Table C1. Heterogeneous effect of the behavioral intervention, all TOUs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	F1	F2	F3	F1	F2	F3	F1	F2	F3	F1	F2	F3
DID	0.227	-0.083	0.266	0.015	-0.093***	-0.095**	0.035	-0.078	-0.078	0.053	-0.079	-0.049
	(0.348)	(0.365)	(0.527)	(0.021)	(0.028)	(0.030)	(0.049)	(0.056)	(0.063)	(0.038)	(0.043)	(0.048)
DID x pre-treat	-0.029	-0.001	-0.051									
	(0.045)	(0.057)	(0.076)									
DID x heating				-0.005	0.034	0.051						
				(0.037)	(0.045)	(0.049)						
DID x employees							-0.001	0.002	0.003			
							(0.004)	(0.006)	(0.006)			
DID x surface										-0.001	0.001	-0.001
										(0.001)	(0.001)	(0.001)
N. branches	570	570	570	570	570	570	570	570	570	570	570	570
Observations	16,501	16,501	16,501	16,501	16,501	16,501	16,501	16,501	16,501	16,501	16,501	16,501

Regression of log monthly electricity consumption on treatment indicator. All models include branch and time fixed effects, temperature of the province and the post-treatment indicator interacted with the heterogeneity variables. *DID* is the difference-in-difference estimator for the behavioral intervention. *Pre-treat* is a continuous variable for average consumption before the launch of the competition (2018). *Heating* is a dummy equal to 1 if the branch has an electric air conditioning, 0 otherwise. *Employees* is a continuous variable for the number of employees at December 2018. *Surface* is a continuous variable for the squared meters. *TOT* denotes total electricity consumption, *F1* electricity consumption during peak working hours, *F2* during low working hours and *F3* during non-working hours. Standard errors clustered at the branch level reported in parentheses. *p < .05, ** p < .01, ***p < .001.

References

Allcott, H. (2011). Social norms and energy conservation. *Journal of Public Economics*, *95*(9–10), 1082–1095. https://doi.org/10.1016/j.jpubeco.2011.03.003

Allcott, H., Mullainathan, S., & Taubinsky, D. (2014). Energy policy with externalities and internalities. *Journal of Public Economics*, *112*, 72–88. https://doi.org/10.1016/j.jpubeco.2014.01.004

Allcott, H., & Rogers, T. (2012). The Short-Run and Long-Run Effects of Behavioral Interventions: Experiment Evidence From Energy Conservation. *American Economic Review*, *104*(10), 3003–3037. https://doi.org/10.1257/aer.104.10.3003

Andor, M., & Fels, K. M. (2018). Behavioral Economics and Energy Conservation – A Systematic Review of Non-price Interventions and Their Causal Effects. *Ecological Economics*, *148*, 178–210. https://doi.org/10.1016/j.ecolecon.2018.01.018

Angrist, J. D., & Pischke, J. S. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Ariely, D., Bracha, A., & Meier, S. (2009). Doing Good or Doing Well? Image Motivation and Monetary Incentives in Behaving Prosocially. *American Economic Review*, *99*(1), 544–555. https://doi.org/10.1257/aer.99.1.544

Asensio, O. I., & Delmas, M. A. (2015). Nonprice incentives and energy conservation. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(6), E510–E515. https://doi.org/10.1073/pnas.1401880112

Bedwell, B., Leygue, C., Goulden, M., McAuley, D., Colley, J., Ferguson, E., … Spence, A. (2014). Apportioning energy consumption in the workplace: a review of issues in using metering data to motivate staff to save energy. *Technology Analysis and Strategic Management*, *26*(10), 1196–1211. https://doi.org/10.1080/09537325.2014.978276

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics*, *119*(1), 249–275. https://doi.org/10.1162/003355304772839588

Bonan, J., Cattaneo, C., D'Adda, G., & Tavoni, M. (2019). *Can we make social information programs more effective? The role of identity and values* (RFF-CMCC EIEE No. 19–21).

Boucher, V., Bramoullé, Y., Djebbari, H., & Fortin, B. (2012). Do peers affect student achievement? Evidence from Canada using group size variation. *Journal of Applied Econometrics*, *29*(1), 91–109. https://doi.org/10.1002/jae

Brandon, A., Ferraro, P. J., List, J., Metcalfe, R. D., Price, M. K., Rundhammer, F., … Rundhammer, F. (2017). *Do The Effects of Social Nudges Persist? Theory and Evidence from 38 Natural Field Experiments* (No. 23277). *NBER Working Paper*. https://doi.org/10.3386/w23277

Brown, Z., Johnstone, N., Haščič, I., Vong, L., & Barascud, F. (2013). Testing the effect of defaults on the thermostat settings of OECD employees. *Energy Economics*, *39*, 128–134. https://doi.org/10.1016/j.eneco.2013.04.011

Buchanan, K., Russo, R., & Anderson, B. (2014). Feeding back about eco-feedback: How do consumers use and respond to energy monitors? *Energy Policy*, *73*, 138–146. https://doi.org/10.1016/j.enpol.2014.05.008

Buchanan, K., Russo, R., & Anderson, B. (2015). The question of energy reduction: The problem(s) with feedback. *Energy Policy*, *77*, 89–96. https://doi.org/10.1016/j.enpol.2014.12.008

Buckley, P. (2020). Prices, information and nudges for residential electricity conservation: A meta-analysis. *Ecological Economics*, *172*, 106635. https://doi.org/10.1016/j.ecolecon.2020.106635

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

Carpenter, J. P. (2007). Punishing free-riders: How group size affects mutual monitoring and the provision of public goods. *Games and Economic Behavior*, *60*(1), 31–51. https://doi.org/10.1016/j.geb.2006.08.011

Carrico, A. R., & Riemer, M. (2011). Motivating energy conservation in the workplace: An evaluation of the use of group-level feedback and peer education. *Journal of Environmental Psychology*, *31*(1), 1–13. https://doi.org/10.1016/j.jenvp.2010.11.004

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

Charlier, C., Guerassimoff, G., Kirakozian, A., & Selosse, S. (2021). Under Pressure! Nudging Electricity Consumption within Firms. Feedback from a Field Experiment. *The Energy Journal*, *42*(1). https://doi.org/10.5547/01956574.42.1.ccha

Deline, M. B. (2015). Energizing organizational research: Advancing the energy field with group concepts and theories. *Energy Research and Social Science*, *8*, 207–221. https://doi.org/10.1016/j.erss.2015.06.003

Delmas, M. A., Fischlein, M., & Asensio, O. I. (2013). Information strategies and energy conservation behavior: A meta-analysis of experimental studies from 1975 to 2012. *Energy Policy*, *61*, 729–739. https://doi.org/10.1016/j.enpol.2013.05.109

Gillingham, K., Harding, M., & Rapson, D. (2012). Split incentives in residential energy consumption. *The Energy Journal*, *33*(2), 37–62. https://doi.org/10.5547/01956574.33.2.3

Gillingham, K., & Palmery, K. (2014). Bridging the energy efficiency gap: Policy insights from economic theory and empirical evidence. *Review of Environmental Economics and Policy*, *8*(1), 18–38. https://doi.org/10.1093/reep/ret021

Giraudet, L. G. (2020). Energy efficiency as a credence good: A review of informational barriers to energy savings in the building sector. *Energy Economics*, *87*, 104698. https://doi.org/10.1016/j.eneco.2020.104698

Goldstein, N. J., Cialdini, R. B., & Griskevicius, V. (2008). A Room with a Viewpoint: Using Social Norms to Motivate Environmental Conservation in Hotels. *Journal of Consumer Research*, *35*(3), 472–482. https://doi.org/10.1086/586910

Grønhøj, A., & Thøgersen, J. (2011). Feedback on household electricity consumption: Learning and social influence processes. *International Journal of Consumer Studies*, *35*(2), 138–145. https://doi.org/10.1111/j.1470-6431.2010.00967.x

Güneralp, B., Zhou, Y., Ürge-Vorsatz, D., Gupta, M., Yu, S., Patel, P. L., … Seto, K. C. (2017). Global scenarios of urban density and its impacts on building energy use through 2050. *Proceedings of* *the National Academy of Sciences of the United States of America*, *114*(34), 8945–8950. https://doi.org/10.1073/pnas.1606035114

Hagmann, D., Ho, E. H., & Loewenstein, G. (2019). Nudging out support for a carbon tax. *Nature Climate Change*, *9*(6), 484–489. https://doi.org/10.1038/s41558-019-0474-0

Handgraaf, M. J. J., Van Lidth de Jeude, M. A., & Appelt, K. C. (2013). Public praise vs. private pay: Effects of rewards on energy conservation in the workplace. *Ecological Economics*, *86*(86–92). https://doi.org/10.1016/j.ecolecon.2012.11.008

Jain, R. K., Gulbinas, R., Taylor, J. E., & Culligan, P. J. (2013). Can social influence drive energy savings? Detecting the impact of social influence on the energy consumption behavior of networked users exposed to normative eco-feedback. *Energy and Buildings*, *66*, 119–127. https://doi.org/10.1016/j.enbuild.2013.06.029

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991). Anomalies: The Endowment Effect, Loss Aversion, and Status Quo Bias. *Journal of Economic Perspectives*, *5*(1), 193–206. https://doi.org/10.1257/jep.5.1.193

Karjalainen, S. (2016). Should we design buildings that are less sensitive to occupant behaviour? A simulation study of effects of behaviour and design on office energy consumption. *Energy Efficiency*, *9*(6), 1257–1270. https://doi.org/10.1007/s12053-015-9422-7

Lee, D., & Cheng, C. C. (2016). Energy savings by energy management systems: A review. *Renewable and Sustainable Energy Reviews*, *56*, 760–777. https://doi.org/10.1016/j.rser.2015.11.067

Levitt, S. D., & List, J. A. (2009). Field experiments in economics: The past, the present, and the future. *European Economic Review*, *53*(1), 1–18. https://doi.org/10.1016/j.euroecorev.2008.12.001

List, J. A., Metcalfe, R. D., Price, M. K., & Rundhammer, F. (2017). *Harnessing Policy Complementarities to Conserve Energy: Evidence from a Natural Field Experiment* (No. 23355). *NBER Working Paper*. https://doi.org/10.3386/w23355

Madrian, B. C. (2014). Applying Insights from Behavioral Economics to Policy Design. *Annual Review of Economics*, *6*(1), 663–688. https://doi.org/10.1146/annurev-economics-080213-041033

Maki, A., Carrico, A. R., Raimi, K. T., Truelove, H. B., Araujo, B., & Yeung, K. L. (2019). Meta-analysis of pro-environmental behaviour spillover. *Nature Sustainability*, *2*(4), 307–315. https://doi.org/10.1038/s41893-019-0263-9

Myers, E., & Souza, M. (2020). Social comparison nudges without monetary incentives: Evidence from home energy reports. *Journal of Environmental Economics and Management*, *101*, 102315. https://doi.org/10.1016/j.jeem.2020.102315

Nolan, J. M., Schultz, P. W., Cialdini, R. B., Goldstein, N. J., & Griskevicius, V. (2008). Normative Social Influence is Underdetected. *Personality and Social Psychology Bulletin*, *34*(7), 913–923. https://doi.org/10.1177/0146167208316691

ODYSSEE-MURE. (2018). *Energy Efficiency Trends in Buildings. Policy brief.*

Orland, B., Ram, N., Lang, D., Houser, K., Kling, N., & Coccia, M. (2014). Saving energy in an office environment: A serious game intervention. *Energy and Buildings*, *74*, 43–52. https://doi.org/10.1016/j.enbuild.2014.01.036

Ornaghi, C., Costanza, E., Kittley-Davies, J., Bourikas, L., Aragon, V., & James, P. A. B. (2018). The effect of behavioural interventions on energy conservation in naturally ventilated offices. *Energy*

Economics, *74*, 582–591. https://doi.org/10.1016/j.eneco.2018.07.008

Panzone, L. A., Ulph, A., Zizzo, D. J., Hilton, D., & Clear, A. (2018). The impact of environmental recall and carbon taxation on the carbon footprint of supermarket shopping. *Journal of Environmental Economics and Management*, 102137. https://doi.org/10.1016/j.jeem.2018.06.002

Peschiera, G., & Taylor, J. E. (2012). The impact of peer network position on electricity consumption in building occupant networks utilizing energy feedback systems. *Energy and Buildings*, *49*, 584–590. https://doi.org/10.1016/j.enbuild.2012.03.011

Ramos, A., Gago, A., Labandeira, X., & Linares, P. (2015). The role of information for energy efficiency in the residential sector. *Energy Economics*, *52*, S17–S29. https://doi.org/10.1016/j.eneco.2015.08.022

Senbel, M., Ngo, V. D., & Blair, E. (2014). Social mobilization of climate change: University students conserving energy through multiple pathways for peer engagement. *Journal of Environmental Psychology*, *38*, 84–93. https://doi.org/10.1016/j.jenvp.2014.01.001

Staddon, S. C., Cycil, C., Goulden, M., Leygue, C., & Spence, A. (2016). Intervening to change behaviour and save energy in the workplace: A systematic review of available evidence. *Energy Research and Social Science*, *17*, 30–51. https://doi.org/10.1016/j.erss.2016.03.027

Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving decisions about health, wealth, and happiness.* New Haven: Yale University Press.

Tiefenbeck, V., Goette, L., Degen, K., Tasic, V., Fleisch, E., Lalive, R., & Staake, T. (2018). Overcoming salience bias: How real-time feedback fosters resource conservation. *Management Science*, *64*(3), 1458–1476. https://doi.org/10.1287/mnsc.2016.2646

Tiefenbeck, V., Wörner, A., Schöb, S., Fleisch, E., & Staake, T. (2019). Real-time feedback promotes energy conservation in the absence of volunteer selection bias and monetary incentives. *Nature Energy*, *4*(1), 35–41. https://doi.org/10.1038/s41560-018-0282-1

Wolske, K. S., Gillingham, K. T., & Schultz, P. W. (2020). Peer influence on household energy behaviours. *Nature Energy*, *5*(3), 202–212. https://doi.org/10.1038/s41560-019-0541-9

Yuriev, A., Boiral, O., Francoeur, V., & Paillé, P. (2018). Overcoming the barriers to pro-environmental behaviors in the workplace: A systematic review. *Journal of Cleaner Production*, *182*, 379–394. https://doi.org/10.1016/j.jclepro.2018.02.041

Zhang, X. M., & Zhu, F. (2011). Group size and incentives to contribute: A natural experiment at chinese wikipedia. *American Economic Review*, *101*(4), 1601–1615. https://doi.org/10.1257/aer.101.4.1601