Technological and behavioral policy levers to save energy in the workplace

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Valeria Fanghella[1], Giovanna D'Adda[2], Massimo Tavoni[3]

[1] University of Trento; [2] University of Milan, EIEE and Fondazione Pesenti; [3] Politecnico di Milano, EIEE and CMCC.

Abstract

Using a large field study, we investigate the impact of two energy conservation programs in the workplace. The first is a technological renovation that envisages the installation of an automated energy management system to optimize building consumption (N= 68 branches). The second is a non-pecuniary intervention that encourages employees' behavioral change through a saving competition amongst branches (N= 516 branches). We find that the technological intervention reduces total energy consumption, especially outside working hours. The behavioral intervention has a significant curtailing effect only outside working hours. Our results suggest that, when implemented together, these tools may overlap (rather than reinforce), as they address similar drivers of consumption.

Keywords: energy consumption; behavioral intervention; energy competition; technological renovation; difference-in-difference.

1 Introduction

Buildings are responsible for over 36% of total primary energy consumption and 40% of energy-related CO2 emissions worldwide [1]. Since 1990, energy consumption from commercial buildings has increased by 1.5% per year [2] and is expected to continue growing [3]. Reducing energy use in buildings is, therefore, a critical strategy for achieving global sustainability goals [4].

One of the primary sources of inefficiencies in buildings energy consumption is human behavior [5], [6]. This is especially true in the workplace, where principal-agent and incomplete information problems are more severe [7]. The conflict of interest is caused by the fact that those who consume energy (employees) are not those who pay for it (the company). Employees also lack information on how much energy they consume: they cannot access the company's energy bills, and even if they did, disentangling their own contribution would be impossible.

Two competing approaches exist to reduce buildings' energy wastes. On the one hand, employees are seen as rational agents who, in the presence of principal-agent problems and information asymmetries, do not make any effort to reduce consumption at the workplace. Hence, savings are possible if the control over energy is taken away from employees and assigned to automation and technology [8]. This entails, for instance, the installation of smart lighting and plugs, and programmable thermostats [9], or the automation of the peak load management [10]. Under this view, if occupants simply stick to the "status quo" provided by the technology, energy consumption will reduce.

On the other hand, employees' decision-making is seen as driven by a broader set of factors than mere rational and self-interested considerations. Hence, they can be motivated to conserve energy by non-pecuniary interventions that appeal to biases in the decisional process -notably, deviations from rational choice theory [11]. As an example, individuals are motivated to conserve energy if they know that they consume more than similar households [12] or that their behavior has negative environmental and health consequences [13]. Implementing behavioral intervention does not guarantee energy curtailment by itself because the physical environment where behaviors occur is not modified. Savings will be achieved only if employees change their way of using appliances and devices.

With this work, we investigate the impact of two initiatives, each based on one of the two approaches mentioned above, implemented by a large Italian bank to reduce its branches' energy consumption. The first program is a structural intervention, started in 2016-2017 and still ongoing, consisting in the installation of a control system that optimizes branches' energy consumption. The second is a behavioral intervention, conducted over the year 2019, combining different non-pecuniary drivers to foster energy saving. This program is centered around an energy saving competition between branches. Every month, the top three branches, in terms of energy conservation, are communicated through the program's newsletter. Winners gain social recognition, along with a small material reward in the shape of an eco-gadget. The competition is reinforced by additional incentives, such as informational materials and individual challenges.

Depending on their consumption profile, branches are assigned to either the renovation or the behavioral intervention. We exploit the different assignment rules and timing of the interventions to estimate their impact on electricity consumption using a difference-in-difference approach over the period 2015-2019. Consistently with earlier work, we find that the technological renovation leads to a significant reduction of 16 percent in average monthly consumption [14]. The behavioral program reduces average monthly consumption by 2.5 percent, but this effect is not statistically significant. This percentage is lower than that achieved in the residential sector, which is estimated between 3.9 to 7 percent [15], [16]. Results also show that the impact of both interventions is higher outside the main working hours.

We use branches' characteristics to explore possible sources of heterogeneity in programs effect and inform similar future efforts. We observe heterogeneity in response to the technological renovation: higher savings are obtained where the control system manages both the services responsible for electricity consumption, as well as the air conditioning. Instead, none of the characteristics investigated (pre-treatment consumption, electric air conditioning, number of employees, and surface) influence the impact of the behavioral program.

Finally, we investigate engagement with the behavioral intervention using survey data and statistics of the interaction with the program's webpage. Results show that, overall, employees appreciate the program. Moreover, they interact with the program's webpage over the whole intervention period: engagement is particularly high when the program starts and when it ends, with a minimum during summer break.

Our study contributes to the literature in several respects. To the best of our knowledge, we are one of the first economic studies that evaluate the impact of behavioral interventions in the workplace. While psychological and engineering studies provide early insights on the topic (see [17] for a review), economists have to date paid more attention to the residential sector [18], [19]. A few notable exemptions exist. [20] show that changing the default settings on office thermostats significantly reduces the office temperature. [21], [22] find that when social influence is used to tackle a specific driver of energy waste (such as office windows open overnights [22]), it effectively prompts behavioral change. However, feedback on a specific outcome is more effective than on aggregate consumption [23]. To what extent existing findings are transferrable to overall consumption is still unclear. By observing an insignificant effect on overall energy usage, this study suggests that non-pecuniary interventions addressed to aggregate consumption may not be effective in the workplace.

Our findings also reveal that the effect of non-pecuniary interventions is lower in the workplace than among households. We explain this in terms of differences between the two settings. Most importantly, the lack of financial incentives to save energy can undermine the effect of behavioral programs [24]. Moreover, as consumption in the workplace is the product of many people's actions, employees may experience low self-efficacy -namely, that personal effort hardly affects overall outcomes [25]. Taken together, these features are likely to undermine the effort to curtail consumption in the workplace. Finally, even if workers want to save energy, they can do so only by changing their behavior. They have therefore fewer savings opportunities than tenants, who respond to non-pecuniary interventions by changing their behavior and investing in energy efficiency [26].

This study also explores the sources of heterogeneity in the impact of non-pecuniary interventions in the workplace. Interestingly, we fail to replicate a common finding of the residential sector [23], [27]–[30]: we do not find heterogeneity in branches' pre-treatment consumption. This means that, contrary to the housing sector, branches with higher pre-treatment consumption are not more reactive to behavioral interventions. Moreover, peer effects, notably others' influence on one's behavior, are usually stronger in smaller groups [31], [32]. Accordingly, we expect that employees in smaller branches discuss more the saving competition and more easily identify those who do not contribute to reducing branch's consumption, leading to higher program's impact. Instead, we do not detect any interaction between the branches' number of employees (or surface) and the behavioral program. Survey data reveal a possible mechanism underlying this finding: peer pressure does not affect the engagement with the behavioral program and, therefore, the resulting energy saving. Hence, heterogeneity may not be detected because the hypothesized mechanism is not at work either in small or large branches. Finally, our heterogeneity analysis reveals that the behavioral intervention mostly prompts efficient usage of lighting and appliances, rather than of heating and cooling systems.

Finally, the implementation of the behavioral and technological interventions within the same setting enables us to explore their interplay.[1] This contributes to the growing interest in the interactions between behavioral and traditional policy instruments (e.g., [33], [34]). Even if we cannot directly quantify the effect of their joint implementation, our results suggest that combining the two programs may fail to create positive synergies. Notably, the technological renovation mostly optimizes the consumption outside working hours. The same is true for the behavioral program: in response to it, employees mostly engage in conservation behaviors that reduce consumption outside working hours. Combining the two interventions may, therefore, not lead to positive synergies because they affect similar drivers of consumption.

The remainder of the paper is organized as follows. Section 2 provides details of the programs and of the project timeline. Section 3 discusses the data and results. Section 4 concludes.

2 Interventions design

This section details the features of the two interventions, i.e., the structural renovation and the behavioral program, and the project timeline.

2.1 Renovation program

The company implemented a technological renovation (henceforth, *Automation*) to optimize buildings' consumption. The renovation was carried out between 2016 and 2017, with the first BEMS installation in August 2016 and the last in May 2017. The selection of the branches to renovate did not follow a strict rule but sought to reduce the investment pay-back time. In general, the company selected the branches with higher consumption levels and with a higher share of consumption outside peak working hours, considered as an indicator of energy waste. 70 branches were selected to receive the renovation.

The restoration consisted of the installation of a building energy management system (BEMS). A BEMS is an integrated software-hardware system that controls the indoor climatic conditions in building

[1] It is beyond the scope of the study comparing the point estimates of the two programs, because branches' allocation to the programs was not random. [68] already showed that technological renovations are more effective than behavioral programs at promoting energy saving.

facilities. It manages the lighting system, air conditioning and ventilation, and appliances, with the goal of optimizing energy consumption while ensuring occupants' comfort [35]. Under a behavioral point of view, why automation works is explained by peoples' tendency to stick to the default option [36] - whether this entails choices on retirement plans enrolment [37], organ donation [38], and green electricity [39]. Automatizing the energy management follows an analogous logic: setting smart and optimal defaults improves conservation because occupants will mostly accept the indoor conditions they are provided with [20].

2.2 Behavioral program

The bank also implemented a behavioral intervention to promote energy conservation among employees (henceforth, *Behavioral*). The project ran in the period January-December 2019. 553 branches were assigned to the behavioral program. None of them belongs to the group assigned to *Automation* -namely, none of the branches receive both the interventions.

The company relied on external consultants, specialized in behavioral interventions, for the design of the program. The core of the intervention consisted in a saving competition among branches, which was complemented by additional incentives. All the materials were communicated through the company's newsletter and web portal. Every month, the ranking of branches was published on the program's web portal in three versions: a podium with the first three ranked, a list with the first ten, and a list with all the branches. The ranking was computed internally by the firm, considering the year-to-date saving compared to the consumption in 2017 and 2018.[2] Due to billing constraints, the ranking was published with two months of delay compared to the reference period.

The competition appeals to people's desire to be perceived as good and pro-social by others [40], [41]. In particular, making the ranking public ensures that the best performers achieve social recognition [21]. Beyond the social incentive, employees of the top three branches in the monthly ranking also received prizes in the form of eco-gadgets.[3] This adds a small material incentive to conserve energy where otherwise it would not be present. At the end of the intervention, the three branches saving the most were publicly awarded bigger prizes compared to monthly rewards (e.g., planting a tree with the certification of the winning branch).

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

[3] The prize can be received only once by each branch. Notably, if a firm that already received the gadget scores again amongst the first three, the prize is assigned to the next firm in the ranking which has not received it yet.

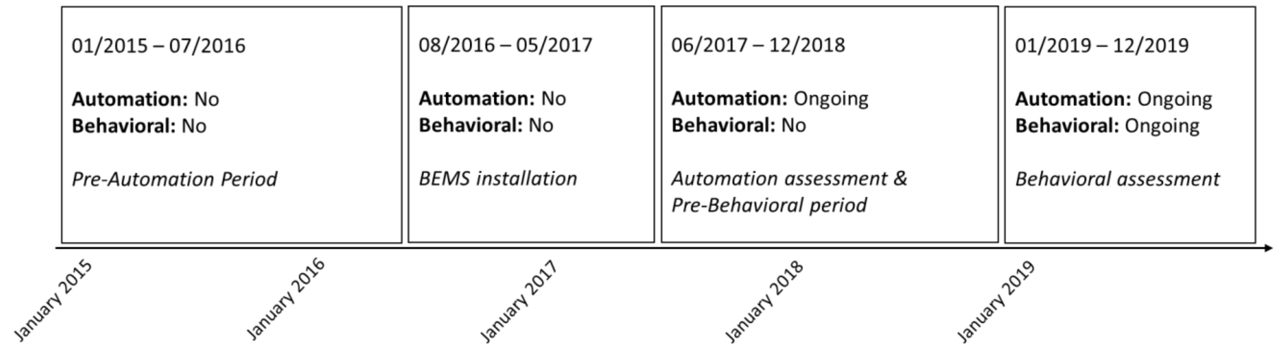
Further material was published on the program newsletter on an ongoing basis. The different contents were posted concurrently in the newsletter to increase program visibility (e.g., the ranking for a month plus the video on how to reduce lighting consumption). First, tips for saving energy and reducing waste were provided, both through fliers and videos. Videos were filmed in the bank's buildings and told the stories of employees seeking to conserve energy to improve their position in the monthly ranking. This design is informed by the finding that individuals are more likely to comply with social norms when they concern a relevant reference group [42]. Second, employees were tasked with 'missions', posted also on the program's web portal. Such missions mostly had engagement, rather than conservation, purposes. Examples comprise the best picture on how to save energy at home or the best suggestion for saving opportunities in the branch. For each mission, the company selected the winner, who was rewarded with an eco-gadget.

2.3 Project timeline

The sample used in this study consists of 623 brank's branches. 70 amongst the branches with higher consumption were assigned to *Automation*; the remaining 553 to *Behavioral*. There was not a control group -namely, all the branches in the sample were assigned to either one or the other intervention.

We observe branches' monthly consumption over the period 2015-2019. The project timeline is summarized in Figure 1 and goes as follows. From January 2015 until the first BEMS installation (August 2016), no intervention was in place. This represents the pre-intervention period for *Automation*. After the last BEMS installation (May 2017) to the end of the observation period, *Automation* was ongoing. Given the technological nature of this program, its effect is assumed constant. The behavioral intervention was put in place in January 2019 and continued until the end of the observation period. The pre-intervention period for *Behavioral* is comprised between the last BEMS installation (May 2017) and the launch of the program (January 2019).

Figure 1. Projects timeline



We use a difference-in-difference estimation to assess interventions' effect on branches' electricity consumption. In particular, the assignment rules and the different timings of the interventions allow first using *Behavioral* as a control group for *Automation*, and then using *Automation* as a control group for *Behavioral*. Even if treatment allocation was not random, as long as the two groups respect the parallel trend hypothesis, differences in magnitude do not constitute a threat to identification in a difference-in-difference estimation [43]. We exploit the more than one-year period preceding *Automation* and *Behavioral* to assess whether the parallel trend assumption holds before each program. Our setting also allows to rule out issues of attrition, self-selection, and partial compliance [44]. This is because programs assignment was managed by bank's managers, who defaulted branches in either one project or the other. Once assigned to a program, branches had no possibility to opt-out.

Amongst the SUTVA assumptions required for a difference-in-difference estimation, the lack of spillovers between treated and non-treated subjects may not be completely satisfied in our setting. In the design of the behavioral program, the bank partially involved non-treated employees in order to maximize their engagement with the company's initiative and, possibly, the overall savings. This entails that the online material of the behavioral intervention was available to all branches, including those that received the technological renovation. Moreover, three times over the year, the ranking was extended to all the branches. However, we believe that the estimation bias is limited in our setting. The non-treated group did not have direct contact with treated units, and mere information disclosure is often not enough to prompt behavioral change [45]. This is especially true for infrequent information: as an example, [46] found that the same feedback significantly reduced consumption when provided monthly, but not when provided bimonthly. Finally, if even any bias occurred in the estimation, it is downward, leading to a conservative assessment of the behavioral program.

3 Results

This section discusses the results of the interventions. After describing the dataset used in the analysis, we present the main effect of automation and behavioral interventions on electricity consumption and their heterogeneous effects by branches' characteristics. Finally, we present employees' engagement with the behavioral program.

3.1 Data and descriptive statistics

The dataset of our empirical analysis combines the company's administrative and electricity consumption data. Administrative data report branches' characteristics. Electricity consumption is 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, divided per time-of-use (TOU). In Italy, electricity is divided into three TOU:

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

Distinct drivers contribute to consumption in the different moments of the day. The standard working schedule of branches is between 8.25 a.m. to 4.55 p.m. Hence, F1 represents peak working hours, and consumption here is mostly due to workers' activities. F2 represents working hours outside the main schedule. Consumption in F2 is partially due to employees' activities, as some branches are open on Saturday, and some employees may work overtime, but mostly to the passive consumption of buildings. F3 is outside working hours, and consumption here only results from buildings' passive consumption. We keep only successful meter readings (i.e., we drop the months in which meter readings were estimated or were non-positive). We derive the total consumption of each branch by summing consumption in the three TOU rates.

The initial sample size is 70 for *Automation* and 553 for *Behavioral* conditions. We drop two branches from the *Automation* sub-sample because the meter is not uniquely identified or because BEMS installation date is not available. We also drop 37 branches from the *Behavioral* sub-sample, for which the meter is not uniquely identified, or which are not included in the monthly ranking (because consumption data in 2017 and 2018 were not available to compute the saving). The final sample size is of 584 branches, 68 for *Automation* plus 516 for *Behavioral.*

Table 1 reports sample descriptive statistics. As branches are not randomly allocated to programs, they feature different characteristics, in terms of pre-treatment consumption and size. Consistent with the targeting criteria of the program, branches assigned to *Automation* feature higher consumption, larger surface, and more employees than those assigned to *Behavioral*. The difference between the two groups reduces when dividing consumption per unit of surface (kWh/m2), compared to consumption in absolute value (kWh). Finally, branches in *Automation* are more often located in the North, and less in the South and Islands, than those in *Behavioral.* Figure 2 reports the consumption per unit of surface over the observation period, divided per consumption slot and program assignment. The dip in consumption in November 2015 is caused by a measurement error in the meters. The figure illustrates the project timeline. The period between January 2015 and August 2016 constitutes the pre-intervention period for *Automation*. Here the consumption of the two groups follows a similar path, making the common trend assumption plausible. After the BEMS installation period, the technological intervention is ongoing. We assess its impact between May 2017 and January 2019. This period also represents the pre-intervention period for *Behavioral*. Figure 2 reveals that the parallel trend assumption is reasonably assumed in these months as well. Moreover, the technological renovation causes the two consumption profiles to become more similar in the amount of energy consumed compared to the period proceeding *Automation* (as also shown in Table 1), increasing the robustness of the difference-in-difference estimation.

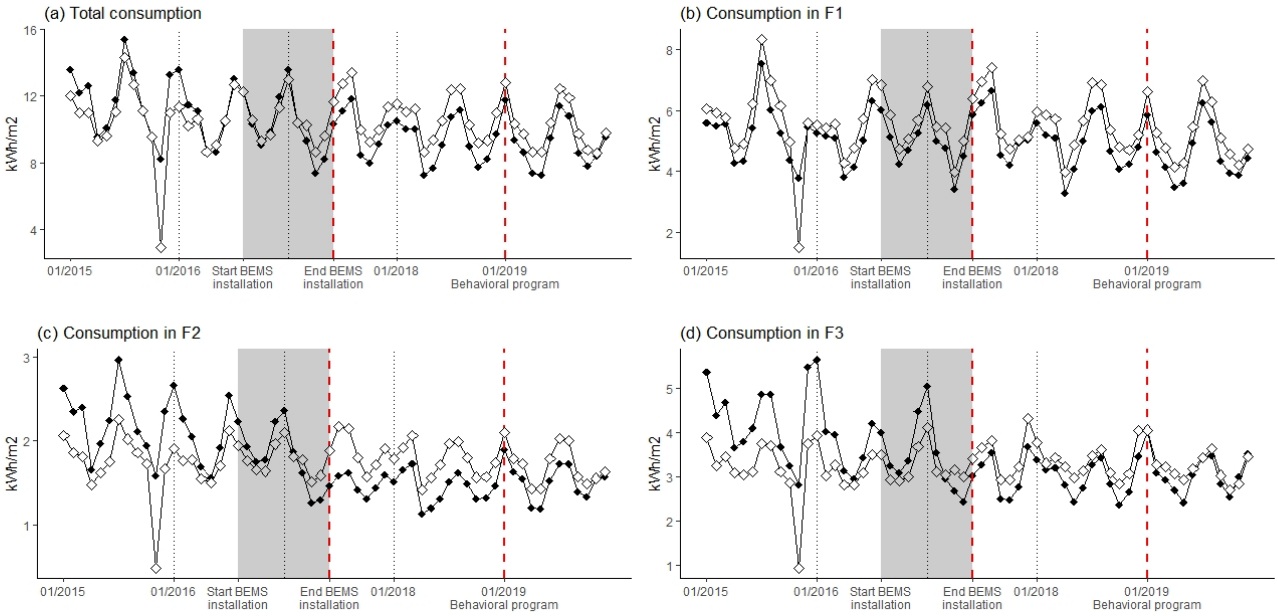
Table 1. Descriptive statistics of the sample

	Automation	Behavioral
N	68	516
Average surface (m2)	528	311
	(353)	(267)
Average number of employees	9.54	5.47
	(5.12)	(3.11)
Electric air conditioning (%)	0.485	0.407
Area		
Centre (%)	0.058	0.096
North (%)	0.783	0.407
South and islands (%)	0.159	0.497
Consumption in 2015		
TOT (kWh)	4876	2846
	(2228)	(1741)
TOT (kWh/m2)	12.00	10.90
	(6.99)	(5.65)
F1 (kWh)	2272	1555
	(1216)	(1107)
F1 (kWh/m2)	5.40	4.86
	(2.98)	(3.19)
F2 (kWh)	909	458
	(436)	(289)
F2 (kWh/m2)	2.28	1.79
	(1.49)	(1.04)
F3 (kWh)	1695	832
	(757)	(513)
F3 (kWh/m2)	4.35	3.29
	(3.04)	(2.00)
Consumption in 2018		
TOT (kWh)	4004	2733
	(2024)	(1479)
TOT (kWh/m2)	9.29	10.60
	(4.95)	(5.04)
F1 (kWh)	2173	1450
	(1270)	(941)
F1 (kWh/m2)	5.84	5.49
	(2.52)	(2.79)
F2 (kWh)	615	448
	(341)	(247)
F2 (kWh/m2)	1.45	1.76
	(0.847)	(0.959)
F3 (kWh)	1216	835
	(596)	(455)
F3 (kWh/m2)	2.98	3.32
	(1.93)	(1.94)

Note: The average number of employees is computed considering the number of employees at 12/2018. Consumption in kWh is calculated as average monthly energy consumption for the considered year. Consumption in kWh/m2 is calculated as average after dividing the branch's monthly energy consumption by its surface. Standard error in parentheses.

Figure 2 also reveals the main results of the programs. The technological intervention substantially reduces energy consumption, whereas the behavioral does not. In particular, installing the building energy management system (BEMS) reduces total energy consumption. This result is driven by the savings outside main working hours (notably, F2 and F3), whereas no effect is observed in consumption in F1. The impact of the behavioral program is less pronounced, making it difficult to detect its effect once it is in place. The consumption of *Behavioral* branches slightly reduces outside peak working hours, but no variations are observed on overall consumption and in F1.

Figure 2. Consumption over time per slot and experimental condition



Monthly consumption for *Automation* (black) and *Behavioral* (white). Vertical dotted lines represent beginning of years. Vertical dashed lines represent the beginning of the interventions. The grey area represents BEMS installation period. The drop in aggregate consumption in November 2015 is caused by a measurement error in the meters.

3.2 Empirical analysis and results

3.2.1 Impact of the programs on energy use

We test the effect that the two interventions have on electricity consumption. To this aim, we estimate on the full sample, for the period ranging from January 2015 to September 2019, the following specification:

$$y_{it} = \beta_0 + \beta_1 * T_i^A * post_{it}^A + \beta_2 * T_i^B * post_t^B + \alpha_i + \lambda_t + \varepsilon_{it} \tag{1}$$

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

T_i^A is the indicator for the *Automation* and is equal to one for branches assigned to the renovation, and zero otherwise. $post_{it}^A$ represents the post-intervention period, and, for each branch, takes the value of zero before the installation and one for all periods after. We exclude from the analysis the installation and the post-installation months, to avoid transition effects. This specification, which is similar to the one adopted in [47], is driven by the staggered start date of the *Automation* intervention. We define the variable $post_{it}^A$ for branches in *Behavioral*, by randomly assigning them to an installation date between August 2016 and May 2017. The number of *Behavioral* branches assigned to each month follows the distribution of actual installation dates of *Automation* branches (see Appendix B for further details).

T_i^B is the indicator for the *Behavioral* intervention, and is equal to one for the branches assigned to the program, and zero otherwise. $post_t^B$ is the post-treatment dummy, and values zero before January 2019 and one for all periods after. The regression also includes branch fixed effects α_i and month-by-year fixed effects λ_t. We allow for arbitrary within-branch correlation by clustering standard errors at the branch level [47].

Results are reported in Table 2. The average effect of *Automation* on monthly energy consumption is negative and significant. The point estimate is -1.920 kWh/m2. The average pre-treatment consumption of *Automation* branches is 12 kWh/m2, leading to a reduction of monthly consumption of 16 percent. The amount is consistent with other BEMS implementations, which, on average, achieve an energy saving of 16-17 percent [14]. The energy curtailment is mostly due to a significant reduction in consumption in F2 (Column 3) and F3 (Column 4), where significant savings of 0.721 kWh/m2 and 1.168 kWh/m2 are achieved. No effect is instead observed in energy consumption during working hours (Column 2). This is consistent with the intent of the renovation program, which mostly aimed to optimize buildings parametrization outside the main working schedule.

The average effect of *Behavioral* on total energy consumption is negative, but it is not statistically significant. Column 1 shows a saving of 0.253 kWh/m2 on monthly energy consumption. Considering an average pre-treatment monthly consumption of 10.6 kWh/m2, the program results in 2.5 percentage savings. This result is lower than the average savings achieved by behavioral interventions in the residential sector, which is estimated between 3.9 and 7 percent [15], [16]. Different mechanisms could explain this outcome. First, the program may have failed to engage bank's employees. Survey and administrative data suggest that this is not a likely explanation (see Section 3.3 for further discussion). Second, the possible spillovers to non-treated branches may reduce our estimate of the behavioral program. However, the substantial difference between our result and that in the housing sector is conceivably too high to be fully explained by spillover effects. We therefore rule out this explanation - or, at least, that this is the only one. Most likely, the different incentives to save energy in the domestic and the non-domestic settings cause the minor effect observed in this study.

The behavioral program is more effective outside peak working hours. The effect is negative and significant on consumption in F2, with a reduction of 0.133 kWh/m2 (Column 3). The reduction on F3, equal to 0.184 kWh/m2 (Column 4), is only marginally non-significant (p= .053). This finding is consistent with earlier literature. [48] found that a serious game in the office mostly reduced energy consumption outside working days. Going beyond a certain saving is indeed hard when people need to perform energy-consuming activities [49]. Moreover, individuals are reluctant to sacrifice their comfort to conserve energy -even when they have a financial incentive to do so [50].

Table 2. Impact of *Automation* and *Behavioral* interventions on electricity usage

	(1) TOT	(2) F1	(3) F2	(4) F3
DD^A	-1.920***	-0.032	-0.721***	-1.168***
	(0.324)	(0.120)	(0.093)	(0.164)
DD^B	-0.253	0.064	-0.133**	-0.184
	(0.199)	(0.104)	(0.044)	(0.095)
Obs.	32,755	32,755	32,755	32,755
R^2	0.013	0.0001	0.035	0.022

Regression of monthly energy consumed per unit of surface (kWh/m2) on treatment indicators. TOT denotes total energy consumption per, F1 consumption during peak working hours, F2 during low working hours and F3 during non-working hours. DD^A is the staggered difference-in-difference estimator for *Automation*. DD^B is the difference-in-difference estimator for *Behavioral*. Standard errors clustered at the branch level are reported in parentheses. *p < .05, ** p < .01, ***p < .001.

Our results are robust to a series of alternative specifications. First, the measurement error in November 2015 may affect consumption in the pre-*Automation* period differently in the two groups. Table C.1 shows that results do not change if we eliminate that month. Second, in Table C.2, we find that results are robust if the main specification is on consumption (in kWh) rather than on consumption per unit of surface (in kWh/m2). Third, we investigate whether programs' evaluation depends on how branches in *Behavioral* are allocated to $post_{it}^{A}$. To this aim, we randomly allocate *Behavioral* branches to different fictitious BEMS installation dates and we re-estimate Eq. 1. We repeat the random assignment 1000 times, and we compute the average coefficients and standard errors. Table C.3 shows that the point estimates are consistent to those reported in Table 2. Hence, our results are insensitive to how the post-*Automation* variable is specified.

Next, we assess programs' effectiveness on yearly, rather than on monthly, consumption. Restricting the analysis to pre-post intervention comparisons is an effective way to eliminate the serial correlation of longitudinal data [47]. We limit the analysis to the years where the renovation did not take place - namely, 2015, 2018, and 2019. This is because consumption over a year is not constant but is influenced by the season. Computing the average annual consumption only on some months (as it would be for years 2016 and 2017) may bias the results as some natural seasonal variations are neglected. Table C.4 shows that the significance levels are in line with the main specification.

Finally, we test whether our main specification is robust to in-time placebo tests. For each of the two interventions, we check whether a fictitious treatment in the pre-intervention period is identified as significant. Again, we restrict the analysis to a subset of the pre-intervention months to prevent seasonal variations from driving the results -i.e., we consider the same periods before and after the fictitious date. Table C.5 and C.6 report the details and the results of this exercise. Our specifications do not detect significant treatment effects when no intervention occurs. Hence, we rule out that our main results are caused by pre-existing differences between the two groups, rather than by the programs.

3.2.2 Heterogeneous programs effects on energy use

We assess heterogeneous effects of the two programs along different branches' characteristics: pre-treatment consumption, whether air conditioning is electric or gas, and size. We assess heterogeneity in response to programs by adding to Eq. 1 interactions between treatments and post-intervention dummies with the relevant branches' characteristics for both programs. In Table 3 we report significant results and in Table D.1 non-significant interactions.

Given the distinct nature of the two interventions, heterogeneity is likely to be driven by different causes. The effectiveness of energy renovations mostly depends on buildings characteristics [51]. Individuals' behaviors may also play a role, because, as a result of the restoration, individuals might increase their consumption, leading to the well-known phenomenon of rebound [52], [53]. The effectiveness of behavioral interventions depends on a broader set of factors that relate to both building characteristics and cognitive aspects. Social norms and group dynamics within the workplace significantly influence employees' energy behaviors [17], [54]. Engineering studies also show that the effect of social influence programs depends on the characteristics of the network [55], [56], and increases when consumption is apportioned to small- to medium-sized groups, particularly when they represent existing communities to which employees identify [57].

The first source of heterogeneity that we examine is pre-treatment consumption. We include this dimension of heterogeneity because, in general, higher initial consumption promises higher energy saving. Regarding the behavioral intervention, insights from the housing sector reveal that high energy users are more responsive to non-pecuniary interventions [23], [27]–[30]. However, evidence on whether this also applies to organizations is still scattered, as previous studies do not investigate this dimension [20]–[22].

We thus estimate Eq. 1, interacting intervention and post-intervention dummies with a continuous measure for consumption in the year before the launch of *Automation* (January-December 2015) and *Behavioral* (January-December 2018). Column 1 to 3 show that interaction between *Automation* and pre-treatment consumption is negative and significant on total energy consumption, and on consumption in F2 and F3. The higher the baseline consumption, the greater the savings generated by

BEMS on these consumption slots. Contrary to the findings from the household setting, we do not detect any interaction between the behavioral program and branches' pre-treatment consumption.

We propose a mechanism underlying this different result. In the domestic setting, non-pecuniary interventions prompt energy efficiency investments [26]. Heterogeneity in pre-consumption levels is partly explained by the fact that low users had already invested in energy efficiency before and have less possibility to do so in response to the intervention [28]. In contrast, employees cannot invest in building renovations -they can only change their behavior to curb consumption. Such a constraint in the response channels probably causes the fact that the behavioral intervention has the same effect on low- and high-consuming branches.

Next, we investigate heterogeneous effects based on other observable branches' characteristics, i.e., heating/cooling sources, and size in terms of number of employees and surface. These aspects influence energy consumption and may affect programs' impacts indirectly because they contribute to pre-consumption levels. However, they may also have a direct impact that we isolate thanks to the branch fixed effects included in the main specification. Namely, we assess how a specific characteristic interacts with the programs, net of all other branches' characteristics.

Regarding the air conditioning, we expect both treatments to be more effective for branches with electric heating and cooling. For these branches, we can monitor how the programs affect the consumption derived from appliances and lighting, as well as from the air conditioning system. Hence, both the centralized system in *Automation*, as well as employees in *Behavioral*, can leverage on both channels to reduce electricity consumption.

Accordingly, Column 4 to 6 show a negative and significant interaction between *Automation* and the electric air conditioning on total consumption and outside working hours. Hence, the technological renovation yields to greater curtailment when it also optimizes the air conditioning. No interaction is instead observed for the behavioral program. Interestingly, the *Behavioral* coefficient becomes significant for branches without electric air conditioning. Hence, the intervention mostly affects employees' usage of appliances and lighting, but not that of heating and cooling devices. The lack of interaction outside working hours also suggests that employees do not optimize climatic conditions (e.g., closing the windows and reducing the air conditioning) when leaving the office. This is consistent with findings from the residential sector, where tenants who do not pay the bills are significantly less likely to change heating settings at night [58]. In contexts where incentives are misaligned, setting optimal defaults may be more effective than expecting people to change their behavior [59].

Finally, for the renovation program, we do not expect heterogeneity in terms of employees and surface [60]. Instead, we predict it for the behavioral intervention, with stronger impact on smaller branches. Peer effects are important drivers of conservation behaviors [61], and they are stronger in smaller groups [31], [32]. Moreover, feedback is more effective when it is possible to monitor how energy is related to individuals' behavior [62], which is again easier in smaller groups.

Contrary to our expectations, we find heterogeneity in the renovation by branches' size. Column 7 to 9 and Column 10 to 12 show that *Automation* has lower effect for branches with more employees and larger surfaces. This result highlights a shortcoming in the selection process of the branches to which apply the renovation. The criterion was based on the absolute amount of energy used (kWh). However, higher levels of energy consumption may be caused by larger buildings, with more employees and bigger areas, rather than by inefficiencies in buildings management. Within the *Automation* group, bigger branches featured higher total (kWh), but not unitary (in kWh/m2 or kWh/employee), energy consumption. Therefore, they were already more efficient before the renovation, as they used less energy per unit of area (and per employee) than smaller branches. This reduces the "slack" in energy consumption that the technological renovation can reduce.

Table 3. Heterogeneous impact of *Automation* and *Behavioral* interventions on electricity usage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	TOT	F2	F3	TOT	F2	F3	TOT	F1	F2	TOT	F2	F3
DD^A	0.915	0.161	0.008	-1.266***	-0.540***	-0.827***	-3.228***	-0.528	-1.097***	-3.353***	-1.172***	-1.855***
	(1.032)	(0.142)	(0.305)	(0.241)	(0.080)	(0.134)	(0.735)	(0.273)	(0.206)	(0.708)	(0.194)	(0.356)
DD^B	-0.157	-0.006	-0.190	-0.440*	-0.189***	-0.242*	-0.073	0.353	-0.149	-0.135	-0.200*	-0.245
	(0.931)	(0.134)	(0.294)	(0.191)	(0.057)	(0.120)	(0.526)	(0.289)	(0.095)	(0.442)	(0.087)	(0.195)
DD^A x Pre	-0.228*	-0.358***	-0.227**									
	(0.098)	(0.072)	(0.081)									
DD^B x Pre	-0.014	-0.098	-0.012									
	(0.112)	(0.100)	(0.115)									
DD^A x Electric				-1.264*	-0.346*	-0.646*						
				(0.604)	(0.175)	(0.309)						
DD^B x Electric				0.347	0.099	0.105						
				(0.390)	(0.086)	(0.190)						
DD^A x Employee							0.137**	0.054*	0.038**			
							(0.052)	(0.022)	(0.015)			
DD^B x Employee							-0.001	-0.023	0.006			
							(0.043)	(0.023)	(0.008)			
DD^A x Surface										0.003**	0.001***	0.001**
										(0.001)	(0.0002)	(0.0004)
DD^B x Surface										-0.00002	0.0002	0.0002
										(0.001)	(0.0001)	(0.0002)
Obs.	32,376	32,376	32,376	32,755	32,755	32,755	32,755	32,755	32,755	32,755	32,755	32,755
R^2	0.038	0.078	0.058	0.017	0.038	0.025	0.017	0.002	0.039	0.018	0.042	0.026

Regression of monthly energy consumed per unit of surface (kWh/m2) on treatment indicators. Regressions include the post-treatments indicators interacted with the heterogeneity variables. TOT denotes total energy consumption per, F1 consumption during peak working hours, F2 during low working hours and F3 during non-working hours. DD^A is the staggered difference-in-difference estimator for *Automation*. DD^B is the difference-in-difference estimator for *Behavioral*. Pre is a continuous variable for average consumption before projects implementation (2015 for Automation, 2018 for Behavioral). Electric is a dummy equal to 1 if the branch has an electric air conditioning, 0 otherwise. Employees is a continuous variable for the number of employees at December 2018. Surface is a continuous variable for the squared meters. Standard errors clustered at the branch level are reported in parentheses. *p < .05, ** p < .01, ***p < .001.

The results of the behavioral intervention also contrast our predictions. Column 7 to 12 show no interaction between *Behavioral* and branches' size, in terms of number of employees and area. Hence, contrary to our expectations, a lower number of employees does not yield to higher program's effect. Despite surprising, this result is in light with the fact that the rate of contributions to public goods [40] and of informal sanctions [63] does not depend on groups' size. Survey data suggest another explanation: others' engagement with the program did not affect individual's participation (see Section 3.3 for further details). Hence, peer effects may not have occurred, regardless of the branch's size.

3.3 Engagement with the Behavioral program

In this section, we further investigate employees' engagement with the behavioral program using survey data and statistics of interaction with the program's web page. The goal is to shed further light on the quantitative results by exploring satisfaction and engagement with the saving competition and the other parts of the program.

The survey, conducted at the end of the behavioral intervention (February-March 2020), was designed in collaboration with the program's manager. It was administered to a subsample of the bank's employees on the occasion of a broader questionnaire on corporate social responsibility. According to the bank's privacy policy, responses were collected anonymously from all branches (*Automation*, *Behavioral,* and offices), with no possibility to link the response to the branch. We therefore cannot discern whether the response is from an employee of a *Behavioral* vs. *Automation* branch. We can distinguish which respondents work in offices -namely, branches that were not directly involved in the behavioral program but could still access the online materials (see Section 2.3). Overall, 1152 responses were collected. 61.1% were male. Age ranged between 18 and more than 50. 43.8% of the respondents work in a branch, the remaining in offices.

Concerning the interaction with the program's webpage, we monitor the number of accesses on the program's webpage. We know the number and the type of contents posted online every month, and how many times each content was visited. As for the survey, we cannot distinguish whether the content was accessed by an employee from a *Behavioral* branch. Hence, this analysis provides a general understanding of the degree of engagement with the behavioral program.

The results of the survey reveal that the initiative was welcomed and known by the employees. Overall, 74.7% of respondents know the behavioral program. Among them, most respondents accessed the program's informative material sometimes over the year (53.7%) or at least once per month (35.2%). Only 5.3% of respondents declared to have never accessed it. These figures are consistent with the data of the engagement with the online platform. Overall, the page was visited around 31444 times during the intervention. Considering that the total number of employees in *Behavioral* branches is 2825,[4] the

[4] Sum of the employees working in *Behavioral* branches at December 2018.

average number of accesses per targeted employee is 11.1 per year -or similarly, 0.9 per month. Even if this is an overestimation, as it also comprises visits from non-targeted employees, it shows a good level of engagement with the intervention.

Survey results also reveal that employees had a positive attitude towards the intervention. 87% considered it useful and 58% interesting. 84% agree that it prompts good behavior and 86% that it gives tips on how to save energy. The majority also report having changed the behavior in response to the intervention: 77% reported to apply some conservation tips in the workplace, and 72% at home. This last number highlights the possibility to create positive spillover [64]: prompting good behaviors in the workplace may also improve energy practices at home [65].

We then focus on which, among the parts of the behavioral intervention, were perceived as more engaging. Participants were asked to indicate the three more important drivers of participation in the program [66]. Results for respondents working in branches and aware of the project (N= 368) are summarized in Table 4, Panel A. Overall, the most relevant driver of engagement is the concern for environmental issues (96.7%), followed by the willingness to save more than other branches (18.5%). Peer pressure (from colleagues and bosses) does not constitute an important aspect. This outcome may explain the absence of interaction between the number of employees and the behavioral program (Section 3.2.2). The hypothesis that smaller branches are more affected by the initiative is based on the finding that peer pressure is stronger in smaller groups. However, survey data suggest that peer influence did not happen in any branch, whether it was small or large.

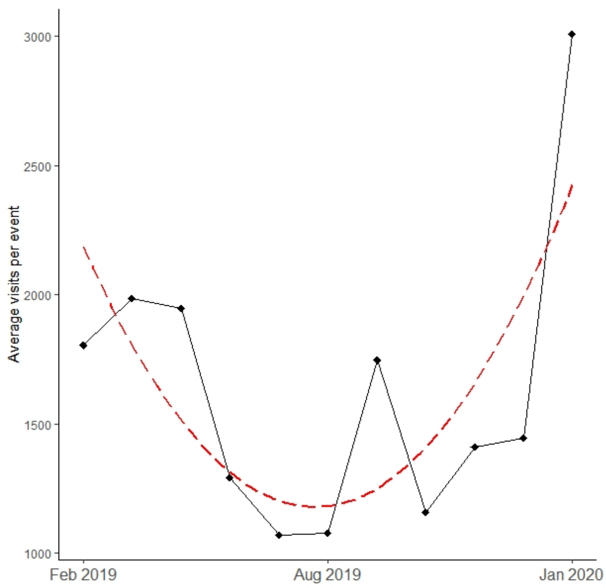
Table 4. Main drivers of participation in and contents accessed of the behavioral program

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

The engagement with the different parts of the initiative mirror the reported drivers of participation. Survey results reveal that news on the initiative page and informative materials were the most accessed content, followed by the monthly rankings (Table 4, Panel B). Missions and videos were less relevant. Engagement data with the program's webpage partially support survey answers. The main page of the intervention was accessed 8100 times, that of rankings 8582 times and that of missions 4505. Videos with conservation tips were seen 4524 times, the rules of the game and the informative material, 2248 and 1530 times, respectively. The main difference between survey and interaction data is that the former indicates that the news was significantly more accessed than the rankings, whereas the latter that the ranking page was slightly more accessed than the news. This contrast is consistent with the fact that people tend to underestimate the effect of social influence on their behavior [67]. Survey and engagement data also show the lower importance of the additional initiatives undertaken to complement the competition -namely, missions, videos, and prizes.

Finally, we use interaction data to monitor employees' engagement over time. The number of contents posted varied with the month, because news, missions, and videos were alternated. We measure engagement as the average number of visits per content posted in that month. Employees' engagement in the period between January 2019 and January 2020 is shown in Figure 3. The relation between time and engagement follows a U-shape: it starts high and reaches its minimum during summer break (August 2019). It then increases again and achieves a peak at the end of the intervention. This shape is conceivably explained by an initial enthusiasm that went down over time, but that was ultimately renovated by the final ranking.

Figure 3. Monthly average number of visits on the platform webpage



Average number of visits per content posted per month. Data from June and July are pooled together because only one ranking was made out of the savings of the two months. Dashed line represents fitted quadratic curve.

4 Conclusion

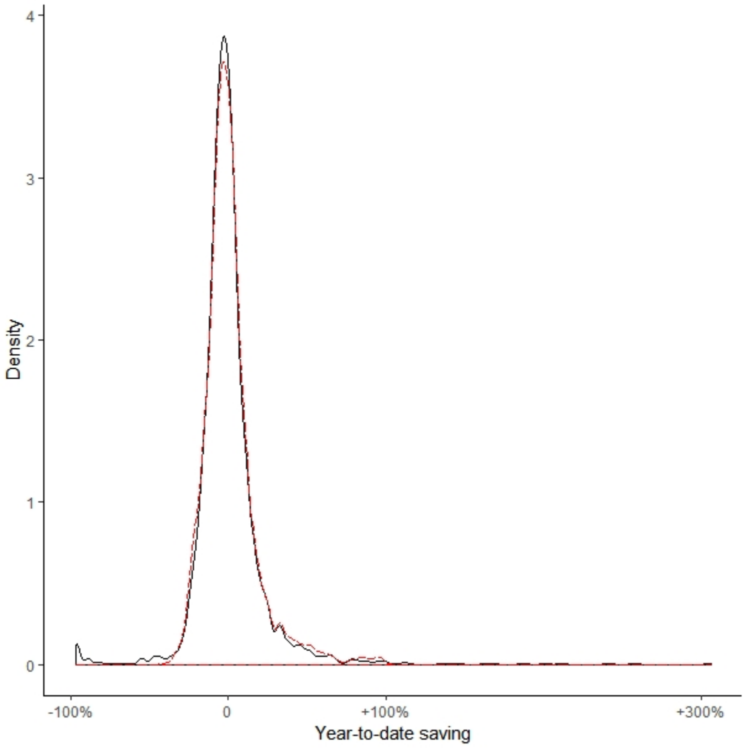
Through a difference-in-difference estimation, this paper assesses two interventions put in place by a large Italian bank to reduce its branches' energy consumption. The first consists of the installation of a building energy management system (BEMS), a control system that autonomously optimizes buildings' energy consumption. Branches receiving this intervention significantly reduce their total energy consumption. The effect of the renovation is maximum outside working hours, and if also the air conditioning falls under its control. The second is a behavioral intervention, in the shape of an energy saving competition among branches, aimed to trigger employees' conservation efforts. Despite the total consumption of branches assigned to this intervention does not significantly reduce, that outside working hours does. Our results suggest that in response to the behavioral intervention, employees switch off appliances and lighting (but no air conditioning) overnight and during weekends.

Our study has some implications for policies. First, a correct selection of the branches to renovate yields to more significant savings. Beyond total energy consumption, also a measure of the efficiency of the building should be taken into account, for instance in terms of consumption per surface or per employee. Our results also show a promising avenue for implementing behavioral policies in the workplace, with the caveat that the context's peculiarities are taken into account. As an example, targeting specific energy acts may achieve better results than addressing consumption in general, because employees can identify the link between the information and their behavior. Also, peer effects may reinforce the effect of non-pecuniary interventions, but mostly if these are addressed to pre-existing groups, where social ties are strong and mutual influence is more likely to occur. Finally, consumption outside working hours is the most negotiable, because it does not require any comfort-consumption compromise. Hence, this is the first source of energy waste that is curbed by conservation programs. When two interventions are jointly implemented, even though of different natures, they may overlap (rather than reinforce) if they address the same drivers of consumption.

Appendixes

A. Saving calculation of monthly ranking

Figure A.1 Calculation of the saving by the company (black line) and by the authors (red line)



B. BEMS installation period for *Automation* and *Behavioral*

The installation of BEMS for *Automation* branches was managed by the bank. The distribution is shown in Table B.1, Panel A. We randomly assigned *Behavioral* branches to a fictious installation month, respecting the distribution of actual BEMS installation. The distribution used for the main specification is shown in Panel B.

Table B.1 Distribution of BEMS installation month

Period	20	21	22	23	24	25	26	27	28	29	TOT
Panel (A): Automation											
N branches	4	8	8	5	4	6	13	9	4	7	68
%	0.059	0.118	0.118	0.074	0.059	0.088	0.191	0.132	0.059	0.103	1
Panel (B): Behavioral											
N branches	34	57	66	42	22	45	91	79	30	50	516
%	0.066	0.110	0.128	0.081	0.043	0.087	0.176	0.153	0.058	0.097	1

C. Robustness checks

Table C.1 Impact of *Automation* and *Behavioral* interventions on electricity usage, excluding November 2015

	TOT	F1	F2	F3
	(1)	(2)	(3)	(4)

DD^A	-1.899***	-0.019	-0.717***	-1.162***
	(0.325)	(0.121)	(0.093)	(0.164)
DD^B	-0.253	0.064	-0.133**	-0.184
	(0.200)	(0.104)	(0.044)	(0.095)
Observations	32,583	32,583	32,583	32,583
R^2	0.013	0.0001	0.035	0.022

Regression of monthly energy consumed per unit of surface (kWh/m2) on treatment indicators. November 2015 is excluded from the analysis. TOT denotes total energy consumption per, F1 consumption during peak working hours, F2 during low working hours and F3 during non-working hours. DD^A is the staggered difference-in-difference estimator for Automation. DD^B is the difference-in-difference estimator for Behavioral. Standard errors clustered at the branch level are reported in parentheses. *p < .05, ** p < .01, ***p < .001.

Table C.2 Impact of *Automation* and *Behavioral* interventions on total electricity usage

	TOT	F1	F2	F3
	(1)	(2)	(3)	(4)
DD^A	-723.225***	1.277	-278.983***	-445.519***
	(81.833)	(37.312)	(25.093)	(43.675)
DD^B	-71.805	42.776	-44.868***	-69.713**
	(59.758)	(28.248)	(17.100)	(32.869)
Observations	32,755	32,755	32,755	32,755
R^2	0.019	0.0003	0.056	0.038

Regression of monthly energy consumed (kWh) on treatment indicators. TOT denotes total energy consumption per, F1 consumption during peak working hours, F2 during low working hours and F3 during non-working hours. DD^A is the staggered difference-in-difference estimator for Automation. DD^B is the difference-in-difference estimator for Behavioral. Standard errors clustered at the branch level are reported in parentheses. *p < .05, ** p < .01, ***p < .001.

Table C.3. Average coefficients and SEs on 1000 random allocations to the staggered period

	TOT	F1	F2	F3
	(1)	(2)	(3)	(4)
DD^A	-1.919	-0.028	-0.721	-1.170
	(0.324)	(0.119)	(0.093)	(0.165)
DD^B	-0.257	0.063	-0.134	-0.187
	(0.200)	(0.104)	(0.044)	(0.095)

Coefficients and standard errors (in parenthesis) of the main specification, computed as mean of 1000 random assignments of Behavioral branches to $post_{it}^{A}$. TOT denotes total energy consumption per, F1 consumption during peak working hours, F2 during low working hours and F3 during non-working hours. DD^A is the staggered difference-in-difference estimator for Automation. DD^B is the difference-in-difference estimator for Behavioral.

Table C.4 Impact of *Automation* and *Behavioral* interventions on annual electricity usage

	TOT	F1	F2	F3
	(1)	(2)	(3)	(4)
DD^A	-2.143***	-0.060	-0.770***	-1.313***
	(0.405)	(0.153)	(0.111)	(0.213)
DD^B	-0.206	0.064	-0.112**	-0.158
	(0.210)	(0.102)	(0.046)	(0.103)

Observations	1,735	1,735	1,735	1,735
R^2	0.057	0.001	0.110	0.071

Regression of annual energy consumed per unit of surface (kWh/m2) on treatment indicators. Included years are 2015, 2018, and 2019. TOT denotes total energy consumption per, F1 consumption during peak working hours, F2 during low working hours and F3 during non-working hours. DD^A is the staggered difference-in-difference estimator for Automation. DD^B is the difference-in-difference estimator for Behavioral. Standard errors clustered at the branch level are reported in parentheses. *p < .05, ** p < .01, ***p < .001.

Table C.5 Placebo test for *Automation*

	TOT (1)	F1 (2)	F2 (3)	F3 (4)
DD^A	-0.332	0.078	-0.124	-0.285
	(0.291)	(0.113)	(0.077)	(0.155)
Observations	7,904	7,904	7,904	7,904
R^2	0.001	0.0001	0.002	0.002

Regression of monthly energy consumed per unit of surface (kWh/m2) on treatment indicators. We set a placebo start date for Automation in January 2016. We exclude the consumption after BEMS installation has started (August 2016) and we include the period January–August 2015 as fictitious pre-intervention period and January–August 2016 as fictitious post-intervention. TOT denotes total energy consumption per, F1 consumption during peak working hours, F2 during low working hours and F3 during non-working hours. DD^A is the difference-in-difference estimator for the placebo Automation treatment Standard errors clustered at the branch level are reported in parentheses. *p < .05, ** p < .01, ***p < .001.

Table C.6 Placebo test for *Behavioral*

	(1) TOT	(2) F1	(3) F2	(4) F3
DD^B	-0.156	0.090	-0.094	-0.151
	(0.185)	(0.103)	(0.049)	(0.096)
Observations	7,951	7,951	7,951	7,951
R^2	0.0001	0.0002	0.001	0.001

Regression of monthly energy consumed per unit of surface (kWh/m2) on treatment indicators. We set a placebo start date for Behavioral in May 2018. We exclude the consumption after the introduction of the behavioral program (January 2019) and we include the period May–December 2017 as fictitious pre-intervention period and May–December 2018 as fictitious post-intervention. TOT denotes total energy consumption per, F1 consumption during peak working hours, F2 during low working hours and F3 during non-working hours. DD^B is the difference-in-difference estimator for the placebo Behavioral treatment. Standard errors clustered at the branch level are reported in parentheses. *p < .05, ** p < .01, ***p < .001.

D. Programs heterogeneous effects

Table D.1 Heterogeneous impact of *Automation* and *Behavioral* interventions on electricity usage (non-significant interactions)

	F1 (1)	F1 (2)	F3 (3)	F1 (4)
DD^A	0.101	0.529	-1.603***	-0.325
	(0.113)	(0.391)	(0.387)	(0.264)
DD^B	-0.009	-0.170	-0.277	0.310
	(0.101)	(0.460)	(0.236)	(0.229)

DD^A x Pre	-0.272			
	(0.229)			
DD^B x Pre	0.143			
	(0.205)			
DD^A x Electric		-0.112		
		(0.084)		
DD^B x Electric		0.045		
		(0.106)		
DD^A x Employee			0.045	
			(0.027)	
DD^B x Employee			0.017	
			(0.019)	
DD^A x Surface				0.001
				(0.0003)
DD^B x Surface				-0.0004
				(0.0003)
Observations	32,755	32,376	32,755	32,755
R^2	0.002	0.013	0.024	0.002

Regression of monthly energy consumed per unit of surface (kWh/m2) on treatment indicators. Regressions include the post-treatments indicators interacted with the heterogeneity variables. TOT denotes total energy consumption per, F1 consumption during peak working hours, F2 during low working hours and F3 during non-working hours. DD^A is the staggered difference-in-difference estimator for *Automation*. DD^B is the difference-in-difference estimator for *Behavioral*. Pre is a continuous variable for average consumption before projects implementation (2015 for Automation, 2018 for Behavioral). Electric is a dummy equal to 1 if the branch has an electric air conditioning, 0 otherwise. Employees is a continuous variable for the number of employees at December 2018. Surface is a continuous variable for the squared meters. Standard errors clustered at the branch level are reported in parentheses. *p < .05, ** p < .01, ***p < .001.

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