“The Power of Nudging: Using Feedback, Competition and Responsibility Assignment to Save Electricity in a Non-Residential Setting”

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Abstract— We use behavioural insights to design nudges leveraging social comparison and assignment of responsibility aimed at reducing electricity consumption in a large provincial government office building with 24 floors. Results from a randomized control trial show that floors participating in a treatment with inter-floor competitions and tips reduced energy consumption by 9%, while those that also included floor-wise 'energy advocates" reduced energy consumption by 14% over a period of 5 months. These reductions – which are among the largest demonstrated in any utilities setting – cause us to re-evaluate the conventional wisdom that asserts that it is harder to nudge behaviour in non-residential settings (such as office buildings) where users do not face the financial consequences of their behaviour than it is in residential settings, where they benefit financially from conservation efforts.

JEL Codes: C90 C21 D03 L94 Q41

Keywords; Behavioural Nudges, Social Competition, Energy Conservation, Randomized Control Trials

1. INTRODUCTION

Global electricity generation is a major contributor to greenhouse gas emissions, as most economies rely heavily on fossil fuels for electricity production (Myhrvold and Caldera, 2012). In South Africa, coal-fired power stations account for over 90% of the electricity generated (Winkler, 2011). Together with its electricity being among of the world's cheapest (City of Cape Town, 2010), this contributes to South Africa currently being ranked among the top 12 emitters of carbon dioxide in the world (Global Energy Statistical Yearbook, 2017).

In 2010, South Africa committed itself to reducing greenhouse gas emissions by 34% by the year 2020 (Winkler et al., 2010), making energy conservation a top priority for both national and local governments. In the Western Cape Province – the country's fourth-largest by population and second largest by economic size – energy conservation efforts must address electricity usage in the City of Cape Town, which accounts for over half of provincial energy consumption and greenhouse gas emissions, with further challenges resulting from rapid urbanization and energy insecurity resulting in periodic "load-shedding" or brownouts.

Electricity consumption contributes 64% to carbon emissions in the City of Cape Town, with residential and commercial sectors accounting for 83% of its total electricity consumption (City of Cape Town, 2011). In thinking about energy (and particularly electricity) efficiency in Cape Town, it is, therefore, necessary to pay special attention to power consumption within these sectors, as well as to particular sub-sectors, such as government which, by being a major employer, is also a major user of electricity.

Policymakers and utility providers internationally and locally have experimented with a variety of ways to incentivise power conservation. The most used are traditional pricing methods such as peak–load pricing and the incentivisation of the adoption of energy-efficient appliances. However, price- based methods have been found to have several challenges in achieving energy conservation (see Allcott, 2011a).

More recently, studies (Brick & Visser, 2018; Brick et al., 2018; Sudarshan, 2017; Agarwal et al., 2016; Datta et al ., 2015; Allcott & Rogers 2014; Smith and Visser, 2014; Costa & Kahn, 2013; Schwartz et al. 2013; Allcott 2011b; Ayres et al. 2009) have emphasized the increasingly prominent role for behavioural, non-monetary interventions based on both recognition of non-price factors and evidence of effectiveness of nudges in achieving reduced energy and water consumption. A typical example is the extensive evaluation of behavioural interventions leveraging social norms on households' electricity and water use (Andor et al. 2017; Bernedo et al., 2014; Ferraro & Price, 2013; Allcott, 2011b; Allcott & Mullainathan, 2010) which have found sustained reductions of over 2% in residential utility consumption across a variety of settings.

Despite this large and growing evidence base about the effectiveness of behavioural interventions in curbing residential electricity use, there is very little research about the effects of such interventions on power use in the non-residential sector. Brown et al., (2013) intended to breach this gap by evaluating how behaviour change from adjusting default thermostat settings can affect energy consumption on a single floor in the OECD headquarters. Our study departs from the work of Brown et al., (2013) by implementing different nudges; social comparison and assignment of responsibility in 21office floors. Also, Delmas and Lessem (2014) investigate private and public information using students in residence halls in California despite the fact that students electricity consumption could be implicitly factored into their residence fees.

Office building context offers a unique case and can be more challenging than the residential sector for two reasons. First, unlike residential consumers, occupants of office buildings – who are not typically liable for electricity bills incurred by their use - do not have any direct financial incentives to reduce their energy use. Secondly, while the average residential household has four members, office floors can have between 50-200 individuals, making coordination much more challenging even where the will exists. At the same time, office buildings are major consumers of electricity in cities and towns worldwide, with the estimate for the United States being that offices consume about 14% of commercial power (US Energy Information Administration, 2017). There is, therefore an enormous need for innovation to develop, test and scale up effective behavioural interventions in this setting.

This paper contributes to filling this gap in knowledge. It describes the development and testing of a set of nudges (social competitions and assignment of responsibility) designed to affect electricity consumption in a single large provincial office building in the City of Cape Town. These nudges were tested in a randomised-control trial over the period June 2015 - October 2016. Floors were assigned to two treatment arms and a control group, with seven floors in each group. Floors in the first treatment arm received general energy conservation information emails and participated in weekly inter-floor competitions. Meanwhile, floors in the second treatment arm received both energy conservation information, participated in weekly inter-floor competitions and were also assigned a weekly energy "floor advocate". These nudges are described in detail in Section 3.

Our interventions led to large declines in electricity consumption, with a 9% reduction due to Treatment 1, and a 14% reduction in energy use from Treatment 2. These findings suggest the need to re-evaluate the conventional wisdom that it is harder to achieve reductions among employees who do not pay for their electricity use than it would be to achieve such reductions in a household setting.

The paper proceeds by first reviewing the literature on traditional price/tax policy instruments and evidence on the impact of behavioural interventions on electricity consumption. Section 3 presents the experiment overview and detailed experimental design of the study. We present data and estimation techniques in Section 4. This is followed by the results in Section 5, with discussion and conclusions presented in Section 6.

2. Literature Review

Policymakers seeking to dampen the demand for power typically use increases in price or information interventions that urge consumers to conserve power to achieve their goals (Allcott & Mullainathan, 2010). The basic microeconomic theory of consumer demand posits that dampening demand for a good can be done in two main ways. First, because demand curves slope down, raising the price of a good reduces the demand for it by moving consumers along a given demand curve. Secondly, since the position of the demand curve for a good reflects consumers' underlying preferences, affecting these preferences negatively can have the effect of shifting a given demand curve inwards, so that consumers demand less of it at any given price.

Price interventions include raising power tariffs, i.e. the unit price of electricity (either for all consumers or for consumers who consume more than a certain amount of electricity), raising taxes on electricity, and using peak-load pricing to affect the timing of consumption in order to enable utilities to better match demand to supply (see Munasinghe 1981). Policymakers also frequently use indirect price interventions to increase demand for products or services which have the effect of reducing demand for (conventionally produced) electric power. These include subsidies or other financial incentives for the adoption of energy-efficient household appliances, light-bulbs or smart energy meters (see Farrell and Remes 2009), and, increasingly, financial incentives to encourage the adoption of off-grid solar or other renewable sources of electricity in order to reduce demand for power (Sawin & Flavin, 2006; Whittington 1985).

On the information side, policymakers seeking to convince consumers to conserve power have focused on labelling of appliances (often in conjunction with the adoption of energy-efficiency standards; see Farrell and Remes 2009) to encourage the adoption of more energy-efficient models, and information or awareness campaigns designed to encourage energy conservation (see Rivas, Cuniberti and Bertoldi 2016 for an overview of evidence on such campaigns in the European Union).

However, human behaviour often departs from the prescriptions of strict economic rationality in systematic ways. Recent advances in the understanding of human behaviour and decision-making coming out of behavioural economics and the broader behavioural sciences suggest that the understanding of human behaviour that underlies classic price, and information interventions may overlook many ways in which human behaviour departs from the classical assumptions of economic rationality (see Mullainathan and Thaler, 2000).

Datta and Mullainathan (2014) argue that these departures from economic rationality can be understood as arising from behavioural economics having a different conception of scarce resources than neoclassical economics. Mullainathan and Thaler (2000) also argue that while economic theory recognises that human beings operate in an environment of scarce physical and financial resources, it often fails to recognize that mental or cognitive resources - from self-control to attention, to understanding, to cognitive capacity, are also limited.

These limits on human cognition and the effect of cognitive scarcity on decision-making can help explain the ineffectiveness of traditional economic interventions. For example, Chetty, Looney and Kroft, (2009) argues that taxes and other price shifts are often ineffective in reducing consumption levels because individuals may fail to notice such taxes, thus hindering their response to them. However, this broadened understanding of the influences on human decision-making also paves the way for new classes of interventions (ranging from commitment devices to timely reminders, to changes in the default).

Empirically, feedback mechanisms and social norms are behavioural intervention tools shown to effectively affect households and consumer behaviours in the area of efficiency and conservation. A review by Fischer (2008) on feedback mechanisms show that providing feedback on energy use to consumers yield energy savings from 1.1% to 20%. The magnitude of savings achieved by using feedback mechanisms is however dependent on the type of feedback (direct or indirect). Darby (2006) explains this in a review by showing that real-time smart meters (direct feedback) induce greater conservation effects than providing billing information on a periodic basis (indirect effect).

A growing body of literature in behavioural economics have applied a combination of feedback mechanism and social norms to test the impact of nudges on utilities. The best-known large-scale field trials of social norms have been the evaluation home energy report by Opower where randomised controlled trials are employed by studying several hundred thousands utility users across the United States. These reports reduced electricity consumption by 2% (Allcott 2011). LaRivere et al. (2014) in a follow-up study revealed that the effectiveness of the social comparison interventions of Opower depends on the form of the comparison; with comparisons expressed in terms of monthly expenditures and CO2 emissions yielding a 1% power use reduction for households initially above the mean and no rebound effect for those initially below it. More recently, Sudarshan (2017) show that weekly reports with peer comparisons of electricity use led households in urban India to reduce summer season consumption by 7%, with the impact of these peer comparisons alone being equivalent to increasing tariffs by about 12.5%.

Similarly, Ferraro and Price (2013) demonstrate the effectiveness of social norms on residential water consumption by conducting a large-scale field experiment on 100,000 households. They conclude that social norms could influence behaviour by achieving a similar effect that a 12%-15% price increase can yield. Furthermore, Smith and Visser (2014), Brick and Visser (2018) and Brick, Visser and De Martino (2018) estimate the reduction of water demand to be between 0.6% and 6% for the City of Cape Town when behavioural nudges are employed.

While evidence shows that behavioural interventions have been largely successful, there are also discussions about the long run impacts and welfare implications of such results, as well as potential spill overs. Ferraro, Miranda and Price (2011) examined the persistence of treatment effects associated with norm-based instruments by running field experiments with residential households to reduce water demand.They conclude that social comparisons have a long rum impact on water demand. Additionally, Brick, Visser and De Martino (2018) and Allcot and Rogers (2014) by continuing their behavioural nudges interventions for two further years found that about two-thirds of the initial treatment effect remained and concluded that reduction in water and energy consumption declines somewhat over time, but this does not disappear.

Allcott and Rogers (2014), Allcott (2011) and Allcott and Mullainatan (2010), further suggest that Opower home energy reports are cost-effective norm-based interventions that can induce energy conservation. However, Andor et al., (2017) based on a randomised control trial in Germany, show that this could be different outside the US where electricity consumption is much lower. Their results suggest that home energy report interventions can only achieve cost-effectiveness if treatment effects are higher. Whittington and Nauges (2017) share a similar view, by demonstrating the uncertainty associated with adopting social norms compared to increasing the price of water for residential users. In this paper, we show how behavioural interventions in an office building context can become a cost-effective way of achieving reductions in employees' energy consumption.

Additionally, potential spillovers are likely when designing behavioural interventions. Jaime Torres and Carlson (2016) investigates this phenomenon by assessing the effects of spillovers from social information campaigns on residential water demand in Colombia. Their results show that interventions directly reduced water demand by 6.8% while untargeted households (control) reduced water usage by 5.8 % in the first six months. This suggests that we can indirectly achieve the desired reduction in utility consumption through spillovers of information to control groups resulting in smaller treatment effect size.

Although behavioural interventions have been successful in reducing household electricity consumption, there is little research to show reductions in energy consumption in commercial settings (Delmas & Lessem, 2014). Brown et al., (2013) addressed the question "how much does changing the default setting in office thermostats affect the chosen thermostat settings in offices?" They concentrate on the first floor of the OECD Marshall Building which has 93 offices. Our study departs from this study by using social comparisons and assignment of responsibility as intervention measures where employees' energy conservation is compared across 21 floors. One potential reason for such limited non-residential studies may lie in the different relationship between consumption reductions and financial savings between residential and commercial settings. In a residential setting, the household itself is the marginal claimant of any financial savings due to decreased energy use. That is not the case in commercial settings, where hundreds of people may be drawing off of the same energy network. Here, any financial savings will accrue to the organization, and not individual employees.

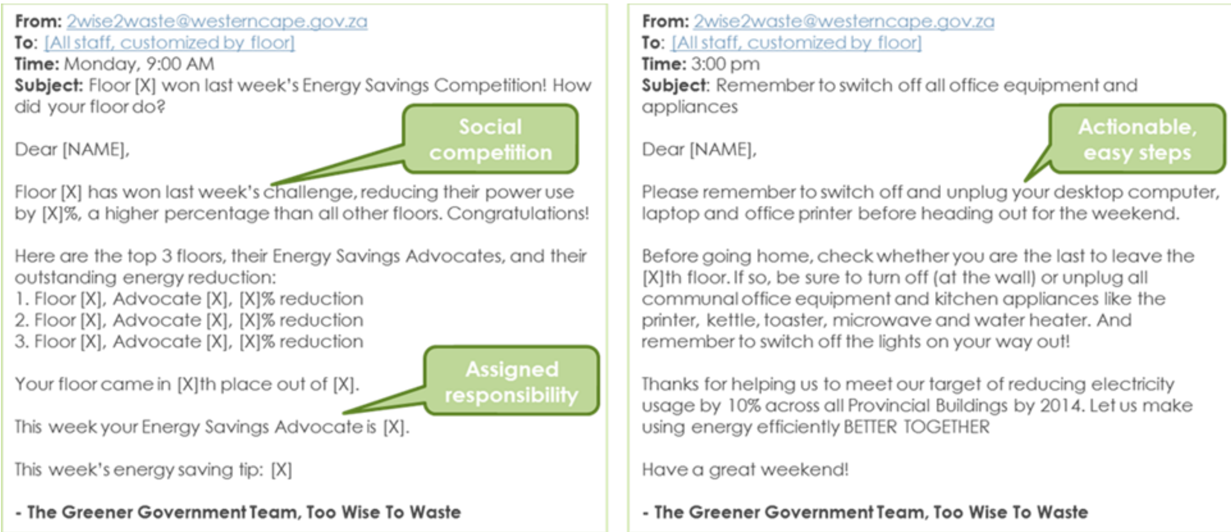
This study fills the gap in the literature by examining the effect of behavioural interventions on electricity consumption in a governmental office building in the City of Cape Town.

3. Experiment Overview

3.1 Intervention Development

Before the commencement of the experiment, we diagnosed six major bottlenecks impeding energy efficient behaviour through interviews, focus groups and site visits. These six bottlenecks include *1.Diffused Responsibility*: Employees are often unsure whose responsibility it is to turn appliances and lights off at the end of the day. *2. Moral Justification:* Employees consider public service as their sole contribution to the environment, rather than reducing personal energy consumption. *3. Unit Confusion:* It is unclear to employees how small individual behaviours translate into and affect energy efficiency. *4. Limited Attention:* Employees sometimes simply forget to turn off devices. *5. Identity:* While at work, employees do not think about translating their energy efficient behaviours at home to the office. *6. Social Norms:* Employees do not know how much energy their colleagues use and therefore have no reference point for how energy efficient they are.

We subsequently designed intervention components to respond to and mitigate the observed bottlenecks by using automated email system to test the effect of different isolated messages that incorporate the following intervention components: *1. Providing information* – Giving easy-to-understand information regarding energy use that employees can easily translate into action and also place specific behaviours into a context that is familiar to them. *2. Social Competition* – A program that compares employees' energy use with other floors to foster a sense of competition and provide regular feedback. *3. Assigning Responsibility* – Assigning given employee's responsibility for energy consumption. For example, one employee is randomly singled out on a weekly basis as the "energy champion" for the entire floor. This employee is subsequently given specific tasks throughout the week (e.g., "turn off lights at the end of the day", "turn off the water heater", "unplug the printer"). *Figure 1* shows sample emails received by treatment floors. *(See Appendix A for other emails)*


From: 2wise2waste@westerncape.gov.za
To: [All staff, customized by floor]
Time: Monday, 9:00 AM
Subject: Floor [X] won last week's Energy Savings Competition! How did your floor do?

Dear [NAME],

Floor [X] has won last week's challenge, reducing their power use by [X]%, a higher percentage than all other floors. Congratulations!

Here are the top 3 floors, their Energy Savings Advocates, and their outstanding energy reduction:
1. Floor [X], Advocate [X], [X]% reduction
2. Floor [X], Advocate [X], [X]% reduction
3. Floor [X], Advocate [X], [X]% reduction

Your floor came in [X]th place out of [X].

This week your Energy Savings Advocate is [X].

This week's energy saving tip: [X]

- The Greener Government Team, Too Wise To Waste

From: 2wise2waste@westerncape.gov.za
To: [All staff, customized by floor]
Time: 3:00 pm
Subject: Remember to switch off all office equipment and appliances

Dear [NAME],

Please remember to switch off and unplug your desktop computer, laptop and office printer before heading out for the weekend.

Before going home, check whether you are the last to leave the [X]th floor. If so, be sure to turn off (at the wall) or unplug all communal office equipment and kitchen appliances like the printer, kettle, toaster, microwave and water heater. And remember to switch off the lights on your way out!

Thanks for helping us to meet our target of reducing electricity usage by 10% across all Provincial Buildings by 2014. Let us make using energy efficiently BETTER TOGETHER

Have a great weekend!

- The Greener Government Team, Too Wise To Waste

Figure1: Emails depicting social comparison and responsibility assignment

3.2 Experimental Design

The experiment was conducted in 4 Dorp Street, a large office building in Cape Town with twenty-four floors, where several provincial government departments are headquartered. Two smart meters each were installed on all floors in the building before the start of the study. These meters were closely monitored for two years while correcting for problems such as anomalies in meter readings, meter breakdowns and tracking of floor inventories. At the end of the "testing period[1]", only twenty-one floors of the twenty-four floors in the 4th Dorp street office building were eligible experimental floors for the study[2]. Out of these twenty-one floors, seven floors are randomly allocated to a control group, and the other fourteen floors are equally allocated to Treatment I and Treatment II groups respectively as depicted in *Figure 2*.

[1] Period before the start of baseline data

[2] The three exempted floors include the ground floor which served as a security checkpoint and access area for visitors while the other two floors were empty due to renovations at the start of the experiment.

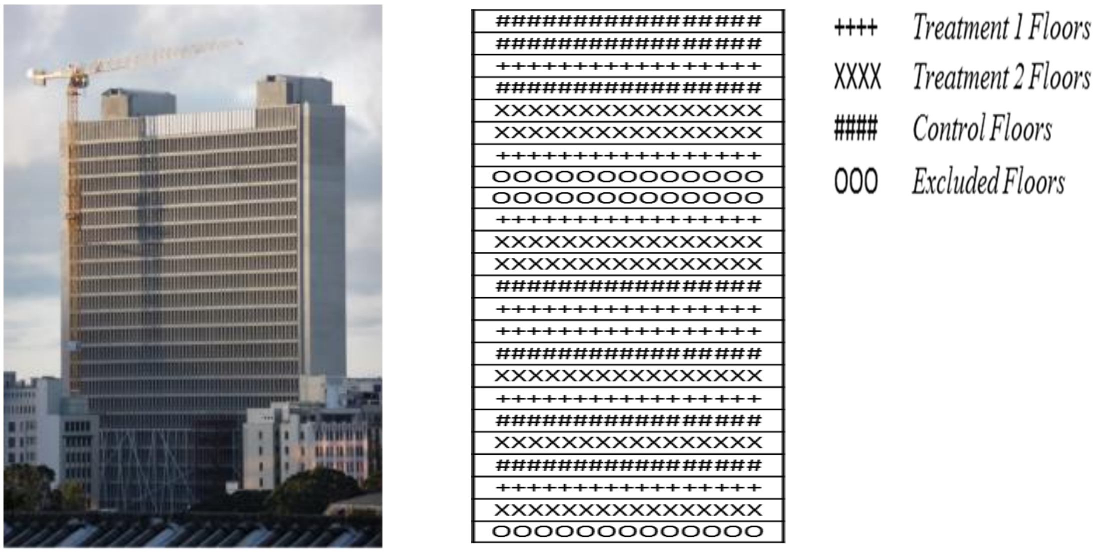


Figure 2: 4 Dorp Street office building and experimental assignment of floors

Based on our designed intervention components, members on treatment floors received specific emails at different time intervals. Floors assigned to Treatment I received both emails that include general information on actionable steps to reduce energy consumption and weekly inter-floor competition results. On the other hand, Treatment II floors received both general information emails, weekly inter-floor competition results and an additional weekly assignment of one person on the floor as an energy champion. The control floors did not receive any emails.

The frequency at which these emails were sent out are as follows: Floor members received general information on how to conserve energy every first Monday of the month. Reminders to turn off light were received every Friday. Kitchen tips were sent out every third Wednesday of the Month. Finally, inter-floor competition results for the week and assignment of new floor energy advocates were received every Monday.

Table 1 gives an overview of the order in which the experiment was run and corresponding start dates and observations. The pre-intervention period ran from June 2015 to October 2015. We spent November 2015 –April 2016 fine-tuning and monitoring the automated email system. During this period occupants of both treatment floors only received general information on ways to reduce electricity consumption. The full roll-out of our study referred to here as “full fidelity period’ where Treatment I floors received general information and weekly inter-floor competition results while Treatment II floors received general information, weekly inter-floor competition results and assignment of a weekly floor energy advocate, commenced in June 2016.

Table 1: Overview of the Experiment

Order of Rollout	Start Date	Observations
Baseline	June 2015- October 2015	262,327
Email System Testing Period	November 2015 – April 2016	278,474
Full fidelity Period – Rollout of Inter-floor competition and assignment of floor advocate	June 2016 – October 2016	266,601

4. Data and Estimation

4.1 Baseline Characteristics

The paper analyses a panel of energy use data for 21 experimental floors for the period 2015-2016. This is possible as the 42 installed smart meters on these floors feed in data every 30 minutes. The high frequency of meter readings gives us a large number of observations despite the limited number of floors used for the experiment.

Table 2 presents descriptive statistics for the experiment. On the average, electricity usage for floors in 4 Dorp office building ranges from 2.49 to 2.59 kilowatts (kW) for every thirty minutes. This implies the daily electricity consumption per floor ranges from 119.52– 124.32[3] kWh. The baseline electricity usage is balanced between the control and treatment floors as depicted by the standard errors in the parenthesis of the fifth column.

Table 2: Pre-intervention Randomization Checks

Variables	Control	Treatment 1	Treatment 2	$\overline{kW_o}$ (kW/30mins)	$kW_0^T - kW_0^c$ Difference
Energy Consumption	2.49	2.59	---	2.54	0.10
	(0.34)	(0.34)		(0.24)	(0.48)
		-	2.49	2.49	-0.003
			(0.38)	(0.26)	(0.52)
Headcount	41.34	42.96	---	42.15	1.61
	(5.96)	(5.96)		(4.21)	(8.43)
		-	34.94	38.36	-6.41
			(6.61)	(4.49)	(9.01)

Standard errors in parenthesis, clustered at floor level. Pre-intervention period: June – October 2016

Apart from electricity usage for floors, we also present a balance test for the number of people occupying these floors, namely the floor headcount. Once again, the number of floor occupants during the baseline period is balanced between the control and treatment floors. Indicating that on the average, both control and treatment floors had the same number floor occupants during the baseline. Given that the number of people occupying a floor can largely influence the amount of electricity a floor will use, we include the headcount variable as a covariate in our subsequent analysis.

4.2 Estimation

We use a difference-in-difference (DiD) specification to evaluate the impact of routine behavioural interventions on energy consumption. This is done by comparing electricity

[3] 2.49 X2 X 24 = 119.52 ; 2.59 X2 X 24 = 124.32

consumption levels of Treatment I and II floors to control floors. The equation of interest is specified below:

$$kw_{it} = \alpha_i + \delta_0 A_{it} + +\delta_1 T_{it}^1 + \delta_2 T_{it}^2 + \gamma_1 T_{it}^1 A_{it} + \gamma_2 T_{it}^2 A_{it} + X_{it}' \beta + \varepsilon_{it} \quad (1)$$

Where kw_{it} is the amount of electricity consumed by individual meters i on each floor at time t in kilowatts/30minutes, $T^1=1$ if meter readings are from Treatment I floors at time t, $T^2=1$ if meter readings are from Treatment II floors at time t. $A=1$ for the post intervention indicator, δ_0 is the time trend common to control and treatment floors, δ_1 and δ_2 are Treatment I and II specific effects which accounts for average time-invariant differences between the treatment and control floors, γ_1 measures the average Treatment I effect, γ_2 measures the average Treatment II effect X_{it} represent the covariates; headcount and monthly fixed effects. ε_{it} is the error term.

The average treatment effect which is the difference-in-difference estimate, therefore, compares the difference between the treatment floors before and after they received intervention emails and the difference between the before-and-after outcomes of the control floors which did not receive the intervention emails but shared similar consumption characteristics (Khander et al., 2010). Therefore, the average impact of social competition and assigned responsibility is estimated as follows:

$$DD_1 = E[kw_{i1}^{T1} - kw_{i0}^{T1}] - \left[kw_{i1}^{C} - kw_{i0}^{C}\right] \quad (2)$$

$$DD_2 = E[kw_{i1}^{T2} - kw_{i0}^{T2}] - \left[kw_{i1}^{C} - kw_{i0}^{C}\right] \quad (3)$$

To account for the unobserved heterogeneity, we use the standard panel OLS fixed effect estimator with robust standard errors. These standard errors are clustered at the meter level given that electricity consumption data is obtained from two unique meters installed on each floor.

5. Results

5.1 Average Treatment Effect

In *Table 3* we present estimation results and their corresponding percentage reductions for the intervention period for different configurations of monthly dummies[4]. Our primary estimation is, however, column two which includes the monthly dummies. Even though we validated 21 floors during the pre-intervention period of June 2015 – October 2015, at the time of starting our interventions in June 2016, one of the floors had a malfunctioning meter and was subsequently dropped from the study explaining why our estimations report on only 20 floors.

Results show that on the average, for every 30 minutes, meters on Treatment II floors consume about 0.349 kilowatts less than control floors in Column (2). From the average treatment effect (ATE) reported we further calculate the percentage reduction using the pre-intervention average electricity consumption values. This implies a 14% reduction (at 10% level of significance) for Treatment II floors (general energy conservation information + inter-floor

[4] As a robustness check, we also estimate a pooled panel OLS regressions which includes both monthly and floor fixed effects using the "xtreg" command in Stata. Results are consistent with the presented results in Table 3 as shown in Appendix B.

competition *with weekly feedback + advocates).* However, the reduction in electricity consumption for Treatment I floors in Column (2) appears to be insignificant.

Table 3: Average Treatment Effects of Interventions on Energy Consumption

VARIABLES	(1) kW/30mins	(2) kW/30mins	(3) kW/30mins
Post	-0.124**	-0.149*	0.000877
	(0.0576)	(0.0777)	(0.125)
Treatment 1 X Post	**-0.116**	**-0.119**	**-0.215***
	(0.168)	(0.169)	(0.123)
Treatment 2 X Post	**-0.324***	**-0.349***	**-0.351****
	(0.180)	(0.179)	(0.179)
Treatment 1	-	-	-
Treatment 2	-	-	-
headcount	0.0148***	0.0171***	0.0173***
	(0.00458)	(0.00470)	(0.00472)
Constant	1.928***	1.846***	1.799***
	(0.190)	(0.190)	(0.184)
Monthly Fixed effects	No	Yes	Yes
Observations	528,928	528,928	502,030
R-squared	0.010	0.014	0.017
F(P-Value)	0.00	0.00	0.00
Control	185,521	185,521	185,521
Treatment1	182,840	182,840	155,942
Treatment 2	160,567	160,567	160,567
Number of floors	20	20	19
Number of meters	40	40	38
Percentage Reduction:			
Treatment 1		**5%**	**9%**
Treatment 2		**14%**	**14%**

Fixed Effects Regressions. Robust standard errors in parentheses clustered at meter level *** p<0.01, ** p<0.05, * p<0. Pre-intervention period: June – October 2015

In column 3 we present regression results without floor 22. This floor was allocated to Treatment I group. However, meter readings indicated that floor 22 was the only floor reporting an increase in energy consumption during the intervention period. Further investigation through site visits and qualitative interviews with floor occupants show that an additional water heating equipment was installed on this floor during the intervention period. We, therefore, show the regression results in column 3 by excluding floor 22 from the analysis. Given this preferred model specification, general energy conservation information, inter-floor competition with weekly feedback and advocates (Treatment II) resulted in the same level of 14% reduction in electricity consumption but now at a 5% significance level. Further, Treatment I floors who received only general energy conservation information and inter-floor competition with weekly feedback subsequently show a reduction of 9% in electricity use significant at a 10% level.

5.2 Attenuation effect

To demonstrate the sustainability of our results over time, we systematically run regressions monthly by adding on to the initial post-intervention month (June 2016). *Table 4* shows an initial decline in percentage reduction for the combined intervention effect of the provision of general energy conservation information, inter-floor competition and assignment of floor energy advocate as we add more months to the estimation, with the treatment effect becoming less significant as more time elapsed (from 5% to a 10% level of significance). Results show that on the average, Treatment II floors reduced electricity consumption by about 0.36 - 0.49 kW for every 30 minutes depending on the period of estimation. Specifically, in Column 1 for the month of June, Treatment II floors recorded a 0.63kW decline in electricity consumption for every 30 minutes relative to control floors. Using pre-intervention average consumption values, this indicates a 28% reduction.

Table 4: Attenuation Effect

VARIABLES	(1) June	(2) June- July	(3) June- August	(4) June- September
Post	0.0877	0.0988	0.00642	0.0172
	(0.226)	(0.171)	(0.135)	(0.136)
Treatment 1 X Post	-0.359	-0.314	-0.213	-0.167
	(0.259)	(0.197)	(0.188)	(0.172)
Treatment 2 X Post	**-0.630****	**-0.511****	**-0.371***	**-0.347***
	(0.294)	(0.224)	(0.219)	(0.192)
Treatment 1	-	-	-	-
Treatment 2	-	-	-	-
headcount	0.0250***	0.0184***	0.0159**	0.0163***
	(0.00804)	(0.00621)	(0.00615)	(0.00465)
Constant	1.579***	1.814***	1.894***	1.879***
	(0.282)	(0.228)	(0.230)	(0.186)
Monthly Fixed Effects	Yes	Yes	Yes	Yes
Observations	88,189	201,570	320,176	432,528
R-squared	0.015	0.011	0.010	0.011
Control	30,721	70,386	111,787	151,580
Treatment 1	30,725	70,223	111,716	149,715
Treatment 2	26,743	60,961	96,673	131,233
F (P-Value)	0.007	0.002	0.000	0.000
Number of Floors	20	20	20	20
Number of meters	40	40	40	40
Percentage Reduction:				
Treatment 2	28%	20.9%	15.3%	14.1%

Fixed Effects Regressions. Robust standard errors in parentheses clustered at meter level *** p<0.01, ** p<0.05, * p<0. Pre-intervention period for each estimation commensurate that of previous year's. The percentage reduction the for June- October 2016 is already established in Table 3 (main regression) to be 14%

Interestingly, the rate at which the percentage reductions attenuates slows down as we continue to add more months. For instance, a movement from June to the period June-July (two months post-intervention) saw about 7.1% reduction from the initial 28% reduction in electricity use achieved in June to a 20.9% in June-July. Further, moving from the period June- July to the period June-August (three-months post-intervention) an attenuation effect of 5.6% is recorded which is below the previously reported 7.1%. As we move to four- month's post-intervention period (June-September) the attenuation effect dropped to only about 1%. By the fifth month of the post-intervention period (June- October[5]), these declines completely die out as shown in figure 3. This implies that despite the decline in our treatment effect size in the initial months, the decline gradually fades out and eventually stabilize by the fifth month of intervention.

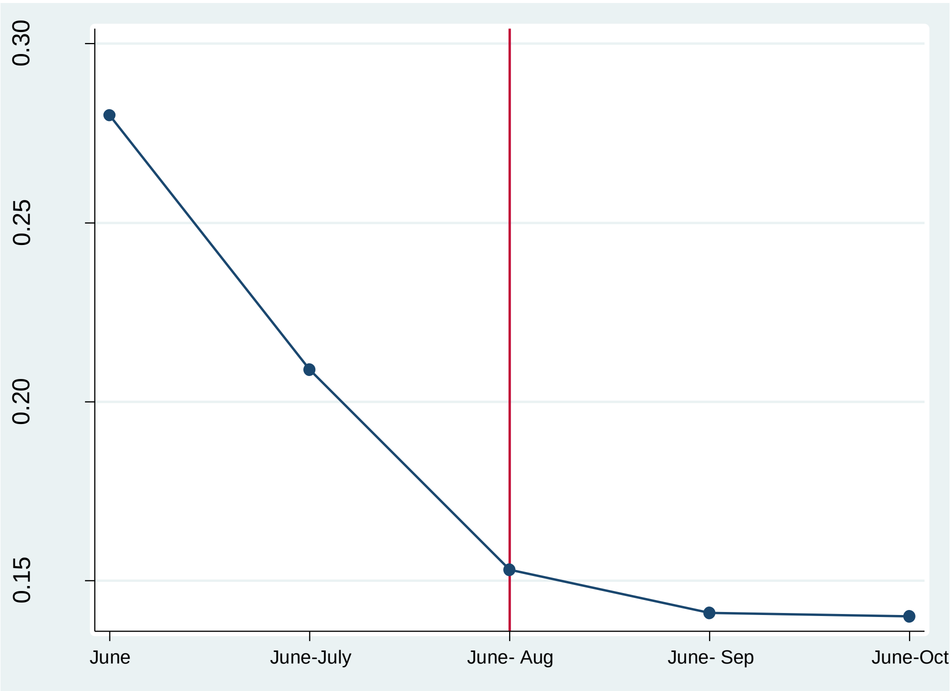


Figure 3: Percentage Reduction

5.3 Effect at different time periods within the day

The average treatment effect for working and non-working hours is presented in *Table 5*. During working hours both Treatment I and Treatment II floors did not yield any significant reduction in electricity use even though Treatment II floors showed a marginally higher decrease in consumption compared to Treatment I floors. However, during out of business hours, electricity usage is much lower for Treatment II floors (at 5% significance level) implying that the main way Treatment II seems to have worked better than Treatment I floors is by empowering the floor advocates to either turn off or ask people to turn off appliances at the end of the workday.

[5] As shown in Table 3

Table 5: Energy conservation and Working Hours

	(1)	(2)
VARIABLES	Working hours	Non-working hours
Post	-0.449***	0.113
	(0.137)	(0.123)
Treatment1 X Post	-0.0650	-0.149
	(0.203)	(0.172)
Treatment 2 X Post	**-0.201**	**-0.440****
	(0.207)	(0.183)
Treatment 1	-	-
Treatment 2	-	-
headcount	0.0232***	0.0135***
	(0.00600)	(0.00434)
Constant	2.899***	1.206***
	(0.258)	(0.162)
Observations	198,836	330,092
R-squared	0.029	0.019
F (P-Value)	0.00	0.00
Control	69,704	115,817
Treatment 1	68,977	113,863
Treatment 2	60,155	100,412
Number of floors	20	20
Number of meters	40	40

Robust standard errors in parentheses clustered at meter level *** p<0.01, ** p<0.05, * p<0.
Pre-intervention period: June – October 2015

5.4 Qualitative Findings

Findings from qualitative research carried out after the conclusion of the experiment is helpful in illuminating some of the mechanisms through which our intervention may have operated. Two major sets of findings stand out from our follow-up surveys.

First, the impressive overall reductions in electricity use due to Treatment II mask considerable variation in how occupants on different floors responded to our nudges. While some treatment floors worked as a team to reduce energy consumption, other floors were lukewarm towards the routinely sent emails. The net effect of such behaviours resulted in an ultimate decline in electricity use for some treatment floors. However, any scale-up of such interventions should take into account such differences in behaviour.

Secondly, interviews with floor occupants confirmed our empirical results about effects being concentrated outside office hours, as major initiatives by floor advocates were implemented after working hours. For instance, unlike before the interventions, floor occupants became conscious of unplugging office equipment, heaters and lights at the end of the day.

5.4 Cost Effectiveness

Assessing the overall cost-effectiveness and the potential for scaling interventions up in other provincial buildings in the Western Cape is important and requires comparing the value of savings achieved due to the intervention and how this compares to the costs of installing energy meters and associated consultancy fees.

In *Figure 4*, we first reflect on the average annual energy (kWh) consumed per floor in the 4 Dorp Street building in the year of study and further project this to the year 2020 with an assumption that electricity prices continue to rise at a rate of 15% every year, which is consistent with the most recent historical trends. We then multiply the average energy consumption per floor (6606 kWh) by an average cost of 0.7987 c/kWh for Small Power Users such as 4 Dorp Street Building which amounts to R5271 per month as indicated in *Table 6*. The costing for 21 floors is then about R110, 842 per month and R1,330,090 annually[6].

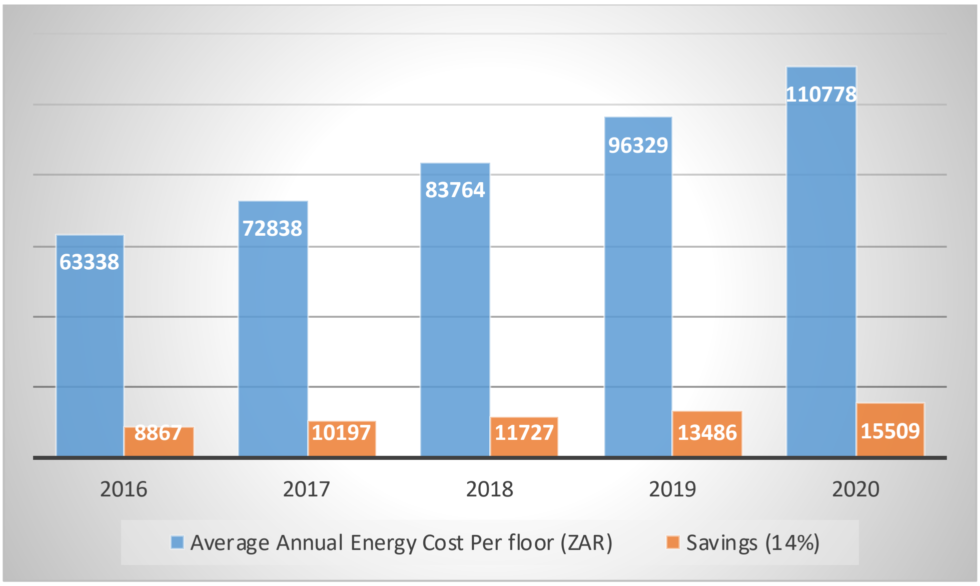


Figure 4: Projected cost of annual energy consumption and savings based on Treatment II floors percentage reductions

[6] As a cross check this corresponds well to the energy costing for 4 Dorp Street Building (as 0,45% of the Annual Energy Consumption value - Combined Consumption for Wale and Keerom St - reported in the Report provided by Public Works for 2014/5)

Table 6: Costs and Savings

		Rands	Savings (14%)
Total average annual cost per floor over five years		R427 047	R 59,786
Average installation cost per floor (2 meters)	R21, 210		
Average additional costs (consulting fees etc.)	R35, 933		
Total Costs of installation per floor	R57, 143		
Years to recoup installation costs			<2(1/2)
Years to recoup total costs			<5
Annual Savings after costs recouped (R's 2020)			R14,955
Annual Savings for 21 floors (R's 2020)			R325,668

Assuming the 14% reductions reported from Treatment II intervention is sustainable and that attenuation of energy savings stabilise as shown in figure 3 or can even be avoided through regular incentivising awards or announcements, total savings over a five year period (assuming energy prices rises at 15% per year) would be R59,786 per floor. The installation cost of meters – R21 210 per floor would, therefore, be recouped within two-and-a-half years after rolling out these interventions. Also, when we account for additional costs of consultancies etc., the total initial costs would amount to R57 143 per floor. In line with the projected savings described above these full expenses would, therefore, be covered in less than five years, after which annual savings would amount R325, 668 (using 2020 consumption figures and prices).

6 Discussion and Conclusion

Treatment II floors, which received general energy conservation emails, weekly inter-floor competition results and an assignment of weekly energy floor advocates, achieved a 14% reduction (at a 5% level of significance) in electricity use relative the control group. Meanwhile, treatment I floors, having received general energy conservation information and also having participated in the weekly inter-floor competition, achieved a 9% reduction in electricity consumption (significant at the 10% level) after accounting for the anomalous data from floor 22.

These are remarkable reductions, given that other studies using similar nudges (with residential households) have typically resulted in only 1-7% (maximum) reductions (Brick et al., 2018; Sudarshan, 2017; Agarwal et al., 2016; Allcott and Rogers 2014; Costa & Kahn, 2013; Schwartz et al. 2013; Allcott 2011; Ayres et al., 2009). Even though our findings are consistent with the work of Ivanov et al. (2013), who found a 15% decline in energy use on peak days and Gans, Alberni and Longo (2013) who reported a decline in energy usage of about 11-17%, both were only able to achieve such effects with residential households after installing programmable thermostats.

In conclusion, we note areas of significance and those that merit further investigation. As discussed earlier, our findings are not just impressive in terms of effect size, but particularly encouraging insofar as occupants of our intervention floors are employees who are not incentivised by monetary savings. The results of this study are therefore a reason to re-evaluate the conventional wisdom that it is harder to achieve reductions in such a setting.

At the same time, List and Metcalfe (2014) suggest that the sustainability and the efficacy of such results over time are major concerns. Indeed, our month-by-month estimates show a gradual decline in the treatment effect, implying that energy reductions are likely to decline over time, however, from our study, this decline in energy reductions dwindles with time and stabilise in the fifth month. Allcot and Rogers (2014) examined the persistent levels of treatment effect arising from social norms and other behavioural nudges by continuing interventions for two further years. They found that about two-thirds of the initial treatment effect remained and concluded that reduction in energy consumption declines somewhat over time, but does not disappear. As we unable to estimate the longrun effect of our interventions, research to establish the durability of the effects we find would be a critical input into efforts towards the sustainably and effectively use of nudges in the commercial sector. In the context of maintaining behavioural results from competition, our interventions could be recalibrated or incentivized anew by awarding prizes, announcement of advocates' names for winning floors on the screens in the foyer of the building and even media releases recognizing the "winners" to keep competing groups motivated. Given the duration and focus of the study we did not experiment with such measures, but it is definitely an avenue for future research.

References

Andor, M. A., Gerster, A., Peters, J., & Schmidt, C. M. (2017). *Social norms and energy conservation beyond the US* (No. 714). Ruhr Economic Papers.

Agarwal, S., Rengarajan, S., Sing, T. F., & Yang, Y. (2017). Nudges from school children and electricity conservation: Evidence from the "Project Carbon Zero" campaign in Singapore. *Energy Economics*, *61*, 29-41.

Allcott, H. (2011). Rethinking real-time electricity pricing. *Resource and energy economics*, 33(4), 820-842.

Allcott, H. (2011). Social norms and energy Conservation. *Journal of public Economics*, *95*(9-10), 1082-1095.

Allcott, H., & Mullainathan, S. (2010). Behavior and energy policy. *Science*, *327*(5970), 1204-1205.

Allcott, H., & Rogers, T. (2014). The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation. *American Economic Review*, 104(10), 3003-37.

Ayres, I., Raseman, S., & Shih, A. (2013). Evidence from two large field experiments that peer comparison feedback can reduce residential energy usage. *The Journal of Law, Economics, and Organization*, 29(5), 992-1022.

Bernedo, M., Ferraro, P. J., & Price, M. (2014). The persistent impacts of norm-based messaging and their implications for water conservation. *Journal of Consumer Policy*, 37(3), 437-452.

Brick, K., & Visser, M. (2018). Green nudges in the DSM toolkit: Evidence from drought-stricken Cape Town. Draft Paper, University of Cape Town, DOI: 10.13140/RG.2.2.16413.00489.

Brick, K., Demartino, S., Visser, M,. 2018. Behavioural nudges for water conservation: Experimental evidence from Cape Town, Draft Paper, University of Cape Town, DOI: 10.13140/RG.2.2.25430.75848

Brown, Z., Johnstone, N., Haščič, I., Vong, L., & Barascud, F. (2013). Testing the effect of defaults on the thermostat settings of OECD employees. *Energy Economics*, 39, 128-134.

CDIAC (2012). List of Countries by 2010 Emission Estimates. United States Department of Energy's Carbon Dioxide Information Analysis Centre. http://cdiac.ornl.gov/trends/emis/perlim_2009_2010_estimates.html.

Chetty, R., Looney, A., & Kroft, K. (2009). Salience and taxation: Theory and evidence. *American economic review*, 99(4), 1145-77.

City of Cape Town: Energy for Large Cities Report. World Energy Congress 2010

City of Cape Town: Moving Mountains Cape Town Action Plan for Energy and Climate City of Cape Town. First edition November 2011.

Costa, D. L., & Kahn, M. E. (2013). Energy conservation "nudges" and environmentalist ideology: Evidence from a randomized residential electricity field experiment. *Journal of the European Economic Association*, *11*(3), 680-702.

Darby, S. (2006). The effectiveness of feedback on energy consumption. *A Review for DEFRA of the Literature on Metering, Billing and direct Displays*, 486(2006), 26.

Datta, S., Josï, J., Zoratto, L., Calvo-Gonzï, O., Darling, M., & Lorenzana, K. (2015). *A behavioral approach to water conservation: evidence from Costa Rica*. World Bank.

Datta, S., & Mullainathan, S. (2014). Behavioral design: a new approach to development policy. *Review of Income and Wealth*, *60*(1), 7-35.

Delmas, M. A., & Lessem, N. (2014). Saving power to conserve your reputation? The effectiveness of private versus public information. *Journal of Environmental Economics and Management*, 67(3), 353-370.

Eberhard, A. (2011). The future of South African coal: Market, investment and policy challenges. *Program on energy and sustainable development*, 1-44.

Farell, D., & Remes, J. (2009). Promoting energy efficiency in the developing world. *McKinsey & Company*.

Jaime Torres, M. M., & Carlsson, F. (2016). Social Norms and Information Diffusion in Water-saving Programs: Evidence from a Randomized Field Experiment in Colombia.

Fischer, C. (2008). Feedback on household electricity consumption: a tool for saving energy?. *Energy efficiency*, 1(1), 79-104.

Ferraro, P. J., Miranda, J. J., & Price, M. K. (2011). The persistence of treatment effects with norm-based policy instruments: evidence from a randomized environmental policy experiment. *American Economic Review*, 101(3), 318-22.

Ferraro, P. J., & Price, M. K. (2013). Using nonpecuniary strategies to influence behavior: evidence from a large-scale field experiment. *Review of Economics and Statistics*, 95(1), 64-73.

Jaime Torres, M. M., & Carlsson, F. (2016). Social Norms and Information Diffusion in Water-saving Programs: Evidence from a Randomized Field Experiment in Colombia. *EfD Discussion Paper Series* 16-05.

Gans, W., Alberini, A., & Longo, A. (2013). Smart meter devices and the effect of feedback on residential electricity consumption: Evidence from a natural experiment in Northern Ireland. *Energy Economics*, 36, 729-743.

Global Energy Statistical Yearbook (2017).

Ivanov, C., Getachew, L., Fenrick, S. A., & Vittetoe, B. (2013). Enabling technologies and energy savings: the case of energywise smart meter pilot of connexus energy. *Utilities Policy*, *26*, 76-84.

Khandker, S. R., Koolwal, G. B., & Samad, H. A. (2010). Handbook on Impact Evaluation: Quantitative Methods and Practices, the International Bank for Reconstruction and Development/the World Bank.

LaRiviere, J., Holladay, S., Novgorodsky, D., & Price, M. K. (2014). Prices vs. nudges: a large field experiment on energy efficiency fixed cost investments. *NBER Working Paper*, 22939.

List, J.A. and R. Metcalfe (2014). "Introduction to Field Experiments." *Oxford Review of Economic Policy* 30(4): 585-596.

Munasinghe, M. (1981). Principles of modern electricity pricing. *Proceedings of the IEEE*, *69*(3), 332-348.

Myhrvold, N. P., & Caldeira, K. (2012). Greenhouse gases, climate change and the transition from coal to low-carbon electricity. *Environmental Research Letters*, 7(1), 014019.

Mullainathan, S., & Thaler, R. H. (2000). *Behavioral economics* (No. w7948). National Bureau of Economic Research.

Ostrom, E. (1998). A behavioral approach to the rational choice theory of collective action: Presidential address, American Political Science Association, 1997. *American*

Political Science Review, 92(1), 1-22.
Sawin, J., & Flavin, C. (2006). National policy instruments: Policy lessons for the advancement & diffusion of renewable energy technologies around the world. *Renewable Energy. A Global Review of Technologies, Policies and Markets*.
Schwartz, D., Fischhoff, B., Krishnamurti, T., & Sowell, F. (2013). The Hawthorne effect and energy awareness. *Proceedings of the National Academy of Sciences*, 110(38), 15242-15246.
Rivas S., Cuniberti B., & Bertoldi P. (2016). Information measures to promote energy use reduction across EU Member States, *JRC Science for Policy Report*, European Commission.
Smith, G. and Visser, M. (2014). Behavioral Nudges as a Water Savings Strategy. *WRC Report*,No. 2091/1/13 ISBN 978-1-4312-0508-0.
Sudarshan, A. (2017). Nudges in the marketplace: The response of household electricity consumption to information and monetary incentives. *Journal of Economic Behavior & Organization*, 134, 320-335.
US Energy Information Administration, 2017.
Whittington, D. (1985). Examination of tax credits for solar hot-water-heating systems. *Energy Systems Policy*; United States, 9(2).
Whittington, D & Nauges, C. (2017). Social Norms Information Treatments in the Municipal Water Supply Sector: Some New Insights on Benefits and Costs. *EfD Discussion Paper Series* 17-16.
Winkler, H. (2011). *Cleaner energy cooler climate: developing sustainable energy solutions for South Africa*. University of Cape Town.
Winkler, H., Marquard, A., & Jooste, M. (2010). Putting a price on carbon: Economic instruments to mitigate climate change in South Africa and other developing countries. Working Paper 15939

Appendix A

1. Tips for Kitchen

From: 2wise2waste@westerncape.gov.za
To: [All staff, customized by floor]
Time: ….

Subject: Reduce electricity use in the kitchen
Dear [name]
The kitchen is a room filled with electrical equipment. Help reduce your building's / floor's electricity use by following the following tips:

- Use hot water sparingly form the tap / hydro boil
- Boil the amount of hot water required
- Switch-off kitchen appliances not in use
- Close the fridge door as soon as possible after opening it, ensure the seal is intact, and that it closes properly.
- Very often fridges are unnecessarily set too cold. Turn the temperature setting dial up a notch.

The 2Wise2Waste Electricity Savings Project

Western Cape Government
BETTER TOGETHER.

2. Tips/ Information Provision

From: 2wise2waste@westerncape.gov.za

To: All staff, customized by floor
Time: Monday, 9:00 AM
Subject: How to save electricity on your floor
Dear [name]
Here are some easy things you can do to save electricity on your floor:
1. [Tip 1]
2. [Tip 2]
3. [Tip 3]

Good luck. Let us make saving electricity BETTER TOGETHER!
- The 2Wise2Waste Electricity Savings Project

3. Weekly Friday Afternoon Reminder

From: 2wise2waste@westerncape.gov.za
To: [All staff, customized by floor]
Subject: Remember to switch off all office equipment and appliances
Time: 3:00 pm

Dear [name]

Please remember to switch off your desktop computer, laptop and office printer before heading out for the weekend.

Before going home, check whether you are the last to leave the [X]th floor. If so, be sure to turn off (at the wall) all communal office equipment and kitchen appliances like the printer, kettle, toaster, microwave and water heater. And remember to switch off the lights on your way out!

Thanks for helping us to meet our target of reducing electricity usage by 10% across all Provincial Buildings by 2015. Let us make using electricity efficiently BETTER TOGETHER!
Have a great weekend!

- The 2Wise2Waste Electricity Savings Project

Appendix B

Table A.1: Treatment Effects of Interventions on Energy Consumption

VARIABLES	(1)	(2)	(3)
Treatment 1	2.788***	2.746***	1.535
	(0.729)	(0.729)	(1.136)
Treatment 2	2.344***	2.384***	2.387***
	(0.626)	(0.626)	(0.627)
Post	-0.124**	-0.312***	-0.341***
	(0.0576)	(0.0843)	(0.0842)
Treatment 1 X Post	-0.116	-0.119	-0.215*
	(0.168)	(0.169)	(0.123)
Treatment 2 X Post	-0.324*	-0.349*	-0.351**
	(0.180)	(0.179)	(0.179)
headcount	0.0148***	0.0171***	0.0173***
	(0.00458)	(0.00470)	(0.00472)
Constant	0.371	0.270	0.269
	(0.458)	(0.454)	(0.455)
Observations	528,928	528,928	502,030
R2	0.166	0.169	0.155
Wald P-Value	0.00	0.00	0.00
Control	185,521	185,521	185,521
Treatment1	182,840	182,840	155,942
Treatment 2	160,567	160,567	160,567
Number of floors	20	20	19
Number of meters	40	40	38

Robust standard errors in parentheses clustered at meter level *** p<0.01, ** p<0.05, * p<0.
Pre-intervention period: June – October 2015