# Evaluating the impact of technological renovation and competition on energy consumption in the workplace

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## Abstract

This study investigates the effect of two interventions aimed at reducing electricity consumption among branches of a large Italian bank. The first intervention consists in the technological renovation of 70 branch buildings through the installation of an automated energy management system. The second is an energy-saving competition that involved more than 500 branches for a year. Using two separate difference-in-differences estimations, we find that the technological renovation curbs electricity consumption by 15.8 percent overall, and by more than 25 percent outside the main work schedule. The behavioral intervention reduces electricity consumption, by around 6 percent outside the main work schedule, and by 2.4 percent overall, although not significantly so. The estimated cost-effectiveness ranges between 3.4 and 8.8 € cents per kWh saved for the technological intervention, and 9.8 and 17.8 € cents per kWh saved for the behavioral intervention. Our findings suggest that for both interventions, energy savings in the workplace are more easily obtained by reducing passive energy waste than through behavioral change during working hours.

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

**JEL codes:** C93, D91, H32, Q41

# 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 (Y. Zhang et al., 2018), especially in the workplace, where market failures lead to the inefficient use of appliances. 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, such as by installing smart appliances or automating peak load management. In this case, little effort is required from employees to reduce their consumption, and their 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, 2011) or that their actions have negative environmental and health consequences (Asensio & Delmas, 2015). Through 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 two large-scale interventions implemented by an Italian bank to save energy. The first is a technological renovation that consists in the installation of a building energy management system (BEMS). This system optimizes branches' energy consumption. Seventy highly consuming branches receive the renovation (*renovation* group) between 2016 and 2017; thereafter, the system is operational. The second is a behavioral intervention, consisting in an energy-saving competition among the bank's branches. Every month, the three branches that save the most are announced through the company's newsletter. Winners gain social recognition along with small material rewards in the form of eco-gadgets. The competition is reinforced by additional incentives, such as individual challenges, and

complemented by informational materials. The program involves more than 500 branches that did not previously receive the renovation (*behavioral* group) and takes place throughout 2019.

We assess the impact of the two interventions on branches' monthly electricity consumption using difference-in-differences (DID) specifications over the years 2015 to 2019. We estimate the effect on total electricity consumption as well as consumption by time of use (TOU), so that we can differentiate the impact of the interventions during and outside working hours. We exploit the different timing of the interventions and assignment rules to estimate two separate DID: the former goes from the beginning of 2015 to the end of 2017 and estimates the impact of the renovation using as comparison the branches in the behavioral group and the yet-to-be-renovated branches of the renovation group. The latter covers the period from mid-2017 to the end of 2019 to assess the impact of the behavioral intervention using as a comparison the branches in the renovation group.

We find that BEMS curbs total electricity consumption by 15.8 percent, which is consistent with engineering studies (Lee & Cheng, 2016). The savings are non-significant during the main work schedule but are substantial outside it (more than 25 percent). The behavioral intervention reduces total electricity consumption by 2.4 percent. However, this effect is not statistically significant, which may be caused by limited statistical power. Outside the main work schedule, the behavioral intervention significantly lowers electricity usage by around 6 percent. Orland et al. (2014) find similar evidence in the context of a serious game intervention to save energy at work. The lack of significant effect for both interventions during the main work schedule is consistent with two explanations. First, there may be little inefficiency in electricity usage during the day, which limits the potential for energy savings regardless of the nature of the intervention. Second, the cost to workers of curbing energy consumption may be higher within than outside working hours. While at work, employees need to use appliances for work-related activities and may not be willing to sacrifice their comfort or exert effort to conserve energy. On the other hand, keeping appliances and lights switched off overnight only requires employees to make an effort when leaving the office. Although the technological renovation reduces employee control over energy consumption, the latter explanation is also valid to explain the null effect of BEMS during the main work schedule. Indeed, while BEMS primarily optimizes consumption outside the main work schedule, consumption during the day results from both efficient energy management and employees' behaviors.

We use branches' characteristics to explore possible sources of heterogeneity in programs' effects and inform similar future efforts. Contrary to our expectations, none of the characteristics investigated –baseline electricity consumption, heating type and size– influence the impact of the behavioral program. This result is striking because it is inconsistent with the heterogeneous

effects of behavioral interventions by baseline consumption in the residential sector (e.g. Allcott, 2011; Andor et al., 2020, 2022; Bonan et al., 2021), and because it suggests that peer effects are not relevant in our setting, contrary to the relevant role they are believed to have (Staddon et al., 2016). The technological intervention instead is more effective in branches with higher passive waste (i.e., energy waste caused by inefficient building parametrization), consistent with its larger effectiveness in reducing consumption outside working hours. We also perform additional analyses. Using data on branches' ranking and employees' engagement with the behavioral program online material, we find that the energy-saving competition is the program's component that drew the most attention among employees.

Our study contributes to the literature on energy conservation. Research on energy conservation in the workplace is relatively scarce (Stern et al., 2016), in spite of the large share of energy consumption coming from the commercial sector and of the peculiarities of this setting that may influence interventions' effectiveness. In particular, employees may not be motivated to save energy, since they do not have financial incentives to do it. The absence of bills also reduces the salience of energy consumption, which is usually relegated to the background relative to work-related tasks. The fact that the workplace's energy consumption is the product of many people's actions may further hamper employees' motivation to change behavior, as they may perceive that their personal efforts to save energy have little effect on the company's total consumption (Carrico & Riemer, 2011). Finally, even if employees want to save energy, they can do so only by changing their behavior, whereas in the residential sector homeowners can also invest in energy efficiency improvements (Brandon et al., 2017).

We add to the limited literature investigating the effectiveness of technological renovations in commercial buildings (e.g. Liang et al., 2018; Qiu, 2014) and show the impact of a behavioral intervention in the workplace. While psychological and engineering studies provide early insights into the effect of this type of intervention on employees' energy use (Staddon et al., 2016), economists to date have paid more attention to the residential sector (Andor & Fels, 2018; Ramos et al., 2015).[1] 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. 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,

[1] A few studies implement behavioral interventions in other settings. For example, for student residences, Myers & Souza (2020) find that a social comparison intervention does not reduce energy consumption whereas Delmas & Lessem (2014) show that combining public and private information generates significant reductions in electricity consumption.

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 the group level reduces total buildings' consumption.

Finally, we provide an estimate for the cost-effectiveness of the two interventions. We find that the cost-effectiveness of the behavioral intervention (between 9.8 and 17.8 € cents/kWh) is at most at the lower end of estimates of interventions à la Opower in the residential sector (e.g. Allcott, 2011; Andor et al., 2020). For the technological renovation, the estimated cost-effectiveness ranges between 3.4 and 8.8 € cents per kWh saved. While these calculations point to greater cost-effectiveness for the technological than for the behavioral intervention, directly comparing the two figures may be misleading. In particular, the lack of random assignment to receive either BEMS or the energy-saving competition implies that pre-existing differences between the two groups may affect the impact estimates for the two programs. Moreover, the two interventions were implemented over different time periods.

The remainder of the paper is organized as follows. In Section 2 we provide a detailed description of the two interventions. Section 3 discusses the data and empirical strategy. Section 4 presents the results, while Section 5 concludes.

# 2 Intervention overview

## 2.1 Technological intervention

The first intervention implemented by the bank consisted in the installation of a building energy management system (BEMS), an integrated software–hardware system that controls the indoor climatic conditions in buildings. The company selected 70 highly consuming branches for the renovation (*renovation* group). The technological renovation took place between 2016 and 2017. Afterward, we assume the system to be operational for the rest of the observation period.

The system consists of a central unit that controls and optimizes climatic conditions on the basis of the information collected through smart sensors. BEMS have control over a series of energy-related building functions, such as heating, ventilation and air conditioning (HVAC) systems, lighting and power systems. It optimizes energy consumption for example by controlling the on/off time for power systems, temperatures and lighting depending on the work schedule and presence of individuals in the building. BEMS therefore reduces the influence of employees' behavior on branches' energy consumption, in particular with respect to passive building waste.

## 2.2 Behavioral intervention

A total of 553 branches were assigned to the behavioral intervention (*behavioral* group). The intervention started in January 2019 and continued until December 2019.

The bank relied on external consultants specialized in nudges to design the intervention, which consisted in an energy-saving competition among its branches and in the provision of tips for energy conservation. Every month, the bank published the energy-saving 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, as year-to-date electricity savings.[2] Due to billing constraints, rankings were published with two months of delay compared to the reference period. For each monthly ranking, all employees of the top three branches received prizes in the form of eco-gadgets (such as mugs and recycled paper USB keys, for a value below 10€ each). At the end of the intervention period, the three branches that saved the most were awarded bigger prizes than monthly rewards (such as solar powerbanks and chargers, for a value of at most 70€ each). The winner branch also received a flowerbed with a tree in its name; this does not constitute a material incentive but warrants social recognition.

To reinforce the energy-saving competition, additional materials were published on the program webpage and the company's 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 et al., 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. Examples of tips to save energy during working hours included hibernating computers when leaving for lunch or long breaks; keeping windows and doors closed when using air conditioning; not heating or cooling unoccupied rooms; and exploiting natural light as much as possible. Tips to save energy outside working hours concerned switching off lights, computers and air conditioning when leaving the office.

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 the same eco-gadgets as the monthly winner. The different contents were posted simultaneously to enhance the program's visibility (e.g., the monthly ranking along with a video on how to reduce lighting consumption).

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

We conceptualize the mechanisms whereby the behavioral intervention may prompt employees' conservation efforts. We focus on non-pecuniary drivers because the material rewards for the winning branches are too small to justify behavioral change.[3] A first possible mechanism is that the company, through the implementation of the intervention, signals the injunctive norm of energy conservation at work. This could increase the "moral cost" of energy use (Allcott, 2011) for employees. The intervention may also prime employees to consider energy use for workplace behaviors (Carrico & Riemer, 2011) or leverage employees' intrinsic motivation to save energy by making salient their pro-environmental self-identity (Bonan et al., 2021).

A prominent element of the behavioral intervention is the energy-saving competition. Extensive research shows that competitions and rankings affect behavior, both when they are privately or publicly conveyed and when they are decoupled from financial rewards (Cadsby et al., 2019; Duffy & Kornienko, 2010; Tran & Zeckhauser, 2012). Private rankings motivate effort by appealing to competitive preferences (Charness & Rabin, 2002; Rustichini, 2008), or by yielding higher self-esteem (Kuhnen & Tymula, 2012) and self-image (Köszegi, 2006) when a person outperforms others. In our study, higher ranks mean more prosocial behavior. Hence, highly-ranked employees may also draw "moral utility" (Levitt & List, 2007) from reducing the company's greenhouse gas emissions. Finally, the fact that rankings are publicly communicated adds another driver of behavioral change. Namely, conservation behavior becomes visible to others, thereby ensuring a green reputation for employees saving the most (Delmas & Lessem, 2014; Griskevicius et al., 2010). Employees wishing to obtain a prosocial reputation provide additional effort to reduce energy use. In sum, we expect both intrinsic motivation and reputation motivation (Bénabou & Tirole, 2006) to drive employees to save energy in order to increase their branch's ranking in the energy-saving competition.

Since the intervention was a bundle of different features and that rankings and information were always delivered jointly, our data do not allow to distinguish between these different mechanisms. We nonetheless provide suggestive evidence on the relevance of different program components by exploiting features of the intervention design and data on employees' engagement with the program online material in Section 4.3.

[3] We support this claim empirically in Section 4.3.

## 2.3 Implementation

The two interventions took place in different periods and on different branches. The technological renovation was the first to be implemented. Each of the 70 branches in the renovation group received BEMS installation between August 2016 to May 2017 (share of installation per month is reported in Table A1). The behavioral intervention ran from January to December 2019, on 553 branches. Branches' allocation to the interventions was not random. Those that received the technological renovation were selected to reduce the investment payback time: they had higher baseline electricity consumption and higher consumption outside working hours,[4] the latter being an indicator of energy waste.

# 3 Empirical strategy and data

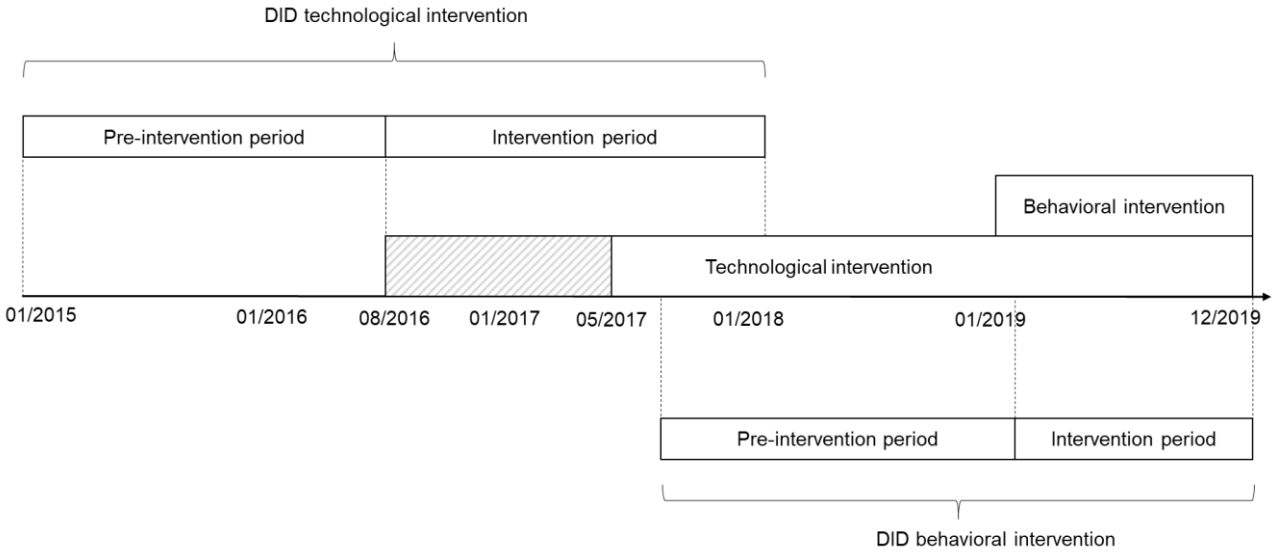
## 3.1 Empirical strategy

We exploit the different timings of the interventions to assess their impacts on branches' monthly electricity consumption. We estimate two separate DID, one for each intervention, as illustrated in Figure 1. For the technological renovation, we estimate a staggered DID (due to the different installation dates) between January 2015 and December 2017. As a comparison group, we use the 553 branches that did not receive the renovation but were then assigned to the behavioral group, as well as the yet-to-be-renovated branches of the renovation group. For the behavioral intervention, we estimate a DID between July 2017, after the completion of all the renovations,[5] and December 2019, when the behavioral intervention ended. In evaluating its impact, we compare these branches to those belonging to the renovation group. This setting allows us to have more than one-year pre-intervention period to assess whether the parallel trend assumption is likely to hold in our setting through placebo tests (see Section 4.1.3), as recommended for DID estimations (Angrist & Pischke, 2008). A priori, there are no theoretical explanations for the parallel trend 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.

[4] The selection of the branches to renovate was based on consumption in 2015.

[5] The installation actually ended in May 2017. We left a gap of two months to prevent possible transition effects from affecting our empirical analysis.

**Figure 1. Implementation of the interventions and related specifications**




Note: the grey striped region (August 2016-May 2017) represents BEMS staggered installation period. The pre-intervention and intervention periods refer to the periods used in the difference-in-differences specification to estimate the effect of the corresponding intervention.

Among the assumptions required for a DID estimation, our setting may not completely satisfy the lack of spillovers between units exposed versus those not exposed to the intervention. The bank partially involved in the behavioral intervention the branches not belonging to the behavioral group in order to maximize employees' engagement with the initiative and possibly the overall electricity savings. The online materials were available to all branches, including those in the renovation group. 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 (we formally test for this in Section 4.1.3). The employees of the branches of the renovation group did not have direct contact with those of the behavioral group, and mere information disclosure is often not enough to prompt behavioral change (e.g. 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. Finally, even if any bias occurred in the estimation, it is downward, leading to a conservative assessment of the behavioral intervention's impact.

Finally, an additional relevant parameter for our estimation is statistical power. Low power may cause incorrect inference as it increases the risk of false negatives and false positives, where non-existent effects are detected. A study may be underpowered both because the sample size is small and because the underlying effect sizes are relatively small (Ioannidis, 2005). When discussing our findings, we report the ex-post Minimum Detectable Effect (MDE), that is, the effect that would

have been detectable with 80% power at the 5% significance level ex-post.[6] This allows us to assess whether issues related to low statistical power affect our results. Note that we did not perform ex-ante power calculations because we did not have any influence on the sample size for the study, as it is not a field experiment. The design and implementation of the two interventions were decided and managed by the company, which simply shared their data ex-post with us.[7] Rather, the MDE allows us to distinguish between cases where intervention effects cannot be ruled out with confidence from precisely estimated null results. This approach also facilitates comparisons with similar studies.

## 3.2 Data and descriptive statistics

Our dataset for the empirical analysis combines the bank's administrative data, including branch 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. 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 electricity 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 the main work schedule and consumption at this time derives from both employees' activities and passive buildings consumption. F2 represents electricity use outside the main work schedule, partly due to human activities as some branches are open on Saturdays and some employees may work overtime, but mostly due to passive building consumption. F3 corresponds to non-working hours, and consumption here results only from passive building consumption. We derive the total electricity consumption of each branch by summing up the consumption in the three TOUs.

[6] Ex-post MDE are computed as $SE(\beta)*2.8$ (Duflo et al., 2007).

[7] For the same reason, we also did not register a pre-analysis plan for this study. Pre-analysis plans are generally required for randomized control trials, but the difficulty of monitoring pre-specification means that they are typically not required in non-experimental studies. In addition, detailed pre-specification is warranted when, within the impact evaluation of field experiments, the dependent variable is not well defined, subgroup analysis is expected to be important, there is the possibility to cherry-pick the dimensions of heterogeneity to focus on, or a party to the study has a vested interest (Duflo et al., 2020). As our main analysis only relies on branches' electricity consumption as outcome variable and bank's administrative data, these conditions do not apply to our case.

The initial sample size is 70 branches for the renovation group and 553 branches for the behavioral group.[8] We drop two branches from the renovation 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 because they are excluded from the monthly rankings due to lack of historical data to compute their 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 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 higher than the branch's mean electricity consumption,[9] or that become negative when log-transformed. 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 564 branches, 67 for the renovation group and 497 for the behavioral group.[10] Figure A2 reports the density plots of electricity consumption per group and per TOU for the final sample. The graphs show that dispersion and number of outliers are higher in the non-transformed data than in the log-transformed data, in particular for total electricity consumption, justifying our use of log-transformed electricity consumption as main outcome variable.

Table 1 reports sample descriptive statistics. As branches are not randomly assigned to the two programs, they have different characteristics. Consistent with the technological renovation targeting criteria, the branches in the renovation group are larger in terms of number of employees and surface than those in the behavioral group. The buildings of these branches are older than those involved in the energy-saving competition, although the renovations implemented with BEMS likely reduce the influence of buildings' age on consumption. The behavioral group branches are more likely to be located in the South and islands and less in the North than the renovation group branches. As branches exposed to the behavioral intervention are smaller, they also use less electricity than those receiving the renovation. The difference between the two groups is highest before the technological renovation, when total electricity consumption, computed as the average monthly consumption in 2015, is around 4800 and 2800 kWh for the renovation and the behavioral groups, respectively. This difference reduces after the technological renovation (year 2018), but remains large. Nevertheless, the distributions of

[8] The bank has a higher number of branches than those considered in the study. To be eligible for one of these two groups, the branch should not be an office, should have a uniquely identified meter and should not be assigned to receive other retrofit interventions in the years that we consider.
[9] For branches in the renovation group, we calculate separate means before and after BEMS installation as electricity consumption significantly changes after this event.
[10] The process of data cleaning reduces the number of observations by about 1000 data points for each DID specification. Section 4.1.3 reports the result of a robustness check that includes all meter readings.

baseline consumption of the two groups of branches largely overlap (as shown in Figure A3), as only a subset of the highest-consuming branches was selected to receive the technological renovations. Across the two groups, more than half of the total electricity consumption is generated during the main work schedule (F1) and between 30 and 35 percent of total usage occurs at night or during holidays (F3). While the differences across the two groups of branches are large, the use of DID specification with branch fixed-effects in the empirical analysis should control for them and prevent them from affecting the results.

Figure 2 and 3 graphically illustrate the monthly electricity consumption divided by TOU and program assignment for our two empirical specifications. In Figure 2, the months from January 2015 to July 2016 represent the pre-intervention period for the technological renovation. Between August 2016 and May 2017 (grey area with stripes), BEMS is under installation with staggered installation date; after this period the technological renovation is complete and operational (grey area). The impact of the retrofit is clearly visible in Figure 2. During the installation period, electricity consumption gradually reduces especially outside the main work schedule (Figure 2C and 2D), and remains low after the installation is completed.

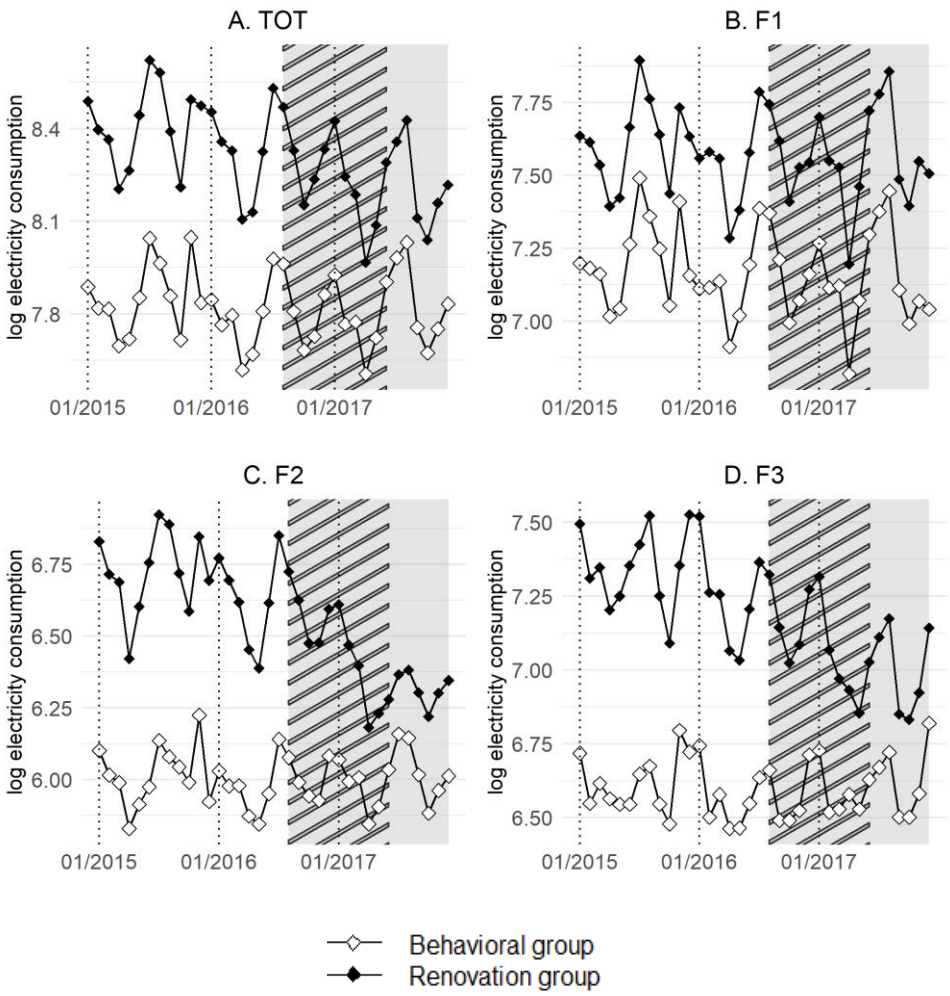
In Figure 3, the months from July 2017 to December 2018 represent the pre-intervention period for the behavioral intervention, which is ongoing between January and December 2019. The (generally) small effect of behavioral interventions makes it difficult to visually detect changes in electricity use after the launch of the competition. A first graphical inspection of the data suggests that assuming a parallel trend for both DID specifications is reasonable in our setting, as the two groups appear to follow the same trend and seasonality in both pre-interventions periods. We provide evidence in support for the parallel trend assumption when discussing the robustness of our main specification (Section 4.1.3).

**Table 1. Descriptive statistics**

| | Renovation (N = 67) | Behavioral (N = 497) |
|---|---|---|
| *Panel A: Branch characteristics* | | |
| Average number of employees | 9.6 | 5.5 |
| | (5.1) | (3.2) |
| Average surface (m2) | 534.5 | 313 |
| | (352.4) | (271.7) |
| Average opening year | 1991 | 2006 |
| | (22.7) | (15.7) |
| Electric heating (%) | 50.7 | 58.6 |
| Area: Center (%) | 6 | 8.2 |
| Area: North (%) | 79.1 | 41.2 |
| Area: South and islands (%) | 14.9 | 50.6 |
| | | |
| *Panel B: Electricity consumption (kWh)* | | |
| 2015 consumption: TOT | 4807 | 2837 |
| | (2055) | (1575) |
| 2015 consumption: F1 | 2246 | 1559 |
| | (1182) | (1046) |
| 2015 consumption: F2 | 893 | 453 |
| | (397) | (243) |
| 2015 consumption: F3 | 1668 | 824 |
| | (695) | (430) |
| 2018 consumption: TOT | 3916 | 2694 |
| | (1860) | (1450) |
| 2018 consumption: F1 | 2142 | 1444 |
| | (1228) | (942) |
| 2018 consumption: F2 | 594 | 439 |
| | (281) | (235) |
| 2018 consumption: F3 | 1180 | 810 |
| | (513) | (414) |
| 2019 consumption: TOT | 3848 | 2591 |
| | (1844) | (1412) |
| 2019 consumption: F1 | 2018 | 1379 |
| | (1163) | (898) |
| 2019 consumption: F2 | 617 | 433 |
| | (284) | (235) |
| 2019 consumption: F3 | 1212 | 780 |
| | (562) | (414) |

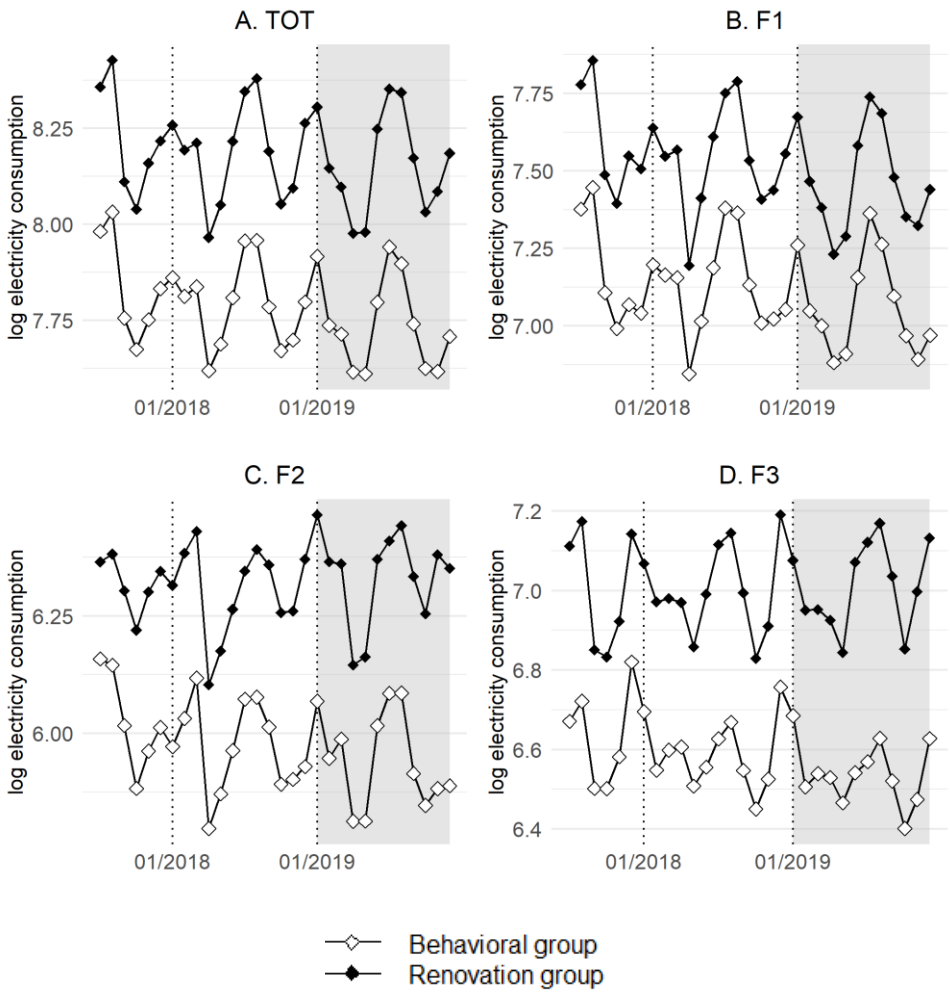
Note: The average number of employees is computed considering the number of employees in December 2018. Electricity consumption is expressed in kWh. Standard deviations in parentheses when applicable. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours.

**Figure 2. Electricity consumption before, during and after BEMS installation per TOU and group**




Note: Log monthly electricity consumption for renovation (black markers) and behavioral (white markers) groups from 2015 to 2017. Vertical dotted lines represent the beginnings of the years. White region (January 2015-July 2016): pre-intervention period; grey striped region (August 2016-May 2017): BEMS staggered installation period; grey region (June 2017-December 2017): intervention period. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours.

**Figure 3. Electricity consumption before and during the behavioral intervention per TOU and group**




Note: Log monthly electricity consumption for renovation (black markers) and behavioral (white markers) groups from mid-2017 to the end of 2019. Vertical dotted lines represent the beginnings of the years. White region (July 2017-December 2018): pre-intervention period; grey region (January-December 2019): intervention period. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours.

# 4 Results

## 4.1 Impact on electricity use

### 4.1.1 Technological intervention

We test the effect of the technological intervention on monthly electricity consumption. To this aim, we estimate the following OLS model on the full sample for the period ranging from January 2015 to December 2017:

$$y_{it} = \beta_0 + \beta_1 * BEMS_{it} + \beta_2 * CDD_{pt} + \beta_3 * HDD_{pt} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where $y_{it}$ is the log monthly electricity consumption of branch $i$ in period $t$; as we assess intervention effect on the different time of use (TOU), $y_{it}$ denotes the total electricity consumption, and the consumption subdivided in F1 (main work schedule, weekdays from 8 a.m. to 7 p.m.), F2 (working hours outside the main work schedule, 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).

$BEMS_{it}$ is the indicator for the technological intervention and is equal to one for treated branches after the retrofit month, and zero otherwise. The month of the installation is excluded from the analysis. This specification, which is similar to that in Bertrand et al. (2004), is driven by the staggered date of the installation. The regression also includes cooling and heating degree days of the main Italian provinces where branches are located, $CDD_{pt}$ *and* $HDD_{pt}$,[11] and branch and month-by-year fixed effects (unique, consecutive time fixed-effects), respectively denoted as $\alpha_i$ and $\lambda_t$. We allow for arbitrary within-branch correlation by clustering the standard errors at the branch level (Bertrand et al., 2004).

Results are reported in Table 2, along with ex-post MDE. We estimate that the technological renovation curbs total monthly electricity consumption by 15.8 percent (Column 1).[12] This amount is in line with recent BEMS implementations, which achieve average savings of around 16 percent (Lee & Cheng, 2016). The reduction in consumption is statistically significant in F2 and F3, reaching electricity savings of 31.3 and 28.2 percent, respectively. No significant effect is instead observed in F1 (Column 2). The MDE for F1 is of an order of magnitude which appears in line with the large effect of this type of retrofit. Moreover, the coefficient is very small and the standard error is not larger than that of total consumption, suggesting that the null result for working hours is predominantly capturing a null effect, rather than low statistical power.

[11] 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).
[12] Since our dependent variable is log-transformed, we calculate the percentage change in the electricity savings from the regression coefficients by applying the transformation $100 * (e^{\beta} - 1)$.

**Table 2. Impact of the technological intervention on electricity consumption**

| | (1) TOT | MDE | (2) F1 | MDE | (3) F2 | MDE | (4) F3 | MDE |
|---|---|---|---|---|---|---|---|---|
| *BEMS* | -0.172*** | 0.053 | -0.001 | 0.048 | -0.375*** | 0.090 | -0.331*** | 0.084 |
| | (0.019) | | (0.017) | | (0.032) | | (0.030) | |
| N. branches | 564 | | 564 | | 564 | | 564 | |
| Observations | 19097 | | 19097 | | 19097 | | 19097 | |

Note: OLS regressions of log monthly electricity consumption on intervention indicator. *BEMS* is the staggered difference-in-differences estimator for the technological intervention. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and month-by-year fixed effects and cooling and heating degree days of the province. Standard errors clustered at the branch level reported in parentheses. *p < .05, ** p < .01, ***p < .001.

### 4.1.2 Behavioral intervention

We estimate the effect of the behavioral intervention on branch monthly electricity consumption, using the following OLS specification on the full sample for the period ranging from July 2017 to December 2019:

$$y_{it} = \beta_4 + \beta_5 * BEH_{it} + \beta_6 * CDD_{pt} + \beta_7 * HDD_{pt} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where all the terms are the same as those in Equation (1), except that the indicator for the behavioral intervention, $BEH_{it}$ is equal to one for the branches assigned to the energy-saving competition after January 2019, zero otherwise.

Results are reported in Table 3, along with MDE. The behavioral intervention's effect on total monthly electricity consumption is -2.4 percent, corresponding to average savings of 64.3 kWh per month per branch,[13] but it is not statistically significant (Column 1). However, it generates statistically significant savings outside the main work schedule. The effect is negative and statistically significant for both F2 (Column 3) and F3 (Column 4), resulting in 6.7 and 6.5 percent savings, respectively. This value is quite high compared to the average effect of behavioral interventions in the residential sector and shows how behavioral interventions can help firms reducing inefficiencies outside the work schedule. That energy savings are highest when employees are not at work is also found by Orland et al. (2014), in the context of a serious game intervention in the workplace.

We consider potential reasons behind the different effects of the energy-saving competition by TOU. One possible explanation is that inefficiencies are small during working hours. Alternatively, this result can be explained by the different efforts and comfort costs of reducing energy usage within and outside working hours. Indeed, employees need to provide continuous effort to

[13] Average baseline consumption for the pre-treatment period (from July 2017 to December 2018) is 2679 kWh per month.

conserve energy during working hours, for example switching on and off appliances depending on usage and regulating the indoor temperature throughout the day; in addition, this may reduce their comfort, for example if they need to wait for their appliances to restart or if the room temperature is not optimal.

**Table 3. Impact of the behavioral intervention on electricity consumption**

| | (1) TOT | MDE | (2) F1 | MDE | (3) F2 | MDE | (4) F3 | MDE |
|---|---|---|---|---|---|---|---|---|
| *BEH* | -0.024 | 0.048 | 0.016 | 0.05 | -0.07*** | 0.062 | -0.067** | 0.067 |
| | (0.017) | | (0.018) | | (0.022) | | (0.024) | |
| N. branches | 564 | | 564 | | 564 | | 564 | |
| Observations | 16177 | | 16177 | | 16177 | | 16177 | |

Note: OLS regression of log monthly electricity consumption on intervention indicator. *BEH* is the difference-in-differences estimator for the behavioral intervention. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and month-by-year fixed effects and cooling and heating degree days of the province. Standard errors clustered at the branch level reported in parentheses. *p < .05, **p < .01, ***p < .001.

We consider alternative explanations for the lack of statistically significant effects of the behavioral intervention on total electricity consumption. First, this null effect may be due to low statistical power. The MDE in Column (2) is 4.8 percent. The existing literature on workplace energy-saving interventions does not provide clear guidance on what effect size we should expect from similar settings. For instance, Charlier et al. (2021) investigate the effect of nudges on daily energy consumption at 47 French companies' sites, for an observation period of three months. They find that visual prompts combined with social comparison or moral appeals lead to statistically significant electricity savings. However, the fact that their baseline period is characterized by lower temperature (and higher electricity consumption) than the treatment period makes it difficult to compare their estimates to ours.[14] The MDE is larger than effect sizes from behavioral and informational interventions in the European residential sector, equal to around 1 percent (Andor et al., 2020; Bonan et al., 2020). If the effect of the energy-saving competition in the workplace were the same as that of social comparison in the residential sector, we would not be able to detect it as statistically significant. However, the differences between the work and residential contexts, and between the intervention that we study and standard social information programs do not allow us to draw conclusions about the relative effect size in the two environments. In sum, existing literature does not offer clear indications on whether our analysis

[14] We cannot compare our estimates to those of Orland et al. (2014), as their participants self-selected into participating the serious game and energy savings are measured by comparing consumption before and after the program. In addition, the intervention and the related energy savings address individuals rather than groups.

suffers from low statistical power. Still, the fact that we detect statistically significant effects for other TOU, but not for total consumption, suggests that we are low-powered in this latter analysis.

Second, the possible spillover to branches in the renovation group may reduce our estimate of the behavioral intervention's effect. We use data on the months when the energy-saving competition was extended to the renovation group to argue that spillover effects are not strong enough to fully explain the lack of significance (Section 4.1.3). Third, the behavioral intervention may have failed to engage the employees or the low salience of energy conservation may have limited employees' responsiveness to it. The significant savings outside the main work schedule suggest that, at least when it comes to behaviors adopted when leaving work, employees did notice the intervention. We look at engagement with program material to further investigate this potential explanation in Section 4.3. Fourth, the overall insignificant effect may mask heterogeneity by branch characteristics: we explore this possibility in Section 4.2.

### 4.1.3 Additional specifications and robustness checks

We test for sensitivity to our DID specifications by varying the outcome, panel length, and sample used to estimate Equation (1) and (2). First, Table A2 shows similar results if we estimate the regression in levels rather than logs. The only difference is that *BEH* turns out to be positively statistically significant for F1 (Column 6), probably due to the presence of outliers in the untransformed dependent variable.

Second, we modify the length of the panel. For the technological renovation, we estimate Equation (1) including also the year 2018, to check whether the effect of the intervention remains constant over the medium term. The point estimates in Table A3 (Columns 1-4) are largely in line with those of Table 2 (for example, for total electricity consumption, the estimated savings reduce from 15.8 to 15.3 percent), suggesting that the BEMS effect is roughly constant over the medium run. For the behavioral intervention, we restrict the analysis to the years 2018 and 2019 so that the lengths of the pre- and post-intervention periods are the same, and we replicate the results in Table 3 (Table A3, Columns 5-8).

Third, we estimate intervention effects on yearly rather than monthly electricity consumption as this is another way to eliminate serial correlation in the data (Bertrand et al., 2004). For the technological intervention, we compare the consumption in 2015 to that of 2018 (as in 2016 and 2017 BEMS was under installation), and for the behavioral intervention, that of 2018 with that of 2019. Results in Table A4 show that the point estimates and significance levels are in line with those of Tables 2 and 3. The only difference is that the coefficient of the behavioral intervention for F3 is statistically significant at $p = .051$ (Column 8). Similar results are obtained if we run Equation (1) on the monthly panel after removing the installation period and replacing the

staggered DID indicator with a dummy equal to 1 for BEMS branches from July 2017, i.e., after the installation period (Table A5).

Fourth, the interventions' impacts are similar when we winsorize the data to eliminate the outliers (5 percent at the top and bottom of the distribution, Table A6) and we keep all the real meter readings in the database (Table A7). The higher noise in the data for this latter robustness causes larger point estimates and standard errors than in the main specifications, making the impact of the variable *BEH* on consumption in F3 only marginally significant (Column 8, p = .098).

Fifth, for the technological renovation, we estimate the staggered DID of Equation (1) excluding the branches of the behavioral intervention, so that the branches of the renovation group that receive the renovation earlier act as comparison group for those that receive it later. Results are fairly in line with the results of Equation (1), but significant savings of 9.1 percent are also detected in F1 (Table A8). Possibly, a non-random starting date of the installation by branch may bias these results and explain the differences with respect to our main specification.

Sixth, for the behavioral intervention, we investigate whether the three months in which the rank was extended to all the branches (including those of the renovation group) present a reduced effect of the behavioral intervention than the other months. To this aim, we add to Equation (2) an interaction between the variable *BEH* and a dummy equal to 1 if in that month the ranking includes all branches, 0 otherwise. We also interact this dummy with post-intervention period. A significant negative effect may indicate the presence of spillover towards the comparison group, and a possible underestimation of the effect of the behavioral intervention in our main analysis. Consistently with our expectation of lack of spillover because of infrequent feedback, the interaction term is not statistically significant for any TOU (Table A9).

Finally, we test whether our DID specifications are robust to in-time placebo tests. For the technological renovation, we eliminate the periods after the beginning of the renovation (July 2016), and we check if the specification of Equation (1) detects as significant a fictitious intervention starting in January 2016. Likewise, for the behavioral intervention, we exclude year 2019, during which the behavioral intervention was ongoing, from Equation (2) and we introduce a fictitious intervention starting in January 2018. Table A10 shows that our specifications do not detect statistically significant intervention effects when no intervention occurred, except a significant negative coefficient for the technological renovation in F3 (Column 4, p= .049). Thus, our main results may overestimate the results for this TOU for the technological renovation. Besides this, this exercise suggests that the pre-existing differences between the two groups do not cause our main results.

## 4.2 Heterogeneous effects of the interventions

We assess heterogeneous effects of the two interventions along different branches' characteristics –baseline electricity consumption, heating type and branch size– by adding to Equation (1) and (2) interactions between intervention dummy and the relevant variable. For simplicity, for the technological renovation we eliminate from the specification the months during which BEMS was under installation, and we create the DID indicator by interacting a post-intervention dummy equal to one after July 2017, with the *BEMS* indicator, equal to one for branches that received the retrofit.[15] We interact the post-intervention dummy with the relevant branch characteristics to control for differential time trends. We use the same estimation approach to assess heterogeneous impacts of the behavioral intervention. We report in Table 4 the results for total electricity consumption: Panel A examines the technological intervention and Panel B the behavioral one. Results for the other TOUs, which are similar to those for total consumption, are reported in Table A11.

Given the distinct nature of the two interventions, heterogeneity is likely to be driven by different aspects. The effectiveness of technological renovations mostly depends on buildings characteristics (Kahn et al., 2014). Individuals' behaviors may also play a role, because employees might increase their consumption as a result of the retrofit, i.e., the well-known phenomenon of rebound effects (Gillingham et al., 2016). The effectiveness of behavioral interventions may instead depend on a broader set of factors that relate to both building characteristics and social aspects that we discuss later in this section.

The first source of heterogeneity that we examine is baseline electricity consumption. We include it because higher baseline consumption generally means higher "slack" in resource usage (Tiefenbeck et al., 2018). Accordingly, households with higher baseline consumption tend to be more responsive to behavioral interventions (e.g. Allcott, 2011; Andor et al., 2020, 2022; Bonan et al., 2021). However, evidence of whether this also applies in the workplace is scattered as previous studies do not investigate this dimension.

[15] This approach is justified by robustness tests showing that this specification produces similar estimates as our main one (Table A5).

**Table 4. Heterogeneous effect of the interventions on total electricity consumption**

| | (1) TOT | MDE | (2) TOT | MDE | (3) TOT | MDE | (4) TOT | MDE |
|---|---|---|---|---|---|---|---|---|
| *Panel A: Technological intervention* | | | | | | | | |
| *BEMS* | -0.171*** | 0.078 | -0.125*** | 0.07 | -0.237*** | 0.143 | -0.224*** | 0.115 |
| | (0.028) | | (0.025) | | (0.051) | | (0.041) | |
| *BEMS* x pre-treat | 0.016 | 0.129 | | | | | | |
| | (0.046) | | | | | | | |
| *BEMS* x heating | | | -0.080 | 0.12 | | | | |
| | | | (0.043) | | | | | |
| *BEMS* x employees | | | | | 0.008 | 0.014 | | |
| | | | | | (0.005) | | | |
| *BEMS* x surface | | | | | | | 0.001 | 0.003 |
| | | | | | | | (0.001) | |
| Observations | 13625 | | 13625 | | 13625 | | 13625 | |
| *Panel B: Behavioral intervention* | | | | | | | | |
| *BEH* | -0.007 | 0.078 | -0.038* | 0.106 | -0.022 | 0.062 | -0.002 | 0.006 |
| | (0.028) | | (0.018) | | (0.048) | | (0.037) | |
| *BEH* x pre-treat | -0.033 | 0.092 | | | | | | |
| | (0.034) | | | | | | | |
| *BEH* x heating | | | 0.027 | 0.095 | | | | |
| | | | (0.034) | | | | | |
| *BEH* x employees | | | | | 0.001 | 0.003 | | |
| | | | | | (0.004) | | | |
| *BEH* x surface | | | | | | | -0.001 | 0.003 |
| | | | | | | | (0.001) | |
| Observations | 16177 | | 16177 | | 16177 | | 16177 | |
| N. branches | 564 | | 564 | | 564 | | 564 | |

Note: OLS regression of log monthly total electricity consumption on intervention indicator. *BEMS* is the difference-in-differences estimator for the technological intervention. *BEH* is the difference-in-differences estimator for the behavioral intervention. *Pre-treat* is a dummy variable for average consumption above the median before the intervention, i.e. before the beginning of BEMS installation (2015) in Panel A and before the launch of the behavioral intervention (2018) in Panel B. *Heating* is a dummy equal to 1 if the branch has electric heating, 0 otherwise. *Employees* is a continuous variable for the number of employees in December 2018. *Surface* is a continuous variable for the squared meters. All models include branch and time fixed effects, cooling and heating degree days of the province and the post-intervention indicator interacted with the heterogeneity variables. Standard errors clustered at the branch level reported in parentheses. *p < .05, ** p < .01, ***p < .001.

We thus estimate Equation (1) and (2), interacting the DID and post-intervention dummies with a dummy equal to one if the branch has baseline electricity consumption (January-December 2015 for the technological renovation, January-December 2018 for the behavioral intervention) higher than the median of the intervention group to which it belongs,[16] zero otherwise. While for the

[16] We operationalized the median split in this way as the two intervention groups have different baseline electricity consumption.

behavioral intervention the interaction goes in the expected direction, it is not statistically significant for any of the two interventions (Column 1).[17]

We also examine heterogeneity along three alternative proxies for baseline efficiency: (i) building energy intensity, i.e., electricity consumption per square meter; (ii) "slack" of resources that employees can act upon to reduce consumption, operationalized as electricity consumption per employee; (iii) passive energy waste, that is, the share of total electricity consumption that is consumed outside the main work schedule.[18]

We find no significant interactions between these three indicators of baseline efficiency and the behavioral intervention, regardless of whether we measure them through median, quartile or quintile splits, or through continuous variables (Table A12 and Tables B6 to B8): for this intervention, the lack of heterogeneity by baseline efficiency appears robust. The technological renovation instead appears to be more effective among branches that in the pre-intervention period have larger passive energy waste (Column 3, Table A12 and Columns 2 and 3, Table B5). This result is consistent with the fact that the technological intervention generates savings mostly outside the work schedule. The other indicators instead do not affect the impact of the technological renovation (Table A12 and Tables B3 and B4).

The reduced scope for behavioral change among employees may explain why we fail to reproduce the heterogeneity in baseline electricity consumption observed in evaluations of behavioral interventions in the residential sector. Among households, behavioral 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 have fewer sources of waste left to address in response to the intervention. The relevance of energy-efficiency investments is suggested by the findings of Myers and Souza (2020), which show no effect of a social comparison intervention among student dorms residents. Likewise, employees cannot invest in building renovations to conserve energy; they can only change their behavior to reduce their consumption. This limits intervention effects to those deriving from behavioral change. Moreover, the fact that energy savings are accrued mostly outside working hours further limits the range of behaviors that employees at different branches can differentially engage in, and which could result in heterogeneous program effects.

[17] This result is robust to alternative coding of baseline electricity consumption, namely, to using a continuous measure of electricity consumption or to splitting branches in quartiles or quintiles of baseline electricity consumption. Results are available in Tables B1 and B2. Out of all the proxies of baseline consumption that we consider, we find only two statistical significant interactions, whose frequency is in line with Type I error at 0.05.

[18] Indeed, the bank considers electricity consumption outside the main work schedule as an indicator of passive waste, and used it to identify the branches to target with the technological intervention.

Of course, we can only claim that we do not find heterogeneity in the effect of the interventions over the range of baseline consumption that we observe across the bank branches in the two groups. It is possible that baseline consumption is too homogeneous within the two groups for us to observe any heterogeneity. We can assess whether this is the case by comparing the range of consumption in our two intervention groups with that observed in other similar studies. To this aim, we calculate the spread of the distribution as the ratio between the 10th and the 90th percentile, on yearly total electricity consumption used to calculate the heterogeneity. For the technological renovation, this ratio equals to 44.1 and 35.9 percent, for 2015 and 2018, respectively, and for the behavioral intervention, to 40.5 and 39.9 percent, for 2015 and 2018, respectively. The corresponding figures from studies of social information programs in the residential sector in Italy – which find heterogeneity in programs' effects by baseline electricity usage – are similar, ranging from 20.8 to 48.4 percent (Bonan et al., 2021).[19]

Next, we investigate heterogeneous effects based on other observable branch characteristics: heating type (gas vs. electricity) and size, in terms of number of employees and surface. These characteristics influence electricity usage and may indirectly affect interventions' impacts through baseline consumption. However, they may also have a direct impact, which we isolate through our fixed effects specifications. That is, we assess how a specific characteristic interacts with the interventions net of all the other branch characteristics.

We expect both interventions to be more effective in branches with electric heating, thanks to the increased opportunities for electricity saving. In contrast to our expectations, both interactions are not statistically significant. However, the significance level of the interaction term *BEMS x heating* is just above the 5 percent threshold (p= .061, Column 2, Panel A, Table 4), possibly indicating that the effect is present but that we lack the statistical power to detect it as statistically significant. Similarly, statistical significance is below the 10 percent level also for F2 and F3 (p= .083 and p= .088, respectively, Columns 5 and 6, Panel A, Table A11). Finally, for the behavioral intervention, the coefficient of *BEH* becomes statistically significant for branches without electric heating for total electricity consumption (Column 2, Panel B, Table 4), as well as for F2 and F3 (Columns 5 and 6, Panel B, Table A11). The existing literature does not provide indications on the sign and magnitude that we should expect from these effects. These results confirm that, if

[19] Although selection into BEMS was based on some indicators of electricity consumption and inefficiency (i.e., total electricity consumption and share of consumption outside the main work schedule), branches within each group still present some heterogeneity in baseline electricity consumption. Appendix Figure A3 shows the distributions of baseline total electricity consumption for the two groups. For both years 2015 and 2018 the two distributions have a high degree of overlap, with the distribution of consumption of the branches in the behavioral group being wider than that of the branches in the renovation group. In fact, only a subset of the highly consuming branches was assigned to the renovation group.

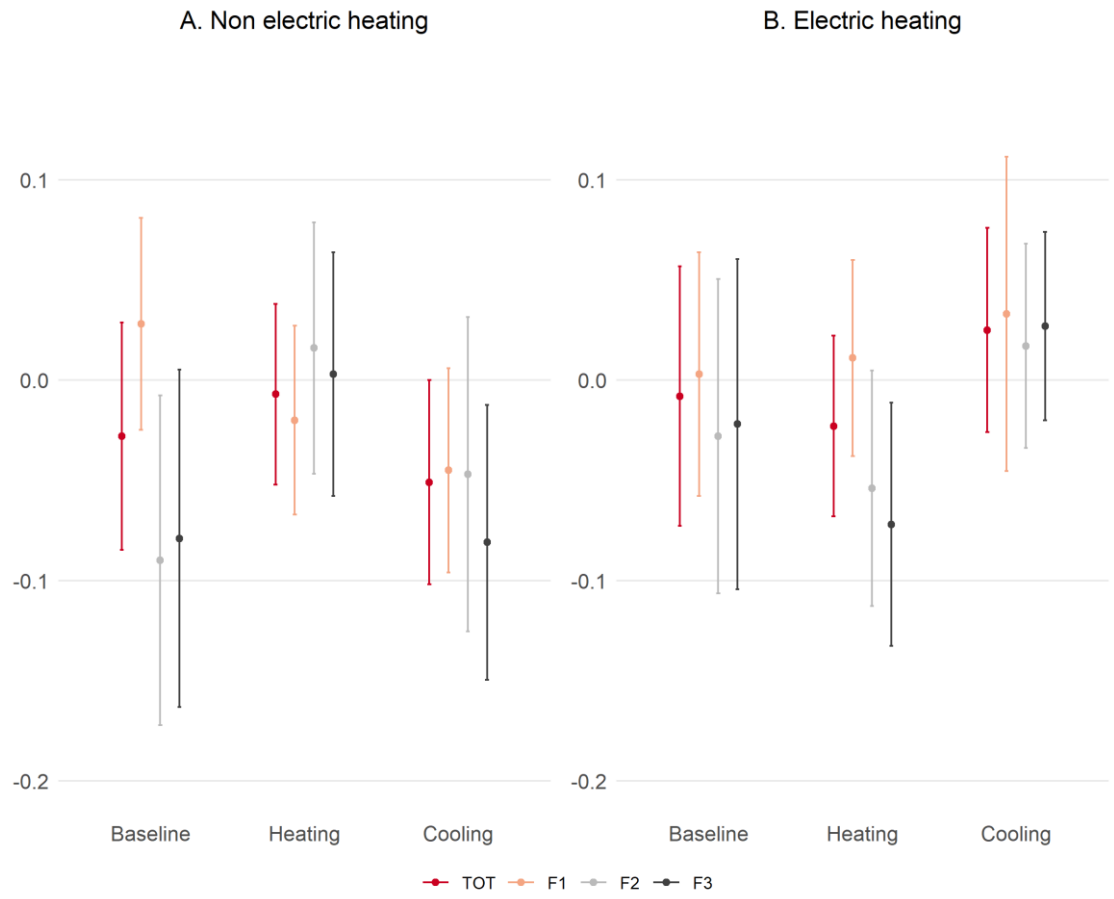
behavior change actually occurs, it primarily consists of employees changing their use of appliances and lighting when leaving overnight.

We complement this analysis by examining seasonal effects of the behavioral intervention. By connecting changes in the intervention effect with the season, we aim to disentangle changes in usage of appliances and lighting from that of heating and cooling devices. Since the seasonality of electricity consumption depends on whether a branch has electric or gas heating, we estimate two separate DID specifications for branches with and without electric heating. We estimate Equation (2), adding an interaction term between the DID and post-intervention dummies with seasonal dummies, coded as follows: heating season from October to March and cooling season from June to August. The remaining months, during which no cooling or heating is needed, represent the baseline. Figures 4A and 4B report the coefficients of the interaction terms and the corresponding 95 percent confidence intervals, for branches without and with electric heating respectively.

For branches without electric heating (Figure 4A), we observe a similar pattern of savings in the baseline and cooling season, with larger reductions outside working hours, while no such pattern is apparent in the heating season. For branches with electric heating (Figure 4B), the reduction in consumption outside working hours is clear also in the heating season. [20] Taken together, these results suggest that the behavioral intervention fosters electricity savings primarily by encouraging employees to switch off electricity-using appliances, such as lighting, computers, air conditioners and electric heaters, when leaving the office overnight or for weekends and holidays. Note that similar seasonal patterns also appear for the technological renovation (Figure B1). In particular, BEMS is more effective during the cooling season outside the main work schedule as well as during the heating season for branches with electric heating. Keeping in mind that the technological renovation mostly reduces energy waste at night by optimizing the on/off time for temperatures and lighting, this result supports our interpretation that the efficiency gains resulting from the behavioral intervention are also obtained thanks to employees acting upon this type of inefficiency.

[20] The lower effect during the cooling season among branches with electric heating may be explained by the fact that these branches are mostly located in the South and Islands of Italy. Possibly, differences in habits or needs of air conditioning usage may explain why these branches reduce less their consumption compared to those in other parts of Italy.

**Figure 4. Seasonal impact of the behavioral intervention, without (Panel A) and with (Panel B) electric heating**




Note: *Baseline* refers to the effect of the behavioral intervention during April, May and September. *Heating* refers to the effect of the behavioral intervention during the heating season (i.e. from October to March). *Cooling* refers to the effect of the behavioral intervention during the cooling season (i.e. from June to August). Vertical lines represent 95% confidence intervals. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours.

Finally, we predict stronger impacts of the behavioral intervention in smaller branches in terms of employees and surface. Social norms and group dynamics within the workplace influence employees' energy-saving behaviors (Staddon et al., 2016). Engineering studies show that the effects of social influence programs depend on the characteristics of the network (Jain et al., 2013; Peschiera & Taylor, 2012). Smaller groups generate stronger peer effects (Boucher et al., 2012). These, in turn, trigger conservation behaviors (Wolske et al., 2020). Moreover, feedback is more effective when it is possible to monitor how energy is related to individual behavior (Grønhøj & Thøgersen, 2011), which is easier to do in smaller groups.

With respect to the technological renovation, we find no heterogeneity by branches' size (Columns 3 and 4 of Table 4, Panel A). In contrast with our expectations, also the interaction between the behavioral intervention and branch size is not significant, as indicated by Columns 3 and 4 of Table

4, Panel B.[21] 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 (X. M. Zhang & Zhu, 2011) and the rate of peer sanctions (Carpenter, 2007) do not depend on group size. Alternatively, the targeted energy-saving behaviors may not be salient enough or may not be subjected to social norms, thereby failing to activate peer effects. Survey data are consistent with this explanation: other employees' engagement with the program does not affect individuals' engagement with it (see Section 4.3 for further details). Hence, peer effects may not have occurred in our setting regardless of the branch size.

## 4.3 Behavioral intervention: mechanisms and employees' engagement

This section exploits survey data, data on employees' engagement with the program webpage and information on the details of the implementation of the behavioral intervention to provide suggestive evidence on the likely mechanisms behind the effect of the energy-saving competition.

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, 1152 employees volunteered to participate in the survey.[22] Respondents are predominantly male (61.1 percent), with ages ranging from 18 to more than 50, and with 43.8 percent 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 renovation 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 information on the number of accesses made to it. The data also illustrate the number and types of content posted online every month, and how many times each of them was viewed. As for the survey, we cannot distinguish whether the access was made by an employee from a behavioral group branch. Although our data are not suitable for estimating any intervention effect, we believe that they still provide insights

[21] For both interventions, results do not change if we interact the intervention and post-intervention dummies with dummies for branches larger than the median (i.e., equal to one if the branch has more employees than the median of its intervention group and if the branch has larger surface than the median of its intervention group, for heterogeneity in number of employees and surface, respectively). Results are available upon request.

[22] The fact that participation in the survey is voluntary raises issues of selection: employees who pay more attention to company announcements may be more likely both to become aware of the energy-saving program and to respond to the survey. The survey may thus not be representative and answers should be taken with caution.

into which parts of the behavioral program were more appreciated and what motivated employees to engage with the intervention.

Survey results indicate that the initiative was known and welcomed by the respondents. Overall, 74.7 percent of them are aware of the behavioral intervention. Of these, most accessed the program's informative materials sometimes over the year (53.7 percent) or at least once per month (35.2 percent). Only 5.3 percent of the respondents declare to have never accessed the program webpage. These figures are consistent with the data on engagement with the program webpage. Overall, it was visited 31444 times during the intervention. Considering that the total number of employees in the branches belonging to the behavioral group is 2825,[23] 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).

The survey also suggests that employees have a positive attitude toward the intervention, with 87 percent considering it useful, 58 percent considering it interesting, 84 percent agreeing that it prompts good behavior, and 86 percent saying that it gives tips on how to save energy. Most respondents also state that the intervention changed their behavior, with 77 percent applying some conservation tips in the workplace and 72 percent 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.

We then focus on which parts of the behavioral intervention employees perceived as more engaging. As in Senbel et al. (2014), participants were asked to indicate the three most important drivers of participation in the program. Panel A, Table 5 summarizes the answers of respondents working in branches and aware of the project (N = 368). Overall, the most relevant driver of engagement reported by respondents is the concern for environmental issues, followed by the willingness to save energy more than the other branches. Peer pressure (i.e., colleagues' and bosses' interest in the initiative) is not cited as an important driver of participation. This outcome (i.e. the lack of peer pressure) may explain the absence of interaction between the number of employees and the behavioral intervention in Section 4.2. Employees' self-reported engagement with the different parts of the initiative corresponds to the stated drivers of participation. Survey responses illustrate that news and informative materials were the most accessed contents, followed by the monthly rankings (Panel B, Table 5). Missions and videos were less relevant.

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

**Table 5. 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 webpage | 0.660 |
| Informative materials | 0.497 |
| Monthly rankings | 0.402 |
| Missions | 0.144 |
| Videos with tips | 0.136 |
| None | 0.046 |

Note: share of respondents working in branches and aware of the project (N = 368) selecting the item in response to the relevant question.

Revealed preferences, captured by engagement data with the program webpage, only partially support survey answers. The intervention's main page was accessed 8100 times, that of the monthly rankings 8582 times, and that of missions 4505 times. Videos with conservation tips were seen 4524 times, and the rules of the game and the informative materials were seen 2248 and 1530 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 webpage 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 et al., 2008). The time trend of engagement also supports the relevance of competition as source of motivation: engagement was highest at the start of the program, then decreased until reaching a minimum over summer months, and peaked at the end of the program, when the final rankings were published.

We exploit a feature of the way in which prizes were allocated to understand whether employees' engagement with the rankings may have been driven by the desire to win the eco-gadgets. Each branch could receive the prize only once. Notably, if a branch 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. If prizes were the reason behind engagement with the competition, then this allocation rule may have led employees to discontinue their efforts to save energy after receiving the prize. Our data suggest that prizes are unlikely to be the main driver of engagement with the competition, as mobility within the monthly rankings is quite low.

From January to September,[24] only 12 branches enter the top-3 positions at least once, and they occupy one of the top-3 positions on average twice. This is in spite of the fact that employees of winning branches could not receive the monthly prizes twice. The fact that prizes were distributed to all employees in a winning branch, regardless of their individual effort, may have further reduced the incentive power associated with them, by encouraging the tendency to free-ride on other employees' efforts.

Next, we examine whether the social recognition generated by the publication of the rankings may explain employees' engagement with them. We exploit the fact that only the first 10 positions in the monthly rankings were published prominently on the program webpage. Using a Regression Discontinuity Design, we obtain weak evidence that being ranked among the top 10 branches in a month is associated with higher electricity consumption outside working hours after two months, i.e., when the ranking was published (Columns 3 and 4, Table A13, $p = .05$ and $p = .08$). This effect is consistent with branches outside the top-10 increasing their energy savings in order to enter the public ranking when they see they did not appear in it. It may also be explained by a boomerang effect, whereby top-10 branches reduce their conservation efforts after being publicly recognized as virtuous.

Overall, the evidence from the survey and engagement data, and from the evaluation of features of the program design suggests that the social recognition embedded in the energy-saving competition represents an important driver of employees' engagement with the program, more than the prizes or the energy conservation tips.

## 4.4 Cost-effectiveness of the interventions

We now compute the cost-effectiveness of the two interventions, by comparing their total costs, as reported by the bank, with their impacts in terms of electricity savings.

The behavioral intervention cost 75640 € and led to a reduction in consumption of 64.3 kWh per month per branch, generating total electricity savings of 426695 kWh during the implementation year (considering 553 branches).[25] We calculate the cost-effectiveness under two scenarios of persistency in behavioral program effect. In our first scenario, we assume no persistence after the end of the program. The absence of statistically significant electricity savings during the

[24] Our partner bank did not share information on the rankings for the whole intervention period but only from January to September.

[25] We include in the cost-effectiveness calculation also the branches that are excluded from the main analysis for data cleaning purpose, assuming that they achieve the same average energy savings of the branches used in our main specification. This assumption has limited effect on our cost-effectiveness estimates. For the behavioral intervention, the marginal costs and savings of adding one branch are small. For the technological renovation, results are largely in line if we rescale the total costs on the 68 branches included in the main analysis and calculate the electricity savings only on this sample.

intervention makes it reasonable to assume lack of effect also afterwards. Moreover, the persistence in behavioral programs' effects can be partly explained by investments in the physical environment (Brandon et al., 2017), a channel that was not available to employees in our setting. Our second scenario assumes that the effect of the behavioral intervention lasts one year after the end of the program, e.g. thanks to persistent behavioral change among employees. We assume a reduction in the program's effectiveness by 20 percent in the year following the end of the intervention, as highlighted by previous by previous studies finding yearly attenuation between 15 and 27 percent (Allcott & Rogers, 2014; Andor et al., 2022). Under this scenarios, the total electricity savings generated by the behavioral intervention amount to 768051 kWh.

Dividing the total cost by the total savings, we estimate a cost-effectiveness of 9.8 and 17.8 € cents per kWh saved (i.e., about 10.8 and 19.7 in US$ per kWh saved) under the two scenarios, respectively. Our cost-effectiveness is at the lower end of what found by previous studies in the residential sector. For example, Allcott (2011) estimates for the Home Energy Report in the US a cost-effectiveness of 3.31 cents/kWh (US$). Andor et al. (2020) estimate that the same intervention, conducted in Italy, would achieve a cost-effectiveness of 4.8-11.5 cents/kWh (US$). Part of the higher cost may be due to greater expenditures associated with the behavioral intervention in our setting, since it includes videos and prizes. On the other hand, our estimation may take into account some costs that were not considered by previous studies: cost-benefit analyses generally neglect the costs of designing the nudges (Carlsson et al., 2021), as well as administrative costs (e.g., Allcott, 2011; Andor et al., 2020). Our estimation is likely to yield a more realistic figure, as all such costs are included.

The technological renovation cost 545000 € in total, or an average of 7786 € per branch. Considering an average reduction in electricity consumption of 759.5 kWh per branch per month, we estimate annual electricity savings of 637980 kWh (for 70 branches). To assess the cost-effectiveness of the technological renovation, we consider different scenarios in terms of its lifespan and discount rate for future electricity savings. We assume that BEMS will generate electricity savings over a lifespan of either 15 or 25 years. This is slightly shorter than estimates for technological renovations based only on changes in the physical capital, such as replacement of heating systems and building envelopes (Georges et al., 2012; Schnieders & Hermelink, 2006), since BEMS also entails software and sensors which may deteriorate more rapidly. For the discount rate, we use 0, 3, 5 and 7 percent. For simplicity, we assume no additional costs throughout the lifespan (e.g., no maintenance costs) and a constant amount of yearly energy savings, which is consistent with our estimates (Section 4.1.3). Table 6 reports the results of this exercise and shows that for all scenarios considered, the technological renovation yields greater

cost-effectiveness than the behavioral intervention,[26] and it is in line with the estimates of Home Energy Reports for Italy.

**Table 6. Cost-effectiveness of the technological renovation**

| | | Discount rate | | | |
|---|---|---|---|---|---|
| | | 0 percent | 3 percent | 5 percent | 7 percent |
| Lifespan | 15 years | 5.7 | 6.9 | 7.8 | 8.8 |
| | 25 years | 3.4 | 4.8 | 5.8 | 6.9 |

Note: Cost-effectiveness is expressed in € cents/kWh.

Overall, these calculations suggest greater cost-effectiveness for the technological than for the behavioral intervention. However, our estimates need to be taken with caution, as they are based on the results of two different impact evaluations, conducted on two different samples of branches over different time periods. The fact that bank branches were not randomly assigned to receive either BEMS or the energy-saving competition implies that pre-existing differences between the two groups may affect the impact estimates for the two programs.

## 5 Conclusion

We evaluate the impact of two energy-saving interventions designed and implemented by an Italian bank through DID designs. The first intervention consists of a technological renovation automating building energy management, and was applied to a subsample of branches with high baseline electricity consumption from 2016 to 2017. Branches receiving this intervention reduced their electricity consumption by 15.8 percent. The highest share of savings is registered outside working hours, reaching more than 25 percent. The second intervention is an energy-saving competition among the branches aimed at triggering employees' conservation efforts. Starting in January 2019, the program lasted one year and involved more than 500 branches. Employees participated in and engaged with the intervention, generating statistically significant electricity savings only outside the main work schedule (by more than 6 percent).

Three main policy implications can be drawn from our results. First, although we cannot compare the effects of the two interventions, we estimate low effect size and cost-effectiveness for the behavioral intervention while large ones for the technological renovation. Thus, our findings point to the importance of the smart management of buildings to conserve energy in the workplace. Second, both the behavioral and technological interventions mostly reduce energy waste outside the main work schedule. This suggests that either there are no inefficiencies during the workday,

[26] Note that the comparison remains favorable for the technological renovation even if we consider a decay in its effectiveness (operationalized as yearly reduction in electricity savings by 1 percent). Under this assumption, we estimate a cost-effectiveness of 9.3 cents per kWh saved for the least favorable scenario (lifespan of 15 years and discount rate of 7 percent).

or that reducing them requires too much effort or loss of comfort from employees engaged in work tasks. Energy conservation interventions should therefore focus on reducing waste when employees are not at work. Third, and relatedly, if energy-efficiency programs of different nature are jointly implemented, they may fail to create synergies if they address the same drivers of energy waste. Future research is needed to formally test this possibility.

Our study has limitations. The lack of electricity consumption data disaggregated by source or of self-reported energy-saving behaviors prevents us from identifying the drivers of the interventions' effects. Moreover, the composite nature of the behavioral intervention keeps us from distinguishing the impact of each of its components. Data on engagement with the program suggest an important role for the energy-saving competition, and a limited one for prizes. Finally, lack of data after the end of the behavioral intervention does not allow us to evaluate the persistence of its effects. Even if such data were available, the energy-saving competition ended just one month before the start of the Covid-19 lockdown in Italy, making any comparisons with previous years impossible. Further research should aim to address these limitations.

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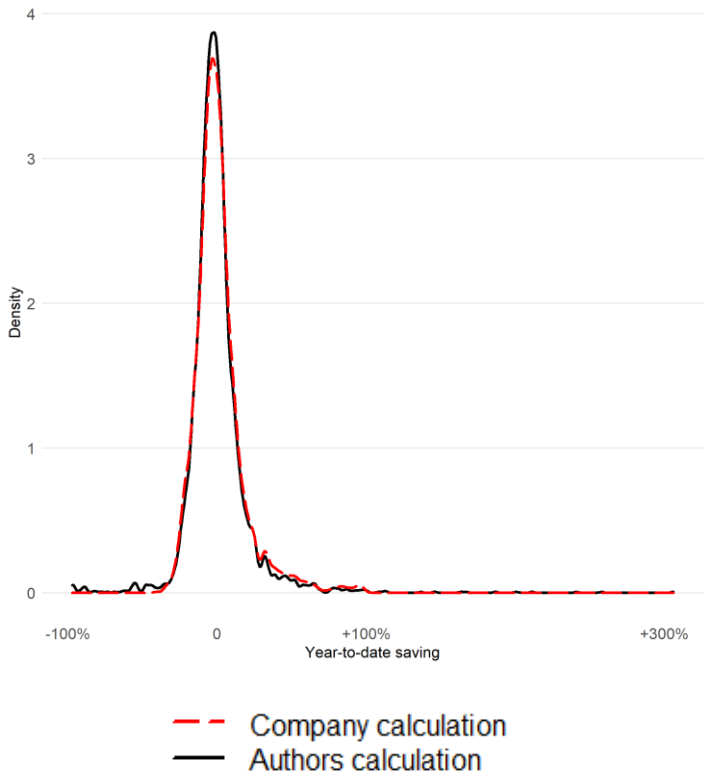
# Appendix

## Appendix A. Additional Tables and Figures

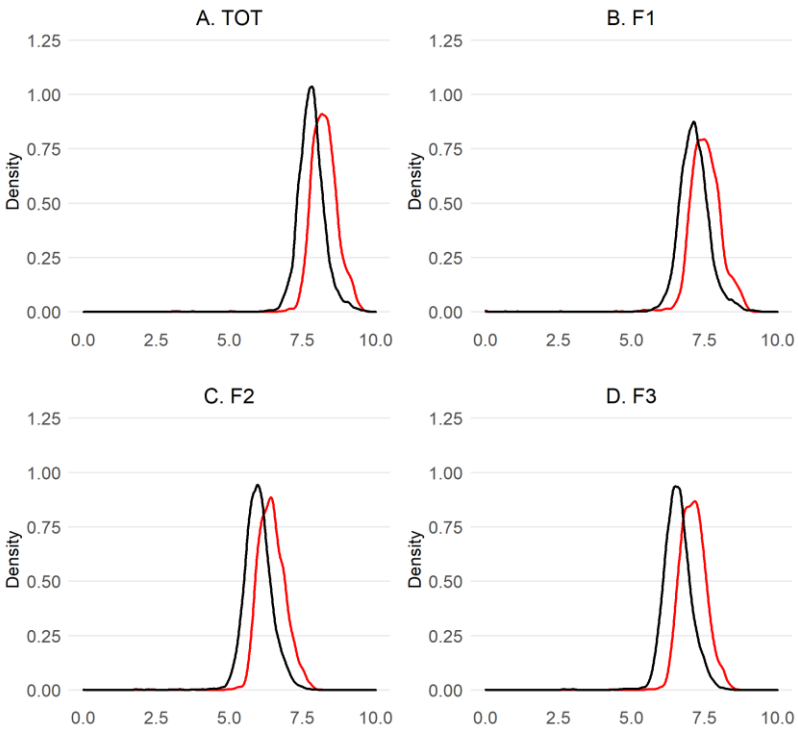
**Figure A1. Saving calculation for monthly ranking**




Note: Distribution of electricity savings calculated by the company (red dashed line) and by the authors (black line).

**Figure A2. Distribution of electricity consumption**

Panel A. Log-transformed electricity consumption




Panel B. Electricity consumption in kWh

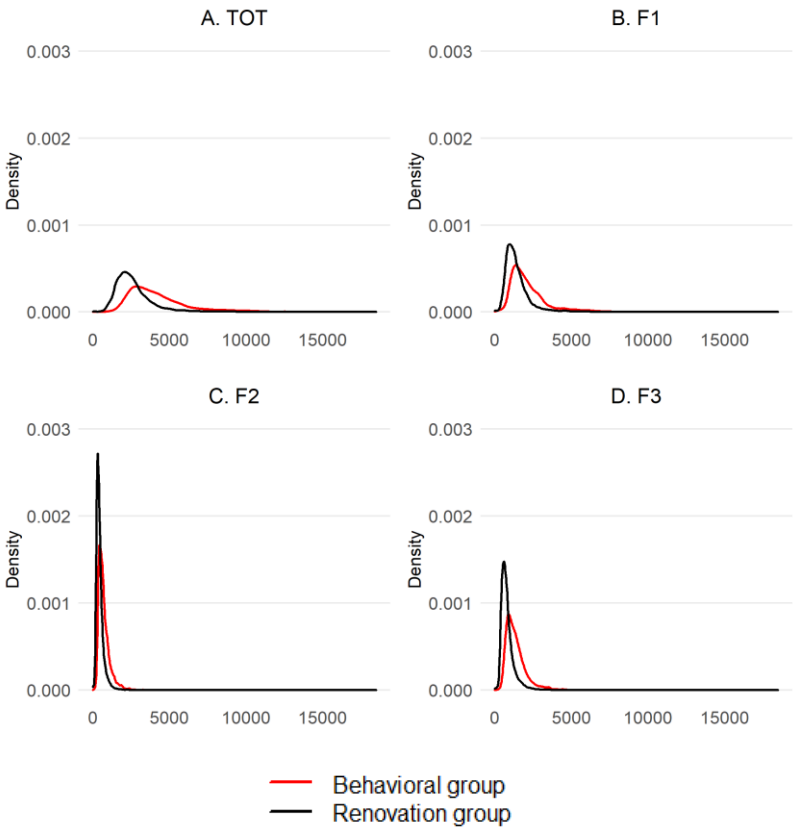


**Figure A3. Distribution of baseline total electricity consumption**

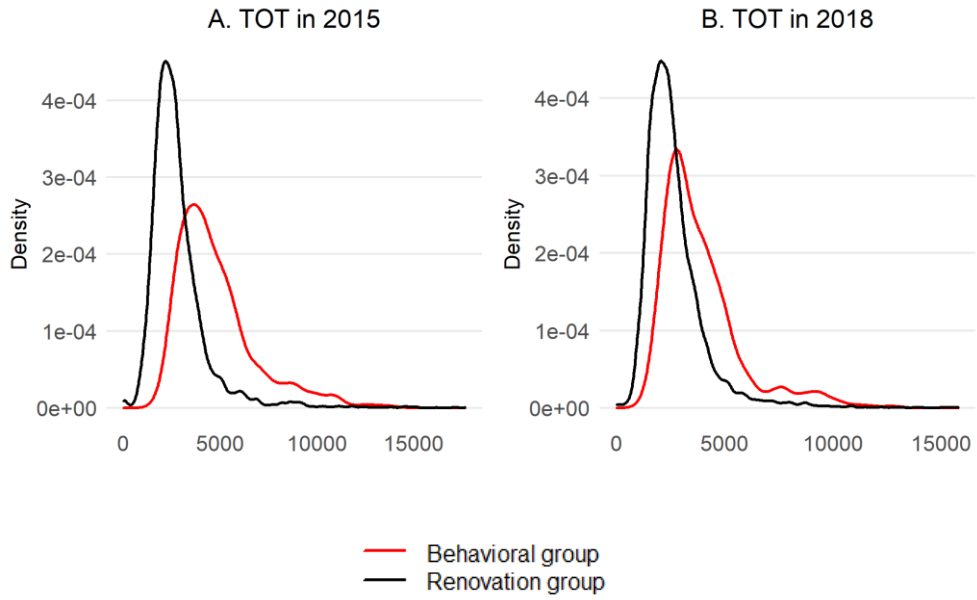



**Table A1. Technological renovation installation date**

| Year | | | 2016 | | | | | 2017 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Month | 08 | 09 | 10 | 11 | 12 | 01 | 02 | 03 | 04 | 05 |
| Share | 5.97 | 11.94 | 11.94 | 7.46 | 5.97 | 8.96 | 19.4 | 13.43 | 5.97 | 8.95 |

Note: Share of branches of the renovation group receiving BEMS installation per month.

**Table A2. Robustness: electricity consumption in levels (kWh)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | TOT | F1 | F2 | F3 | TOT | F1 | F2 | F3 |
| *BEMS* | -741.89*** | 0.18 | -282.95*** | -459.12*** | | | | |
| | (87.16) | (38.9) | (25.74) | (42.89) | | | | |
| *BEH* | | | | | -27.35 | 79.28** | -36.51** | -70.13* |
| | | | | | (48.62) | (29.29) | (11.76) | (27.54) |
| N. | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 |
| Obs. | 19097 | 19097 | 19097 | 19097 | 16117 | 16117 | 16117 | 16117 |

Note: OLS regression of monthly electricity consumption in kWh on intervention indicator. *BEMS* is the difference-in-differences estimator for the technological intervention. *BEH* is the difference-in-differences estimator for the behavioral intervention. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province. Standard errors clustered at the branch level reported in parentheses. *N* represents the number of branches, *Obs* the number of observations. *p < .05, ** p < .01, ***p < .001.

**Table A3. Robustness: changing the observation period**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | TOT | F1 | F2 | F3 | TOT | F1 | F2 | F3 |
| *BEMS* | -0.166*** | -0.003 | -0.363*** | -0.314*** | | | | |
| | (0.019) | (0.018) | (0.030) | (0.029) | | | | |
| *BEH* | | | | | -0.021 | 0.009 | -0.058** | -0.055* |
| | | | | | (0.016) | (0.017) | (0.022) | (0.024) |
| N. | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 |
| Obs. | 25596 | 25596 | 25596 | 25596 | 12956 | 12956 | 12956 | 12956 |

Note: OLS regression of log monthly electricity consumption on intervention indicator. Columns 1-4 evaluate the technological intervention including observations for 2018. Columns 5-8 evaluate the behavioral intervention excluding 2017. *BEMS* is the difference-in-differences estimator for the technological intervention. *BEH* is the difference-in-differences estimator for the behavioral intervention. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province. Standard errors clustered at the branch level reported in parentheses. *N* represents the number of branches, *Obs* the number of observations. *p < .05, ** p < .01, ***p < .001.

**Table A4. Robustness: using yearly consumption**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | TOT | F1 | F2 | F3 | TOT | F1 | F2 | F3 |
| *BEMS* | -0.176*** | 0.005 | -0.380*** | -0.333*** | | | | |
| | (0.024) | (0.022) | (0.037) | (0.037) | | | | |
| *BEH* | | | | | -0.022 | 0.005 | -0.063* | -0.055 |
| | | | | | (0.021) | (0.022) | (0.025) | (0.028) |
| N. | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 |
| Obs. | 1124 | 1124 | 1124 | 1124 | 1128 | 1128 | 1128 | 1128 |

Note: OLS regression of log yearly electricity consumption on intervention indicator. Columns 1-4 compare yearly consumption of 2015 and 2018. Columns 5-8 compare yearly consumption of 2018 and 2019. *BEMS* is the difference-in-differences estimator for the technological intervention. *BEH* is the difference-in-differences estimator for the behavioral intervention. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province. Standard errors clustered at the branch level reported in parentheses. *N* represents the number of branches, *Obs* the number of observations. *p < .05, ** p < .01, ***p < .001.

**Table A5. Robustness: evaluating impact of technological intervention excluding the installation period**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | TOT | F1 | F2 | F3 |
| *BEMS* | -0.163*** | 0.026 | -0.395*** | -0.331*** |
| | (0.023) | (0.021) | (0.035) | (0.034) |
| N. | 564 | 564 | 564 | 564 |
| Obs. | 13625 | 13625 | 13625 | 13625 |

Note: OLS regression of log monthly electricity consumption on intervention indicator, excluding BEMS installation period (August 2016-May 2017). *BEMS* is the difference-in-differences estimator for the technological intervention. *BEH* is the difference-in-differences estimator for the behavioral intervention. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province. Standard errors clustered at the branch level reported in parentheses. *N* represents the number of branches, *Obs* the number of observations. *p < .05, ** p < .01, ***p < .001.

**Table A6. Robustness: winsorizing electricity consumption**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | TOT | F1 | F2 | F3 | TOT | F1 | F2 | F3 |
| *BEMS* | -0.142*** | -0.001 | -0.298*** | -0.26*** | | | | |
| | (0.018) | (0.016) | (0.029) | (0.027) | | | | |
| *BEH* | | | | | -0.019 | 0.019 | -0.060** | -0.052* |
| | | | | | (0.014) | (0.015) | (0.020) | (0.021) |
| N. | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 |
| Obs. | 19097 | 19097 | 19097 | 19097 | 16117 | 16117 | 16117 | 16117 |

Note: OLS regression of log monthly electricity consumption on intervention indicator, winsorizing the consumption distribution at the top and bottom 5 percent. *BEMS* is the difference-in-differences estimator for the technological intervention. *BEH* is the difference-in-differences estimator for the behavioral intervention. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province. Standard errors clustered at the branch level reported in parentheses. *N* represents the number of branches, *Obs* the number of observations. *p < .05, ** p < .01, ***p < .001.

**Table A7. Robustness: including all meter readings**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | TOT | F1 | F2 | F3 | TOT | F1 | F2 | F3 |
| *BEMS* | -0.180*** | -0.012 | -0.378*** | -0.334*** | | | | |
| | (0.020) | (0.017) | (0.032) | (0.030) | | | | |
| *BEH* | | | | | -0.034 | -0.022 | -0.115** | -0.072 |
| | | | | | (0.040) | (0.045) | (0.043) | (0.043) |
| N. | 578 | 578 | 578 | 578 | 584 | 584 | 584 | 584 |
| Obs. | 20039 | 20039 | 20039 | 20039 | 17182 | 17182 | 17182 | 17182 |

Note: OLS regression of log monthly electricity consumption on intervention indicator, including all real meter readings. *BEMS* is the difference-in-differences estimator for the technological intervention. *BEH* is the difference-in-differences estimator for the behavioral intervention. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province. Standard errors clustered at the branch level reported in parentheses. *N* represents the number of branches, *Obs* the number of observations. *p < .05, ** p < .01, ***p < .001.

**Table A8. Robustness: evaluating impact of technological intervention through staggered DID**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | TOT | F1 | F2 | F3 |
| *BEMS* | -0.200*** | -0.095* | -0.324*** | -0.302*** |
| | (0.042) | (0.044) | (0.057) | (0.059) |
| N. | 67 | 67 | 67 | 67 |
| Obs. | 2215 | 2215 | 2215 | 2215 |

Note: OLS regression of log monthly electricity consumption on staggered intervention indicator, excluding behavioral group branches. *BEMS* is the difference-in-differences estimator for the technological intervention. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province. Standard errors clustered at the branch level reported in parentheses. *N* represents the number of branches, *Obs* the number of observations. *p < .05, ** p < .01, ***p < .001.

**Table A9. Robustness: evaluating the effect of extending the monthly ranking to all branches**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | TOT | F1 | F2 | F3 |
| *BEH* | -0.021 | 0.019 | -0.074*** | -0.064** |
| | (0.017) | (0.019) | (0.022) | (0.024) |
| *BEH* x Extended ranking | -0.011 | -0.013 | 0.017 | -0.011 |
| | (0.011) | (0.013) | (0.017) | (0.015) |
| N. | 564 | 564 | 564 | 564 |
| Obs. | 16177 | 16177 | 16177 | 16177 |

Note: OLS regression of log monthly electricity consumption on intervention indicator. *BEH* is the difference-in-differences estimator for the behavioral intervention. *Extended ranking* denotes the three months when the energy savings ranking was extended to all branches, including those of the renovation group. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province. Standard errors clustered at the branch level reported in parentheses. *N* represents the number of branches, *Obs* the number of observations. *p < .05, ** p < .01, ***p < .001.

**Table A10. Robustness: placebo tests for the main specification**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | TOT | F1 | F2 | F3 | TOT | F1 | F2 | F3 |
| BEMS | -0.023 | 0.012 | -0.049 | -0.055* | | | | |
| | (0.018) | (0.017) | (0.027) | (0.028) | | | | |
| BEH | | | | | -0.007 | 0.021 | -0.037 | -0.035 |
| | | | | | (0.013) | (0.014) | (0.019) | (0.021) |
| N. | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 |
| Obs. | 9,851 | 9,851 | 9,851 | 9,851 | 9,720 | 9,720 | 9,720 | 9,720 |

Note: OLS regression of log monthly electricity consumption on placebo intervention indicator. *BEMS* is the difference-in-differences estimator for a fictitious technological intervention starting in January 2016 and evaluated until August 2016 excluded (start of the real technological intervention). *BEH* is the difference-in-differences estimator for a fictitious behavioral intervention starting in January 2018 and evaluated until January 2019 excluded (start of the real behavioral intervention). *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province. Standard errors clustered at the branch level reported in parentheses. *N* represents the number of branches, *Obs* the number of observations. *p < .05, ** p < .01, ***p < .001.

**Table A11. Heterogeneous effect of the interventions on electricity consumption, all TOUs**

| | (1) F1 | (2) F2 | (3) F3 | (4) F1 | (5) F2 | (6) F3 | (7) F1 | (8) F2 | (9) F3 | (10) F1 | (11) F2 | (12) F3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Technological intervention* | | | | | | | | | | | | |
| *BEMS* | 0.024 | -0.351*** | -0.304*** | 0.039 | -0.336*** | -0.273*** | -0.053 | -0.454*** | -0.328*** | -0.013 | -0.458*** | -0.378*** |
| | (0.026) | (0.039) | (0.042) | (0.024) | (0.042) | (0.041) | (0.048) | (0.079) | (0.081) | (0.041) | (0.064) | (0.064) |
| *BEMS* x pre-treat | 0.004 | -0.091 | -0.058 | | | | | | | | | |
| | (0.043) | (0.069) | (0.066) | | | | | | | | | |
| *BEMS* x heating | | | | -0.034 | -0.118 | -0.113 | | | | | | |
| | | | | (0.041) | (0.068) | (0.066) | | | | | | |
| *BEMS* x employees | | | | | | | 0.008 | 0.006 | -0.001 | 0.000 | 0.000 | 0.000 |
| | | | | | | | (0.005) | (0.008) | (0.008) | (0.000) | (0.000) | (0.000) |
| *BEMS* x surface | | | | | | | | | | | | |
| Observations | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 |
| *Panel B: Behavioral intervention* | | | | | | | | | | | | |
| *BEH* | 0.041 | -0.052 | -0.037 | 0.013 | -0.093*** | -0.090** | 0.039 | -0.071 | -0.078 | 0.057 | -0.070 | -0.050 |
| | (0.032) | (0.035) | (0.035) | (0.021) | (0.027) | (0.030) | (0.049) | (0.055) | (0.063) | (0.038) | (0.043) | (0.049) |
| *BEH* x pre-treat | -0.051 | -0.036 | -0.060 | | | | | | | | | |
| | (0.036) | (0.043) | (0.048) | | | | | | | | | |
| *BEH* x heating | | | | 0.004 | 0.043 | 0.043 | | | | | | |
| | | | | (0.036) | (0.043) | (0.048) | | | | | | |
| *BEH* x employees | | | | | | | -0.001 | 0.002 | 0.003 | | | |
| | | | | | | | (0.004) | (0.006) | (0.006) | | | |
| *BEH* x surface | | | | | | | | | | -0.001 | 0.001 | -0.001 |
| | | | | | | | | | | (0.001) | (0.001) | (0.001) |
| N. branches | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 |
| Observations | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 |

Note: OLS regression of log monthly electricity consumption on intervention indicator. *BEMS* is the difference-in-differences estimator for the technological intervention. *BEH* is the difference-in-differences estimator for the behavioral intervention. *Pre-treat* is a dummy variable for average consumption above the median before the intervention, i.e. before the beginning of BEMS installation (2015) in Panel A and before the launch of the competition (2018) in Panel B. *Heating* is a dummy equal to 1 if the branch has electric heating, 0 otherwise. *Employees* is a continuous variable for the number of employees in December 2018. *Surface* is a continuous variable for the squared meters. *F1* denotes the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province and the post-intervention indicator interacted with the heterogeneity variables. Standard errors clustered at the branch level reported in parentheses. *p < .05, ** p < .01, ***p < .001.

**Table A12. Heterogeneous intervention effects for alternative parametrizations of energy efficiency**

| | (1) TOT | (2) TOT | (3) TOT | (4) TOT | (5) TOT | (6) TOT |
|---|---|---|---|---|---|---|
| *BEMS* | -0.131*** | -0.147*** | 0.443** | | | |
| | (0.033) | (0.028) | (0.142) | | | |
| *BEMS* x pre-treat (m2) | -0.066 | | | | | |
| | (0.045) | | | | | |
| *BEMS* x pre-treat (empl) | | -0.033 | | | | |
| | | (0.045) | | | | |
| *BEMS* x pre-treat (F2+F3/TOT) | | | -1.107*** | | | |
| | | | (0.280) | | | |
| *BEH* | | | | -0.036 | -0.032 | 0.062 |
| | | | | (0.019) | (0.019) | (0.104) |
| *BEH* x pre-treat (m2) | | | | 0.026 | | |
| | | | | (0.034) | | |
| *BEH* x pre-treat (empl) | | | | | 0.018 | |
| | | | | | (0.034) | |
| *BEH* x pre-treat (F2+F3/TOT) | | | | | | -0.180 |
| | | | | | | (0.238) |
| N. branches | 564 | 564 | 564 | 564 | 564 | 564 |
| Observations | 13625 | 13625 | 13625 | 16177 | 16177 | 16177 |

Note: OLS regression of log total monthly electricity consumption on intervention indicator. *BEMS* is the difference-in-differences estimator for the technological intervention. *BEH* is the difference-in-differences estimator for the behavioral intervention. *Pre-treat (m2)* is an indicator for above-median consumption per square meter before the intervention. *Pre-treat (empl)* is an indicator for above-median consumption per employee before the intervention. *Pre-treat (F2+F3/TOT)* is the ratio of consumption outside the main work schedule over total consumption before the intervention. All models include branch and time fixed effects, cooling and heating degree days of the province and the post-intervention indicator interacted with the heterogeneity variables. Standard errors clustered at the branch level reported in parentheses. *N* represents the number of branches, *Obs* the number of observations. *p < .05, ** p < .01, ***p < .001.

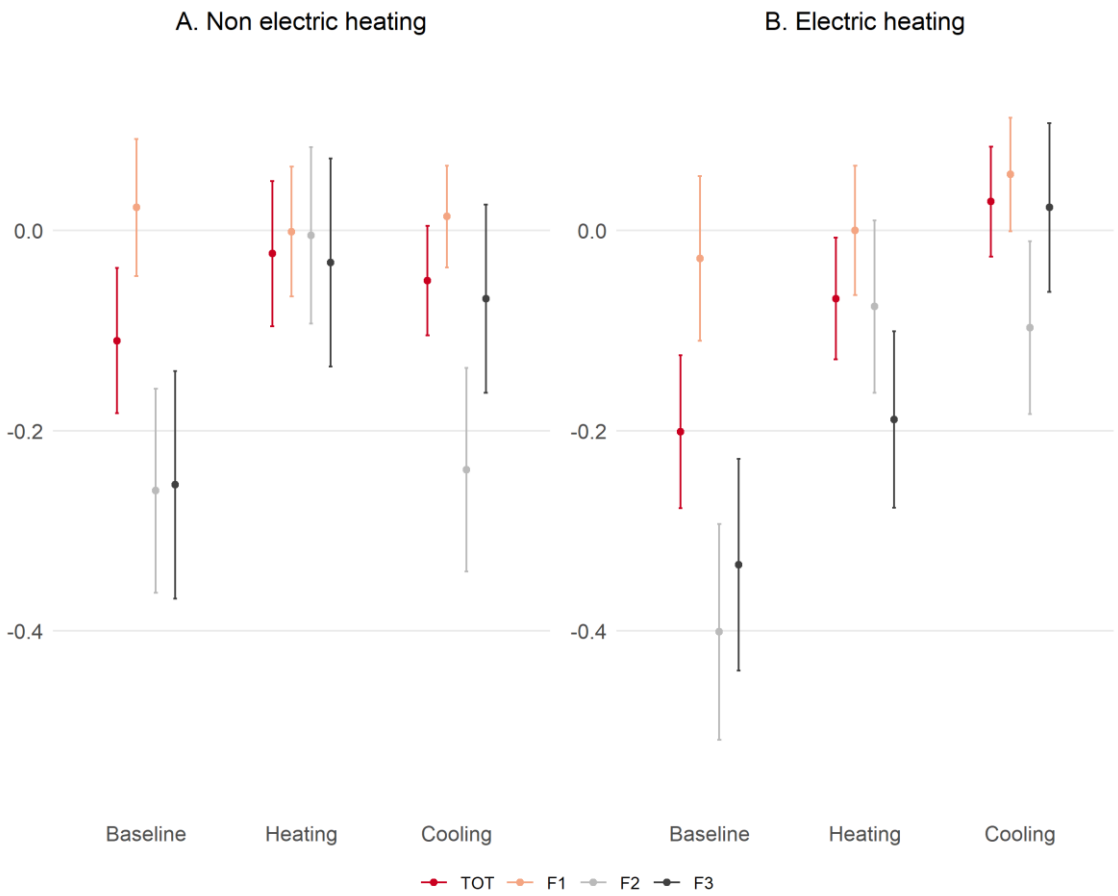
**Table A13. Regression discontinuity design for being in the top 10 of the monthly ranking**

| | (1) TOT | (2) F1 | (3) F2 | (4) F3 |
|---|---|---|---|---|
| Top10 | 0.066 | 0.023 | 0.106 | 0.095 |
| | (0.049) | (0.048) | (0.055) | (0.055) |
| Rank | -0.000 | -0.000 | -0.000* | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| N. branches | 493 | 493 | 493 | 493 |
| Observations | 3310 | 3310 | 3310 | 3310 |

Note: Regression discontinuity design estimate, on the behavioral branches only. *Top10* is a dummy variable equal to 1 if the branch is in the top 10 in the monthly ranking of two months before, 0 otherwise. *Rank* is a continuous variable for the position of the branch in the monthly ranking of two months before. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province. Standard errors clustered at the branch level reported in parentheses. *N* represents the number of branches, *Obs* the number of observations. *p < .05, ** p < .01, ***p < .001.

## Appendix B. Tables and Figures for online publication only

**Figure B1. Seasonal impact of the technological intervention, without (Panel A) and with (Panel B) electric heating**




Note: *Baseline* refers to the effect of the technological intervention during April, May and September. *Heating* refers to the effect of the technological intervention during the heating season (i.e. from October to March). *Cooling* refers to the effect of the technological intervention during the cooling season (i.e. from June to August). *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours.

**Table B1. Heterogeneous effect of the technological intervention based on baseline consumption, supplementary analyses**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | TOT | F1 | F2 | F3 | TOT | F1 | F2 | F3 | TOT | F1 | F2 | F3 |
| *BEMS* | -0.165*** | 0.012 | -0.326*** | -0.245*** | -0.180*** | -0.018 | -0.323*** | -0.203*** | -0.237*** | -0.037 | -0.247** | -0.157 |
| | (0.037) | (0.038) | (0.052) | (0.060) | (0.044) | (0.042) | (0.063) | (0.060) | (0.063) | (0.045) | (0.095) | (0.125) |
| *BEMS* x Q14 | -0.020 | 0.026 | -0.019 | -0.116 | | | | | | | | |
| | (0.055) | (0.053) | (0.072) | (0.078) | | | | | | | | |
| *BEMS* x Q24 | 0.001 | -0.019 | -0.179 | -0.141 | | | | | | | | |
| | (0.047) | (0.064) | (0.093) | (0.086) | | | | | | | | |
| *BEMS* x Q34 | 0.027 | 0.054 | -0.075 | -0.084 | | | | | | | | |
| | (0.076) | (0.055) | (0.096) | (0.099) | | | | | | | | |
| *BEMS* x Q15 | | | | | 0.014 | 0.073 | -0.047 | -0.224* | | | | |
| | | | | | (0.060) | (0.057) | (0.082) | (0.087) | | | | |
| *BEMS* x Q25 | | | | | 0.010 | 0.006 | -0.095 | -0.094 | | | | |
| | | | | | (0.059) | (0.063) | (0.099) | (0.079) | | | | |
| *BEMS* x Q35 | | | | | 0.047 | 0.062 | -0.094 | -0.148 | | | | |
| | | | | | (0.062) | (0.078) | (0.111) | (0.099) | | | | |
| *BEMS* x Q45 | | | | | 0.015 | 0.084 | -0.120 | -0.181 | | | | |
| | | | | | (0.087) | (0.058) | (0.107) | (0.106) | | | | |
| *BEMS* x cons | | | | | | | | | 0.000 | 0.000 | -0.000 | -0.000 |
| | | | | | | | | | (0.000) | (0.000) | (0.000) | (0.000) |
| N | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 |
| Obs. | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 |

Note: OLS regression of log monthly electricity consumption on intervention indicator. *BEMS* is the difference-in-differences estimator for the technological intervention. *Q14* to *Q34* are dummies representing branches in the first, second and third quartile of average consumption before the beginning of BEMS installation (year 2015). *Q15* to *Q45* are dummies representing branches in the first, second, third and fourth quintile of average consumption before the beginning of BEMS installation (year 2015). *Cons* is a continuous variables for the average consumption before the beginning of BEMS installation (year 2015). *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province and the post-intervention indicator interacted with the heterogeneity variables. Standard errors clustered at the branch level reported in parentheses. *p < .05, ** p < .01, ***p < .001.

**Table B2. Heterogeneous effect of the behavioral intervention based on baseline consumption, supplementary analyses**

| | (1) TOT | (2) F1 | (3) F2 | (4) F3 | (5) TOT | (6) F1 | (7) F2 | (8) F3 | (9) TOT | (10) F1 | (11) F2 | (12) F3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *BEH* | -0.013 | 0.044 | -0.041 | -0.101* | -0.016 | 0.016 | -0.069 | -0.120** | -0.001 | 0.044 | -0.067 | -0.021 |
| | (0.051) | (0.056) | (0.054) | (0.040) | (0.060) | (0.059) | (0.064) | (0.046) | (0.047) | (0.045) | (0.057) | (0.075) |
| *BEH* x Q14 | 0.020 | -0.006 | -0.022 | 0.131 | | | | | | | | |
| | (0.057) | (0.066) | (0.072) | (0.067) | | | | | | | | |
| *BEH* x Q24 | -0.027 | -0.059 | -0.028 | 0.004 | | | | | | | | |
| | (0.060) | (0.061) | (0.066) | (0.059) | | | | | | | | |
| *BEH* x Q34 | -0.036 | -0.047 | -0.064 | -0.003 | | | | | | | | |
| | (0.055) | (0.060) | (0.063) | (0.061) | | | | | | | | |
| *BEH* x Q15 | | | | | 0.010 | 0.035 | 0.033 | 0.171* | | | | |
| | | | | | (0.068) | (0.074) | (0.077) | (0.081) | | | | |
| *BEH* x Q25 | | | | | 0.054 | 0.028 | 0.008 | 0.059 | | | | |
| | | | | | (0.070) | (0.068) | (0.080) | (0.063) | | | | |
| *BEH* x Q35 | | | | | -0.067 | -0.037 | -0.005 | 0.050 | | | | |
| | | | | | (0.066) | (0.064) | (0.079) | (0.070) | | | | |
| *BEH* x Q45 | | | | | -0.037 | -0.027 | -0.038 | -0.012 | | | | |
| | | | | | (0.065) | (0.063) | (0.076) | (0.069) | | | | |
| *BEH* x cons | | | | | | | | | -0.000 | -0.000 | -0.000 | -0.000 |
| | | | | | | | | | (0.000) | (0.000) | (0.000) | (0.000) |
| N. | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 |
| Obs. | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 |

Note: OLS regression of log monthly electricity consumption on intervention indicator. *BEH* is the difference-in-differences estimator for the behavioral intervention. *Q14* to *Q34* are dummies representing branches in the first, second and third quartile of average consumption before the beginning of the behavioral intervention (year 2018). *Q15* to *Q45* are dummies representing branches in the first, second, third and fourth quintile of average consumption before the beginning of the behavioral intervention (year 2018). *Cons* is a continuous variables for the average consumption before the beginning of the behavioral intervention (year 2018). *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province and the post-intervention indicator interacted with the heterogeneity variables. Standard errors clustered at the branch level reported in parentheses. *p < .05, ** p < .01, ***p < .001.

**Table B3. Heterogeneous effect of the technological renovation based on baseline efficiency (kWh per square meter), supplementary analyses**

| | (1) F1 | (2) F2 | (3) F3 | (4) TOT | (5) F1 | (6) F2 | (7) F3 | (8) TOT | (9) F1 | (10) F2 | (11) F3 | (12) TOT | (13) F1 | (14) F2 | (15) F3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *BEMS* | 0.023 | -0.336*** | -0.320*** | -0.133*** | -0.028 | -0.373*** | -0.312*** | -0.161*** | -0.011 | -0.401*** | -0.360*** | -0.065 | 0.078 | -0.247*** | -0.236*** |
| | (0.025) | (0.045) | (0.045) | (0.033) | (0.038) | (0.052) | (0.052) | (0.036) | (0.039) | (0.061) | (0.058) | (0.071) | (0.064) | (0.069) | (0.066) |
| *BEMS* x pre | 0.006 | -0.118 | -0.024 | | | | | | | | | | | | |
| | (0.043) | (0.069) | (0.067) | | | | | | | | | | | | |
| *BEMS* x Q14 | | | | 0.015 | 0.102* | 0.086 | -0.013 | | | | | | | | |
| | | | | (0.064) | (0.050) | (0.089) | (0.090) | | | | | | | | |
| *BEMS* x Q24 | | | | -0.064 | 0.116* | -0.067 | 0.017 | | | | | | | | |
| | | | | (0.043) | (0.056) | (0.075) | (0.083) | | | | | | | | |
| *BEMS* x Q34 | | | | -0.068 | -0.003 | -0.102 | -0.075 | | | | | | | | |
| | | | | (0.061) | (0.060) | (0.098) | (0.087) | | | | | | | | |
| *BEMS* x Q15 | | | | | | | | 0.066 | 0.066 | 0.189* | 0.166 | | | | |
| | | | | | | | | (0.060) | (0.059) | (0.087) | (0.094) | | | | |
| *BEMS* x Q25 | | | | | | | | -0.023 | 0.071 | -0.093 | -0.048 | | | | |
| | | | | | | | | (0.070) | (0.060) | (0.095) | (0.086) | | | | |
| *BEMS* x Q35 | | | | | | | | 0.002 | 0.070 | 0.032 | 0.113 | | | | |
| | | | | | | | | (0.043) | (0.057) | (0.085) | (0.087) | | | | |
| *BEMS* x Q45 | | | | | | | | -0.051 | -0.014 | -0.080 | -0.065 | | | | |
| | | | | | | | | (0.070) | (0.067) | (0.113) | (0.098) | | | | |
| *BEMS* x cons | | | | | | | | | | | | -0.008 | -0.011 | -0.062* | -0.017 |
| | | | | | | | | | | | | (0.006) | (0.012) | (0.030) | (0.014) |
| N. | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Obs. | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 |

Note: OLS regression of log monthly electricity consumption on intervention indicator. *BEMS* is the difference-in-differences estimator for the technological intervention. *Pre* is a dummy for above-median consumption per square meter before the intervention. *Q14* to *Q34* are dummies representing branches in the first, second and third quartile of average consumption per square meter before the beginning of BEMS installation (year 2015). *Q15* to *Q45* are dummies representing branches in the first, second, third and fourth quintile of average consumption per square meter before the beginning of BEMS installation (year 2015). *Cons* is a continuous variables for the average consumption per square meter before the beginning of BEMS installation (year 2015). *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province and the post-intervention indicator interacted with the heterogeneity variables. Standard errors clustered at the branch level reported in parentheses. *p < .05, ** p < .01, ***p < .001.

**Table B4. Heterogeneous effect of the technological renovation based on baseline efficiency (kWh per employee), supplementary analyses**

| | (1) F1 | (2) F2 | (3) F3 | (4) TOT | (5) F1 | (6) F2 | (7) F3 | (8) TOT | (9) F1 | (10) F2 | (11) F3 | (12) TOT | (13) F1 | (14) F2 | (15) F3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *BEMS* | 0.040 | -0.354*** | -0.355*** | -0.167*** | 0.047 | -0.342*** | -0.321*** | -0.152** | 0.032 | -0.321*** | -0.347*** | -0.146** | 0.070 | -0.366*** | -0.357*** |
| | (0.025) | (0.044) | (0.042) | (0.041) | (0.041) | (0.063) | (0.062) | (0.047) | (0.046) | (0.068) | (0.071) | (0.048) | (0.052) | (0.071) | (0.062) |
| *BEMS* x pre | -0.028 | -0.084 | 0.047 | | | | | | | | | | | | |
| | (0.042) | (0.069) | (0.068) | | | | | | | | | | | | |
| *BEMS* x Q14 | | | | 0.039 | -0.008 | -0.023 | -0.073 | | | | | | | | |
| | | | | (0.057) | (0.051) | (0.088) | (0.080) | | | | | | | | |
| *BEMS* x Q24 | | | | 0.022 | 0.014 | -0.067 | 0.063 | | | | | | | | |
| | | | | (0.054) | (0.052) | (0.092) | (0.090) | | | | | | | | |
| *BEMS* x Q34 | | | | -0.046 | -0.085 | -0.115 | -0.027 | | | | | | | | |
| | | | | (0.069) | (0.068) | (0.099) | (0.100) | | | | | | | | |
| *BEMS* x Q15 | | | | | | | | -0.016 | -0.004 | -0.108 | 0.041 | | | | |
| | | | | | | | | (0.060) | (0.063) | (0.095) | (0.088) | | | | |
| *BEMS* x Q25 | | | | | | | | 0.015 | 0.072 | -0.045 | -0.021 | | | | |
| | | | | | | | | (0.064) | (0.055) | (0.092) | (0.096) | | | | |
| *BEMS* x Q35 | | | | | | | | 0.017 | -0.057 | -0.052 | 0.067 | | | | |
| | | | | | | | | (0.063) | (0.070) | (0.103) | (0.108) | | | | |
| *BEMS* x Q45 | | | | | | | | -0.071 | -0.040 | -0.160 | -0.002 | | | | |
| | | | | | | | | (0.080) | (0.069) | (0.113) | (0.116) | | | | |
| *BEMS* x cons | | | | | | | | | | | | -0.000 | -0.000 | -0.000 | 0.000 |
| | | | | | | | | | | | | (0.000) | (0.000) | (0.000) | (0.000) |
| N. | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Obs. | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 | 13625 |

Note: OLS regression of log monthly electricity consumption on intervention indicator. *BEMS* is the difference-in-differences estimator for the technological intervention. *Pre* is a dummy for above-median consumption per employee before the beginning of BEMS installation (year 2015). *Q14* to *Q34* are dummies representing branches in the first, second and third quartile of average consumption per employee before the beginning of BEMS installation (year 2015). *Q15* to *Q45* are dummies representing branches in the first, second, third and fourth quintile of average consumption per employee before the beginning of BEMS installation (year 2015). *Cons* is a continuous variables for the average consumption per employee before the beginning of BEMS installation (year 2015). *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province and the post-intervention indicator interacted with the heterogeneity variables. Standard errors clustered at the branch level reported in parentheses. *p < .05, ** p < .01, ***p < .001.

**Table B5. Heterogeneous effect of the technological renovation based on baseline efficiency (F2+F3/TOT), supplementary analyses**

| | (1) | (2) | (3) |
|---|---|---|---|
| | F1 | F2 | F3 |
| *BEMS* | 0.214 | 0.437 | 0.376 |
| | (0.156) | (0.235) | (0.212) |
| *BEMS* x pre (F2+F3/TOT) | -0.389 | -1.503** | -1.217** |
| | (0.306) | (0.467) | (0.408) |
| N. | 564 | 564 | 564 |
| Obs. | 13625 | 13625 | 13625 |

Note: OLS regression of log monthly electricity consumption on intervention indicator. *BEMS* is the difference-in-differences estimator for the technological intervention. *Pre (F2+F3/TOT)* is the ratio of consumption outside the main work schedule over total consumption before the beginning of BEMS installation (year 2015). *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province and the post-intervention indicator interacted with the heterogeneity variables. Standard errors clustered at the branch level reported in parentheses. *p < .05, ** p < .01, ***p < .001.

**Table B6. Heterogeneous effect of the behavioral intervention based on baseline efficiency (kWh per square meter), supplementary analyses**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | F1 | F2 | F3 | TOT | F1 | F2 | F3 | TOT | F1 | F2 | F3 | TOT | F1 | F2 | F3 |
| *BEH* | 0.001 | -0.072** | -0.074* | -0.024 | 0.008 | -0.066 | -0.068 | -0.028 | 0.020 | -0.068 | -0.062 | -0.105 | -0.090 | -0.113 | -0.108 |
| | (0.023) | (0.027) | (0.030) | (0.027) | (0.030) | (0.041) | (0.046) | (0.032) | (0.036) | (0.048) | (0.047) | (0.061) | (0.059) | (0.062) | (0.061) |
| *BEH* x pre | 0.030 | 0.006 | 0.015 | | | | | | | | | | | | |
| | (0.036) | (0.044) | (0.048) | | | | | | | | | | | | |
| *BEH* x Q14 | | | | -0.025 | -0.016 | -0.010 | -0.006 | | | | | | | | |
| | | | | (0.038) | (0.048) | (0.055) | (0.062) | | | | | | | | |
| *BEH* x Q24 | | | | -0.010 | -0.014 | -0.027 | 0.002 | | | | | | | | |
| | | | | (0.035) | (0.036) | (0.055) | (0.060) | | | | | | | | |
| *BEH* x Q34 | | | | 0.039 | 0.060 | 0.024 | 0.008 | | | | | | | | |
| | | | | (0.059) | (0.059) | (0.070) | (0.079) | | | | | | | | |
| *BEH* x Q15 | | | | | | | | 0.019 | -0.054 | 0.001 | 0.017 | | | | |
| | | | | | | | | (0.041) | (0.042) | (0.062) | (0.069) | | | | |
| *BEH* x Q25 | | | | | | | | -0.060 | -0.013 | -0.039 | -0.032 | | | | |
| | | | | | | | | (0.043) | (0.057) | (0.067) | (0.064) | | | | |
| *BEH* x Q35 | | | | | | | | -0.002 | -0.010 | -0.027 | -0.032 | | | | |
| | | | | | | | | (0.041) | (0.051) | (0.059) | (0.067) | | | | |
| *BEH* x Q45 | | | | | | | | 0.069 | 0.054 | 0.057 | 0.025 | | | | |
| | | | | | | | | (0.069) | (0.063) | (0.079) | (0.087) | | | | |
| *BEH* x cons | | | | | | | | | | | | 0.009 | 0.022 | 0.039 | 0.016 |
| | | | | | | | | | | | | (0.007) | (0.013) | (0.045) | (0.022) |
| N. | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 |
| Obs. | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 |

Note: OLS regression of log monthly electricity consumption on intervention indicator. *BEH* is the difference-in-differences estimator for the behavioral intervention. *Pre* is a dummy for above-median consumption per square meter before the beginning of the behavioral intervention (year 2018). *Q14* to *Q34* are dummies representing branches in the first, second and third quartile of average consumption per square meter before the beginning of the behavioral intervention (year 2018). *Q15* to *Q45* are dummies representing branches in the first, second, third and fourth quintile of average consumption per square meter before the beginning of the behavioral intervention (year 2018). *Cons* is a continuous variables for the average consumption per square meter before the beginning of the behavioral intervention (year 2018). *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province and the post-intervention indicator interacted with the heterogeneity variables. Standard errors clustered at the branch level reported in parentheses. *p < .05, ** p < .01, ***p < .001.

**Table B7. Heterogeneous effect of the behavioral intervention based on baseline efficiency (kWh per employee), supplementary analyses**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | F1 | F2 | F3 | TOT | F1 | F2 | F3 | TOT | F1 | F2 | F3 | TOT | F1 | F2 | F3 |
| *BEH* | 0.001 | -0.071* | -0.049 | -0.015 | 0.007 | -0.054 | -0.076 | -0.006 | 0.013 | -0.036 | -0.102* | -0.081 | -0.050 | -0.132* | -0.085 |
| | (0.017) | (0.028) | (0.028) | (0.030) | (0.030) | (0.040) | (0.041) | (0.034) | (0.037) | (0.042) | (0.044) | (0.059) | (0.056) | (0.060) | (0.064) |
| *BEH* x pre | 0.030 | 0.003 | -0.037 | | | | | | | | | | | | |
| | (0.036) | (0.043) | (0.049) | | | | | | | | | | | | |
| *BEH* x Q14 | | | | -0.028 | -0.013 | -0.029 | 0.061 | | | | | | | | |
| | | | | (0.038) | (0.035) | (0.058) | (0.055) | | | | | | | | |
| *BEH* x Q24 | | | | -0.026 | 0.029 | -0.059 | -0.095 | | | | | | | | |
| | | | | (0.042) | (0.054) | (0.054) | (0.055) | | | | | | | | |
| *BEH* x Q34 | | | | 0.018 | 0.020 | 0.022 | 0.072 | | | | | | | | |
| | | | | (0.055) | (0.053) | (0.063) | (0.074) | | | | | | | | |
| *BEH* x Q15 | | | | | | | | -0.038 | -0.036 | -0.094 | 0.112 | | | | |
| | | | | | | | | (0.046) | (0.041) | (0.068) | (0.062) | | | | |
| *BEH* x Q25 | | | | | | | | -0.058 | 0.024 | -0.038 | 0.008 | | | | |
| | | | | | | | | (0.039) | (0.049) | (0.053) | (0.064) | | | | |
| *BEH* x Q35 | | | | | | | | -0.009 | -0.005 | -0.065 | -0.044 | | | | |
| | | | | | | | | (0.051) | (0.060) | (0.062) | (0.064) | | | | |
| *BEH* x Q45 | | | | | | | | 0.018 | 0.029 | 0.019 | 0.095 | | | | |
| | | | | | | | | (0.063) | (0.064) | (0.071) | (0.082) | | | | |
| *BEH* x cons | | | | | | | | | | | | 0.000 | 0.000 | 0.001 | 0.000 |
| | | | | | | | | | | | | (0.000) | (0.000) | (0.001) | (0.000) |
| N. | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 | 564 |
| Obs. | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 | 16177 |

Note: OLS regression of log monthly electricity consumption on intervention indicator. *BEH* is the difference-in-differences estimator for the behavioral intervention. *Pre* is a dummy for above-median consumption per employee before the beginning of the behavioral intervention (year 2018). *Q14* to *Q34* are dummies representing branches in the first, second and third quartile of average consumption per employee before the beginning of the behavioral intervention (year 2018). *Q15* to *Q45* are dummies representing branches in the first, second, third and fourth quintile of average consumption per employee before the beginning of the behavioral intervention (year 2018). *Cons* is a continuous variables for the average consumption per employee before the beginning of the behavioral intervention (year 2018). *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province and the post-intervention indicator interacted with the heterogeneity variables. Standard errors clustered at the branch level reported in parentheses. *p < .05, ** p < .01, ***p < .001.

**Table B8. Heterogeneous effect of the behavioral intervention based on baseline efficiency (F2+F3/TOT), supplementary analyses**

| | (1) | (2) | (3) |
|---|---|---|---|
| | F1 | F2 | F3 |
| *BEH* | 0.030 | 0.031 | -0.013 |
| | (0.119) | (0.164) | (0.152) |
| *BEH* x pre (F2+F3/TOT) | -0.029 | -0.210 | -0.110 |
| | (0.277) | (0.351) | (0.331) |
| N. | 564 | 564 | 564 |
| Obs. | 16177 | 16177 | 16177 |

Note: OLS regression of log monthly electricity consumption on intervention indicator. *BEH* is the difference-in-differences estimator for the behavioral intervention. *Pre (F2+F3/TOT)* is the ratio of consumption outside the main work schedule over total consumption before the beginning of the behavioral intervention (year 2018). *F1* the electricity consumption during the main work schedule, *F2* working hours outside the main work schedule and *F3* during the non-working hours. All models include branch and time fixed effects, cooling and heating degree days of the province and the post-intervention indicator interacted with the heterogeneity variables. Standard errors clustered at the branch level reported in parentheses. *p < .05, ** p < .01, ***p < .001.