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Saving water at Cape Town schools by using smart metering and behavioural change*

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Abstract

The city of Cape Town suffered a severe water crisis in 2018. At the peak of the drought in South Africa's Western Cape, a randomised control trial at 105 schools investigated the impact of two behavioural interventions to encourage responsible water usage: detailed water usage data feedback from smart meters, and an interschool competition. Interventions reduced water usage in these schools by 15 to 26%. The information feedback was found to be more effective in reducing night time water use, indicating better water usage by the staff, while the competition was found to be more effective during the day time, indicating better water usage by the pupils. The contrast highlights the way feedback was understood differently by the two groups, with different effects on their assumption of responsibility. This example from Cape Town demonstrates the effectiveness of combining smart technologies with nudges. It provides a model of water conservation interventions for sustainable cities.

Keywords: behavioural insight; nudge; social comparison; smart water meter; water conservation; Cape Town drought

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1. Introduction

Cape Town made world headlines in 2018 as a major city on the brink of seeing its taps run dry. Its predicament drew attention to the challenge that water scarcity presents for cities in the 21st century. Globally, over four billion people face severe freshwater shortages and this number is expected to rise (Mekonnen and Hoekstra, 2016). The Water Resources Group (2017) predicts that by 2030 there will be a 40% gap between freshwater supply and demand if business-as-usual water management continues. . Clearly this challenge requires supply-side solutions, but water demand management is increasingly being recognised as an important aid to ensuring a sustainable water supply (Arbués et al., 2003; Russell and Fielding, 2010).

Traditionally, water demand management has relied on the use of direct incentive-augmenting schemes and pecuniary policy such as high tariffs. However, there is increasing evidence of the effectiveness of behavioural insights and nudges in changing water usage behaviour (Sønderlund et al., 2014). Nudges can be an attractive alternative for policymakers because they are cost-effective and easy to implement. Our study investigated how nudges can be applied in schools.

Schools offer an ideal platform for promoting conservation behaviour because they are big water users and because the interventions will have a ripple effect in the community (Booysen et al., 2019a). We conducted a randomised control trial at a sample of 105 schools in the Western Cape, South Africa, in which we tested two behavioural treatments: information feedback and a social comparison in the form of an interschool competition. We used data from smart water meters to track usage patterns accurately and give the schools detailed usage feedback. Thirty of the schools constituted the control group, receiving smart meter installation but no usage feedback.

2. The Cape Town water crisis

Between 2015 and 2018 the Western Cape Province of South Africa endured an extremely severe drought (Maxmen, 2018). Dam levels fell to below 22% of capacity in March 2018, bringing Cape Town close to becoming the world's first major city to run out of water. Apart from the drought, factors that compounded the water crisis were rapid population growth, heavy dependence on rainfall and poor investment in water supply infrastructure (Muller, 2018). Contingency plans were made for a purported "Day Zero", when the city council would have to turn off the municipal water supply (Enqvist and Ziervogel, 2019).

In response to the water crisis, the City of Cape Town adopted a number of demand-side-management interventions to curb residential water usage. These included water restrictions, media campaigns, dramatic tariff escalations and green nudges (Parks et al., 2019; Visser and Brühl, 2018). At the height of the crisis, the City of Cape Town introduced Level 6B water restrictions that limited residents to 50 litres per person per day.

Water prices had increased by 337% since the start of the drought (Brühl and Visser, 2019). The combination of these interventions led to an unprecedented overall water usage reduction of close to 50% in less than three years (Brühl and Visser, 2019). In the process, Cape Town avoided the "Day Zero" that had been predicted for the summer of 2018. This achievement highlights the importance of demand-side management for city water. Our study accentuates the role that behavioural interventions can play in bolstering water demand management and promoting conservation behaviour in cities.

3. Behavioural insights and water conservation behaviour

Traditional economic theory, springing from the works of Adam Smith (1776) and John Stuart Mill (1836), works on the premise that people are utility-maximising perfectly rational agents. Behavioural economics now casts doubt on the notion of *homo economicus* and recognises the effects of biases and heuristics on decision making (Kahneman, 2003; Thaler and Sunstein, 2008). Greater understanding of cognitive biases has produced nudge theory and choice architecture, which offer ideas on how to improve human decision-making. Nudges have been applied and tested in many contexts, including energy (Vine et al., 2013), healthcare (Koshy et al., 2008; Martin et al., 2012), finance (Karlan et al., 2010; Thaler and Benartzi, 2004) and education (Bradbury et al., 2013). Growing evidence of how nudges can bring about behavioural change is now inspiring researchers to experiment with this approach in the field of water conservation.

One of the reasons for residential water wastage is that users are ill-informed. This can be difficult to remedy. Information failure is of many kinds: asymmetrical, inaccurate, incomplete, uncertain or misunderstood. Some domestic water usage, such as toilet flushing, is invisible to the user, and where it is visible it is hard to quantify. And because water billing information is aggregated over long periods, consumers are generally unaware of the amount of water they use for their household activities. Complex, obscure, infrequent and delayed information makes it hard for users to link their behaviour to usage (Kahneman, 2003; Thaler and Sunstein, 2008). Information failure is particularly prevalent in South Africa because municipalities rely on manual reading of water meters. The time lag between using the water and getting the bill means that users experience a disconnect between water use and cost. This limits their ability to respond to water pricing and make optimal resource use decisions (Datta et al., 2015; Gaudin, 2006). They may understand the importance of resource conservation, but fail to link it to their own behaviour (Darby, 2006). Recognising the problem of information failure, the conservation behaviour literature has identified improved usage feedback as an important tool in managing resource demand (Nielsen et al., 2017). However, more research has been done on this topic in the field of energy conservation than in water conservation (Sønderlund et al., 2014).

3.1. Energy usage behaviour

There is substantial evidence of the effectiveness of behavioural interventions in curbing energy usage, with resulting reductions in energy use of between 5% and 20% (Gans et al., 2013; Houde et al., 2013; Vine et al., 2013). Insights from energy usage research are particularly translatable to water usage because the management of both resources is prone to information failure, non-obvious pricing and the impossibility of observing usage directly. The literature review by Vine et al. (2013) identifies features of user feedback that have been found effective in inducing energy saving: it must be clear and meaningful and related to a standard, and there must be minimal delay between energy use and feedback. An earlier review by Fischer (2008) identifies other features that have made feedback effective: frequent reports over a long period, an appliance-specific breakdown and computerised interactive tools.

Social norm messaging and comparison have also been found effective in reducing energy usage (Allcott, 2011; Klege et al., 2018). In an inter-floor randomised control trial in a large provincial government office building, Klege et al. (2018) found that social comparison nudges reduced energy usage by between 9% and 14% over five months. However, there is some debate about the effectiveness of social comparison. Some studies have found that it can cause a “boomerang” effect in which water usage increases (Fischer, 2008; Schultz et al., 2007). Individuals whose usage is lower than that of their competitors may feel entitled to increase their usage. To avoid this adverse effect, social comparison can be combined with injunctive norms (Frederiks et al., 2015).

3.2. Water usage behaviour

Findings have been similar in the water demand management literature, where usage feedback is usually either mail-based (Aitken et al., 1994; Brick et al., 2018; Datta et al., 2015; Ferraro et al., 2011; Ferraro and Price, 2013; Geller et al., 1983; Kurz et al., 2005), or provided by smart water meters (Booysen et al., 2019b; Erickson et al., 2012; Fielding et al., 2013; Liu et al., 2016; Petersen et al., 2007). Mail-based usage feedback is often provided through the existing utility bill infrastructure, thus minimising intervention costs (Sønderlund et al., 2014). Brick et al. (2018) used mail-based feedback to test eight behavioural nudges on a sample of 400,000 households over six months at the onset of the Cape Town water crisis. The nudges reduced water use by between 0.6% and 1.3% across the various treatments when compared to a control group. Publicly recognising water conservation (social recognition) or appealing to households to act in the public interest (appeal to the public good) were found to be the most effective motivators for water saving.

Ferraro and Price (2013) also highlight the importance of social incentives. They find that appeals to prosocial norms and the use of social comparison were effective in reducing water use in Georgia, USA. Interestingly, they found that the effect on households that received a prosocial norm appeal dissipated within a year, but the effect on the social comparison group was still detectable five years after intervention (Bernedo et al., 2014; Ferraro et al., 2011). Similarly, Datta et al. (2015) found that a neighbourhood-wide social comparison in Belén, Costa Rica, reduced water use by between 3.7% and 5.6% over two months. However, a social comparison at municipal level did not influence behaviour. In contrast, Kurz et al. (2005) found that social comparison feedback did not significantly reduce water use in Perth, Australia, but that environmental impact awareness labels at water usage points were effective.

Smart water meters have the advantage over municipal meters in providing more frequent and more detailed usage information, thus allowing both the researcher and the user to monitor usage habits more closely and detect leaks earlier (Sønderlund et al., 2014). The more detailed information that smart water meters provide can also be used to design behavioural interventions.

Fielding et al. (2013) used smart water meters to test the effect of three once-off treatments (social comparison, feedback and water-saving education) on residential water use in Queensland, Australia. On average, households in the experimental groups used 7.9% less water than those in the control group. However, there were no significant differences across the different treatments, and all treatment effects dissipated within a year. In contrast to the once-off treatment approach, Erickson et al. (2012) applied usage feedback over nine weeks using smart water meters in Dubuque, USA. Water use feedback, along with a social comparison, was provided to residential users every three hours through an online portal. The experimental group used 6.6% less water than the control group. Although these two studies found evidence that usage feedback can improve water usage behaviour, the shortage of research on this topic makes it difficult to draw strong conclusions, particularly as most of the research has been on residential usage.

One exception is a study by Petersen et al. (2007) of the effect of water and electricity usage feedback in twenty-two university residences. The study used smart meters, provided feedback through an online portal, and conducted an inter-residence usage reduction competition. On average across the residences there was a 3% reduction in water use and a much larger 32% reduction in electricity use. However, it should be noted that as the study was primarily framed in terms of energy conservation, the students were probably more focused on electricity saving. An important difference in this study is that, unlike household users, these users (students) were not directly responsible for the utility bills. This was also the case in our schools study, where school staff and pupils were not directly responsible for the water bills. This is an important distinction from studies that evaluate water use in households, where the user is directly responsible for the bill.

Apart from Petersen et al. (2007), there is a real scarcity of research on the effect that a combination of smart technologies and behavioural insights and nudges can have on conservation behaviour beyond the household context. A study by Samuels and Booysen (2019) on a small sample of five schools, found that presenting electricity usage feedback to staff in a visual and intuitive format decreased electricity usage by between 11% and 14%. Conducting research in large public settings, such as schools, is challenging because of the financial outlay, diversity of stakeholders and complexity of technology that is required for rigorous evaluation. Our study thus makes a vital contribution to the literature by using smart water meters to evaluate behavioural interventions in a substantial sample of 105 schools. Furthermore, the majority of such studies have been done in developed countries (Datta and Mullainathan, 2014). Our study was in a developing country setting, where it is vital to ensure that contextual nuances are accounted for in policymaking.

4. Study methods

This study used ideas from the reviewed literature to design an experimental behavioural intervention to reduce water usage in a sample of 105 schools. This sample included both primary and secondary government schools. We sent usage reports as feedback to the users, taking presentation, timing and personalisation into careful consideration, and ran a social comparison in the form of an inter-school competition. Scalability of the intervention was also an important consideration. The duration of the study was eight months.

4.1. Experimental design

A randomised control trial was used to evaluate the effect of a behavioural intervention that took two forms: usage feedback and an inter-school competition. After smart water meters had been installed, all the schools received a once-off leak detection and maintenance upgrade. Thereafter, they underwent a nine-week baseline period before treatments were applied. The maintenance upgrades that were done after meter installation and before baseline readings were taken helped to minimise the schools' infrastructural differences prior to treatment. The 105 schools were divided into three groups: a control group of 30 schools that received smart meter installation but no feedback on their usage; a treatment group of 33 schools (labelled 'T1 – feedback') that received feedback about their daily and weekly water usage; and a treatment group of 42 schools (labelled 'T2 – social comparison') that received feedback about their daily and weekly water usage and also comparative feedback on their water usage relative to other schools.

Groups T1 and T2 received weekly usage reports via email and text message to the principal and two additional staff members. Both T1 and T2 received feedback information about their water usage. The schools also received a pre-designed poster that could be updated weekly with the latest water usage information. The poster was displayed next to the school's notice board with the intention of improving information transfer from staff to pupils. In addition, T2 also received a social comparison treatment consisting of a leader board showing the percentage of water saved (relative to the pre-intervention baseline) by other T2 schools. To bring this information to the attention of pupils, principals were asked to share this information with the pupils during weekly assemblies. This encouraged competition.

Schools were randomly allocated to the three groups on the basis of usage in the pre-intervention baseline period and stratified on usage terciles to ensure that schools across the usage distribution were equally distributed among the treatment and control groups. Feedback reports were sent to the schools every Monday. Many of the schools did not have reliable internet access, thus treatment had to be applied through text message and email rather than through an online portal in order to ensure equality of treatment across schools. Examples of the information and posters can be seen in the Appendix.

Table I: Waves and schools per treatment

Wave	Start of baseline	Start of treatment	Control	Treatment 1	Treatment 2
1	12 February 2018	15 April 2018	9	10	14
2	16 April 2018	3 June 2018	15	16	19
3	21 May 2018	22 July 2018	6	7	9
			30	33	42

Control: Schools not provided with water usage feedback.
Treatment 1: Schools provided with water usage feedback.
Treatment 2: Schools provided with water usage feedback and a comparison with other schools.

The schools entered the study in three waves as shown in Table I. This stepped approach to treatment implementation (Kremer, 2003) was necessary firstly because the severity of the drought made water saving a top priority and the City of Cape Town and corporate funders of the intervention wanted feedback reports as soon as possible, and secondly because installing the smart water meters and doing the maintenance work was a lengthy process.

4.2. Dataset

The dataset was provided by BridgIoT, the company that managed the installation of smart water meters and data collection as part of a water savings campaign.[‡] The dataset contains water flow rates at 30-minute intervals for the 105 schools over a period ranging from February 2018 to October 2018.

Table II: Descriptive statistics

		Water volume litres/30 minutes			
Group	Period	Mean	Median	SD	N
All hours (00:00-24:00)					

‡ http://www.schoolswater.co.za/

Cont.	Pre	95	30	169	62 814
	Post	106	35	161	132 513
T1	Pre	114	30	181	69 516
	Post	109	40	156	152 197
T2	Pre	109	40	176	90 682
	Post	114	50	165	171 927
Night hours (00:00-04:00)					
Cont.	Pre	47	10	126	9 163
	Post	54	10	106	19 327
T1	Pre	60	0	144	10 136
	Post	47	0	93	22 197
T2	Pre	53	0	107	13 230
	Post	57	0	108	25 067
School hours (07:00-14:00)					
Cont.	Pre	225	160	224	11 604
	Post	255	200	223	24 838
T1	Pre	271	213	219	12 075
	Post	273	240	194	27 916
T2	Pre	267	190	253	15,998
	Post	273	210	230	32 533

Cont.: Control Group. T1: Treatment 1. T2: Treatment 2

Table II shows basic summary statistics of the water usage data across different times of the day. Overall, taking into account all hours and days and not just school hours and days, the mean water usage in the pre-intervention period was 107 litres/30min across all three groups. For school day hours (07:00–14:00) and night hours (01:00–04:00) the pre-intervention water usage means were 256 litres/30min and 53 litres/30min respectively.

4.3. Pre-intervention analysis

The difference-in-differences model used in this study relies on the common trend assumption, i.e. that in the absence of treatment water usage trends are the same in the control and treatment groups, implying that a deviation from the common trend after the treatment is a result of the treatment (Angrist and Pischke, 2008). To investigate whether the assumption held, we did pre-intervention balance tests and a time trend analysis.

Table III: Pre-intervention balance tests

	(1) Volume	(2) Volume	(3) Volume	(4) Pupils	(5) Fees
Treatment 1	8.935	8.864	16.84	46.19	-0.125
	(21.56)	(20.18)	(32.29)	(88.86)	(0.128)
Treatment 2	8.168	5.676	24.22	60.03	-0.106
	(17.51)	(16.91)	(30.40)	(74.24)	(0.121)
Hours	All 00:00-24:00	Night 00:00-04:00	School 07:00-14:00	All 00:00-24:00	All 00:00-24:00
Days	All	All	School	All	All
Observations	223,012	32,529	39,677	223,012	223,012
No. of schools	105	105	105	105	105

Pre-intervention period. Robust standard errors in parentheses, clustered at the school level. Suppressed coefficients on usage tercile (randomisation stratified on usage tercile). School days excludes weekends and holidays.
Water volume in litres/30min

*** p<0.01, ** p<0.05, * p<0.1.

Table III presents the pre-intervention balance tests. These tests are performed by regressing the dummy variables indicating treatment group on water usage. To control for stratification, usage tercile dummy variables are also included as explanatory variables (Bruhn and McKenzie, 2009). The table shows that water usage was balanced across treatment groups with none of the coefficients in columns (1), (2) and (3) being significant. Columns (4) and (5) show that the schools are also balanced as regards pupil numbers and fees (fees being a variable that indicates whether a school is fee-paying or not). As the treatment groups are well balanced, we expect extraneous factors such as increased awareness about the need to save water because of the drought to be consistent across the control and treatment groups.

To investigate whether the control and treatment groups have different water usage time trends, a constant linear time trend model was also estimated. Table IV includes models for both the treatments and across two different time specifications: all hours (columns 1 and 2) and school day hours (columns 3 and 4). Any differences in the time trends of water use are captured in the interaction of the treatment indicators and the weekly pre-treatment trend. Across all specifications, the coefficient on the interaction term does not differ significantly from zero. As a result, we conclude that there are no significant differences in the time trends between the control and treatment groups. The balance tests and time trend analysis indicate that the control group provides a valid counterfactual for both treatments.

Table IV: Pre-intervention time trend analysis

Variables	(1) T1	(2) T2	(3) T1	(4) T2
Pre-trend	-0.00962**	-0.00962**	-0.00611	-0.00629
	(0.00414)	(0.00411)	(0.00480)	(0.00480)
Treatment	75.43	44.13	22.53	41.93
	(54.47)	(39.27)	(64.46)	(46.92)
Treatment X Pre-trend	-0.0128	-0.00720	-0.000779	-0.00400
	(0.00947)	(0.00676)	(0.0113)	(0.00797)
Hours	All hours	All hours	School hours	School hours
	00:00-24:00	00:00-24:00	07:00-14:00	07:00-14:00
Days	All	All	School	School
Observations	132,330	153,496	23,679	27,602
No. of schools	63	72	63	72

Robust standard errors in parentheses, clustered at the school level. Pre-intervention period. Suppressed coefficients on usage tercile (randomisation stratified on usage tercile).
*** p<0.01, ** p<0.05, * p<0.1.
T1: Treatment group 1
T2: Treatment group 2

5. Econometric models

To estimate the effect of the behavioural interventions we used the difference-in-differences (DiD) model.

5.2. Difference-in-differences (DiD) model

$$\begin{aligned} v_{it} = \beta_0 + \beta_1 treatment_{it}^{T1} + \beta_2 treatment_{it}^{T2} + \beta_3 post_{it} \\ + \delta_1(treatment_{it}^{T1} \times post_{it}) + \delta_2(treatment_{it}^{T2} \times post_{it}) \\ + \lambda X_{it} + \varepsilon_{it} \end{aligned} \quad (1)$$

where v_{it} is the volume of water used per 30 minutes by school i at time t in litres/30min, $treatment_{it}^{TX}$ are dummy variables for each treatment group, and $post_{it}$ is a dummy variable coded as 0 for all pre-treatment observations and 1 for all post-treatment observations. Interaction variables between treatment dummies and the $post_{it}$ variable also form part of the model. X represents other control variables: number of pupils, water consumption tercile, dummy variables for holidays, weekends and an indicator for after hours (14:00 – 07:00). In addition, X also contains an indicator for major leaks that took place in the post period and for periods when high night-time water flow occurred. Night flow indicates a minor leak such as a faulty toilet or dripping tap. Days with night flow were those where average consumption between 01:00 and 04:00 exceeded 10 litres/30min. Major leaks were either recorded by schools or were periods when consumption exceeded ten times the school's average water usage over the entire study. Monthly indicator variables are also included to account for seasonality.

The difference-in-differences estimators for the information and competition treatments are provided by the coefficients on the interaction dummies δ_1 and δ_2, respectively. This is because the $post_{it}$ variable coefficient captures breaks from the general trend in water usage in the post period, while the treatment variables capture mean differences in the water usage of treatment schools relative to control schools in the estimation sample (Angrist and Pischke, 2008). Thus δ_1 and δ_2 are measures of the difference in the water usage of treatment schools in the post-treatment periods relative to what we would expect to observe based on all the covariates and the pre-existing trend. Therefore, the average impact of the information feedback and interschool competition is estimated as follows:

$$DD_1 = E[{v_{i1}}^{T1} - {v_{i0}}^{T1}] - E[{v_{i1}}^{C} - {v_{i0}}^{C}] \quad (2)$$
$$DD_2 = E[{v_{i1}}^{T2} - {v_{i0}}^{T2}] - E[{v_{i1}}^{C} - {v_{i0}}^{C}] \quad (3)$$

To account for any unobserved heterogeneity, the standard panel OLS fixed effect estimator with robust standard errors is used. These standard errors are clustered at the school level.

6. Results

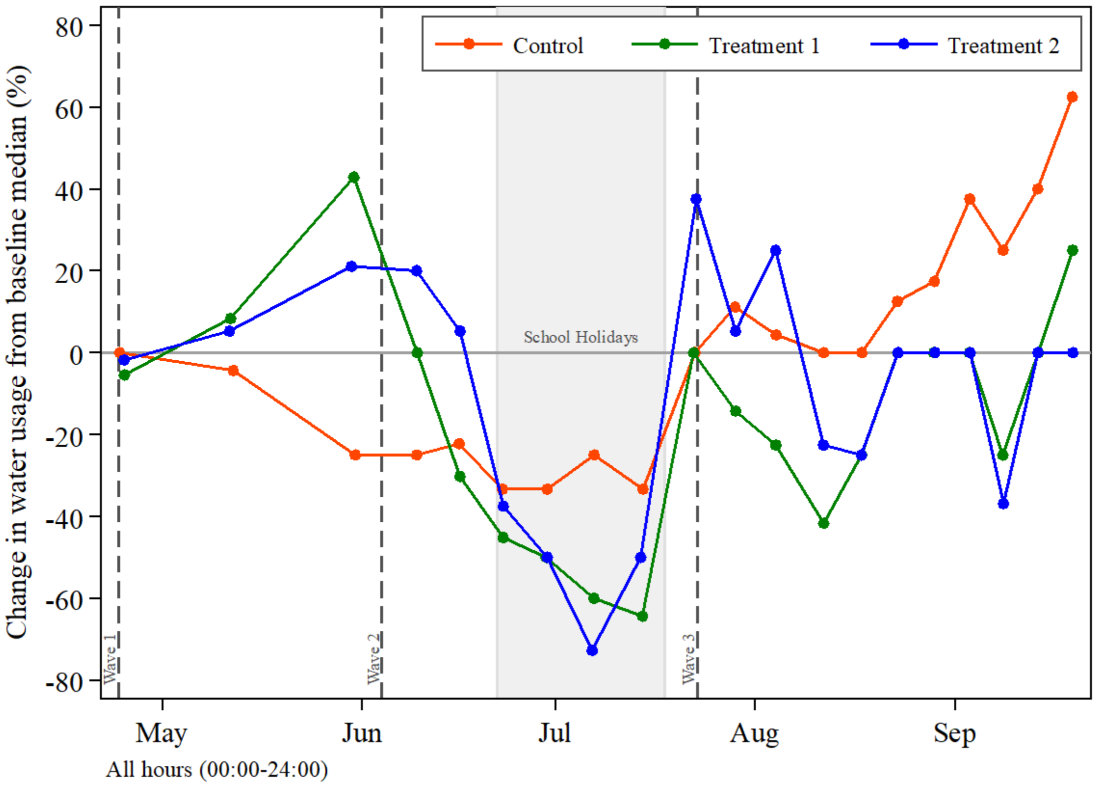

Figure 1: Median change in water usage from baseline median by treatment group

Figure 1 plots the median change in water usage from the baseline median over the sampling period for the different treatment groups. The decline in usage in July for all three groups coincides with the school holidays over this period. During the holidays, the control group's usage decreased by less than both T1 and T2. As schools close over this period, we would expect water usage to drop to very low levels. Follow-up surveys with staff in the treatment groups found that schools turned off their main water supply valves during holidays in order to save water. The subsequent increase in usage across all groups during July coincides with the end of the holidays and the arrival of the rainy season in the Western Cape. During August and September, Figure 1 indicates another distinct difference in water usage change across the groups with the control group increasing more than the treatment groups.

6.1. Difference-in-differences results

Table V presents the difference-in-differences regression results with four different time specifications across the three waves.

Table V: Difference-in-difference regressions

Dependent variable: Water usage volume litres/30min

	(1) All	(2) Night	(3) School	(4) After
Post	19.59**	19.98**	25.34**	22.14**
	(8.454)	(8.398)	(10.08)	(8.826)

Treatment1 X Post	-27.29**	-31.23**	-26.96*	-31.53**
	(13.02)	(12.93)	(13.84)	(13.58)
Treatment2 X Post	-16.13**	-11.73	-28.48***	-16.13**
	(7.515)	(8.344)	(9.291)	(8.064)
Major leak	938.6***	1,530***	695.4***	1,297***
	(54.53)	(160.4)	(33.35)	(76.69)
Night flow	61.62***	101.5***	40.66***	65.40***
	(6.610)	(8.907)	(7.835)	(6.649)
Constant	208.3***	36.85***	318.1***	80.70***
	(12.69)	(11.72)	(15.11)	(10.76)
Hours	All hours 00:00-24:00	Night hours 01:00-04:00	School hours 07:00-14:00	After hours 14:00-07:00
Weekends & holidays	Yes	Yes	No	No
Observations	679,649	99,120	124,964	274,935
R-squared	0.377	0.397	0.270	0.270
No. of schools	105	105	105	105
Baseline mean vol.	106.6	53.48	255.7	70.97
Percentage reduction:				
Treatment 1	-25.60%	-58.40%	-10.54%	-44.43%
Treatment 2	-15.13%	-21.93%	-11.14%	-22.73%

Fixed effects regressions. Robust standard errors clustered on school in parentheses. Suppressed coefficients on month, week, afterhours, weekends, public holidays and school holidays.
*** p<0.01, ** p<0.05, * p<0.1

The full model in column (1) shows that information feedback treatment (T1) decreased water usage by 27.29 litres/30min on average, while the information feedback plus social comparison treatment (T2) decreased water use by 16.13 litres/30min on average. This equates to reductions of 25.60% and 15.13% respectively. Both these results are statistically significant and robust to standardisation of the dependent variable to usage per pupil. Table A1 in the Appendix shows that when standardised to per pupil, coefficients are negative and significant across all specifications.

The division of the DiD analysis across time of day is important as water is used for different purposes during the day. During school hours most of the usage is by pupils. Column (3) therefore mostly represents pupil responses to the behavioural treatment. Night time usage mostly indicates the presence of leaks and water management practices. Water management practices refers to how staff maintain water infrastructure, do leak detection and manage water flow. Although reductions in night time flow could be due to changes in the behaviour of pupils (for example, being more careful not to leave taps running), they are more likely to be due to reductions in leaks as a result of staff members improving water management. Column (2) therefore mostly represents changes in the behaviour of staff members responsible for water management.

Column (3) shows that the T1 group reduced its water use by 26.96 litres/30min on average, and the T2 group by 28.48 litres/30min on average, suggesting that T2 was marginally more effective in changing pupils' water usage behaviour than T1. The T2 result is also substantially more significant than the T1 result, indicating greater precision in the social comparison treatment effect during school hours. Column (3) indicates that pupils are more motivated to save water within the comparative setting.

In contrast to the school hour results, the night time and after hours models (columns 2 and 4) show larger reductions for T1 than for T2. Column (2) shows that T1 reduced its water use by 31.23 litres/30min and T2 by 11.73 litres/30min on average during night hours. It may seem counterintuitive that feedback alone achieved bigger reductions than feedback plus competition, suggesting that the competition had a negative effect. However, as night time flow is largely an indicator of staff behaviour, we suggest three possible explanations that have been proposed in the literature. One is information overload: too much complex information may have hindered rather than helped the staff to manage water usage and fix leaks (Roetzel, 2018). Another is the "boomerang" effect: staff at schools with usage above the mean responded negatively to their school being compared with other schools and reduced their water saving efforts (Clee and Wicklund, 1980; Schultz et al., 2007). And another is the "social loafing" effect: the staff may have shifted the burden of responsibility to the pupils, seeing them as the primary target of the competition, and reduced their own water-saving efforts in consequence (Karau and Williams, 1993; Latane et al., 1979; Ringelmann, 1913).

A pilot study and follow-up surveys indicated that information overload in the weekly reports was not a problem for staff. The weekly reports were clear, simply formatted and easily understandable (examples are provided in the Appendix: Figure A1 – A4). Table A2 in the Appendix shows that there was no boomerang effect, as schools above and below the baseline mean reduced water usage after treatment. Qualitative feedback from staff also showed that although there was some negative sentiment towards inclusion in the social comparison, most staff responded positively to being able to compare their usage to other schools. Thus, the third explanation above is the most likely reason why T1 did better than T2 on after-hour usage, i.e. social loafing (individuals making less effort because they are in a group) and staff abdicating responsibility because they thought the competitive effort was the responsibility of the pupils and the school at large, i.e. not taking personal ownership of water saving.

Evidence for this explanation can be seen in Table V. Considering that reductions in night flow (00:00–04:00) reflect improvements in water management behaviour by staff and that school time (07:00–14:00) water use largely reflects pupil behaviour, the fact that T2 is more effective during school hours while T1 is more effective during night hours points to staff making less effort to save water when a social comparison is applied. More simply, the results in Table V imply that when comparative information is provided, night time water saving due to staff behaviour declines and school hours water saving by pupils increases. Staff in T1, who received only feedback, took responsibility for water saving and improved their behaviour accordingly, for example by making regular searches for leaks and switching off the water mains over night and on weekends.

The sensitivity of the results to schools that had high water usage as a result of leaks is evaluated in Table A3 in the Appendix. In this table the schools with a median water usage greater than 200 litres/30min are dropped in columns (2), (5) and (11) and schools with median water usage greater than 150 litres/30min are dropped in columns (3), (6) and (12). As more high users are excluded, the treatment effect of T2 increases and remains significant. In contrast, the treatment effect of T1 decreases and becomes less significant. This indicates that the estimates for T2 are more robust and accurate than those for T1. This is an important result as it provides further support for the different effects of the two treatments on staff and pupils. The greater variation that we find in T1 points to staff behaviour. Individual staff members can have a dramatic effect on a school's water usage by improving water management decisions. An individual pupil cannot do this, hence the lesser variation in T2 and the more accurate estimates.

The results indicate that significant amounts of water were saved. Over the course of the study more than 8.5 megalitres of water were saved at the treatment schools as a result of the behavioural interventions. Should this level of saving be maintained, it would amount to an average saving of over 380 kilolitres per school per year. This saving equates to an annual saving of R36 453 (US$2 430) per school based on drought tariffs of R97.17/kilolitre (Department of Water and Sanitation, 2018). The cost of meter installation, maintenance at the schools and administration of behavioural treatments for a year cost a total of R30 000 (US$2 000) per school. This indicates that the behavioural nudges were cost effective as schools recuperated these costs within ten months. However, this does not include the savings made as a result of the maintenance upgrades that were implemented prior to the behavioural study. Accounting for the additional savings from maintenance, although less robust, further increases the return on investment.[§]

6.2. Treatment effect over time

Past studies have found that treatment effects dissipate over time (Ferraro and Price, 2013; Fielding et al., 2013; Klege et al., 2018). Table VI shows the effect of our interventions over four months after treatment through DiD regression specifications that define the 'post' period as cumulative months after intervention. Specifications (1) to (5) include all hours and days and (6) to (10) restrict the sample to school day hours.

The table shows that the treatment effects intensified over the four months. Columns (1) to (5), covering all hours, show that the effect of T1 increases from a reduction of 16.88 litres/30min after one month of treatment to a reduction of 27.29 litres/30min after four months of treatment, and that the effect of T2 increases correspondingly, from 10.94 litres/30min to 16.13 litres/30min. The same trend can be seen in columns (6) to (10), limited to school hours only. The longer the treatment period, the more the water saving decisions improved. Staff took time to internalise the information they received and learn how to use it to manage water use better and encourage pupils to save water. A longer-term study would reveal whether the treatment effects would intensify or dissipate.

[§] Booysen et al. 2019a estimate a saving of R9 694 (US$646) per school per month as a result of the maintenance upgrades made prior to the behavioural interventions.

Table VI: Cumulative month-by-month difference-in-difference regressions

Dependent variable: Water usage volume litres/30min

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1 Month	2 Month	3 Month	4 Month	All	1 Month	2 Month	3 Month	4 Month	All
Post	17.43*	5.028	16.80**	15.54*	19.59**	24.86*	9.960	19.01*	21.29**	25.34**
	(9.500)	(8.315)	(8.414)	(8.676)	(8.454)	(13.04)	(11.00)	(10.48)	(10.56)	(10.08)
Treatment 1 X Post	-16.88*	-16.49*	-22.20*	-26.60**	-27.29**	-12.36	-15.60	-22.58*	-26.33*	-26.96*
	(9.472)	(9.464)	(11.64)	(12.84)	(13.02)	(13.87)	(11.23)	(11.99)	(13.62)	(13.84)
Treatment2 X Post	-10.94	-8.427	-10.19	-14.98*	-16.13**	-16.43	-15.56*	-19.74**	-26.27***	-28.48***
	(8.525)	(7.427)	(7.889)	(7.846)	(7.515)	(11.59)	(9.071)	(8.837)	(9.292)	(9.291)
Major leak	1,008***	971.2***	970.9***	947.7***	938.6***	711.8***	697.1***	706.4***	697.8***	695.4***
	(74.97)	(67.23)	(63.00)	(58.20)	(54.53)	(40.38)	(37.58)	(38.04)	(35.83)	(33.35)
Constant	212.0***	187.3***	201.8***	199.9***	208.3***	354.6***	306.8***	315.1***	311.9***	318.1***
	(17.11)	(14.02)	(14.72)	(13.88)	(12.69)	(20.61)	(16.64)	(17.44)	(17.23)	(15.11)
Hours	All	All	All	All	All	School	School	School	School	School
	00:00-24:00	00:00-24:00	00:00-24:00	00:00-24:00	00:00-24:00	07:00-14:00	07:00-14:00	07:00-14:00	07:00-14:00	07:00-14:00
Weekends & holidays	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
Observations	347,776	464,463	558,256	629,357	679,649	62,527	85,041	97,521	113,414	124,964
R-squared	0.400	0.385	0.382	0.377	0.377	0.297	0.278	0.280	0.275	0.270
No. of schools	105	105	105	105	105	105	105	105	105	105
Baseline mean vol.	106.6	106.6	106.6	106.6	106.6	255.7	255.7	255.7	255.7	255.7
Percentage reduction										
Treatment 1	-15.83%	-15.47%	-20.83%	-24.95%	-25.60%	-4.83%	-6.10%	-8.83%	-10.30%	-10.54%
Treatment 2	-10.26%	-7.91%	-9.56%	-14.05%	-15.13%	-6.43%	-6.09%	-7.72%	-10.27%	-11.14%

Fixed effects regressions. Suppressed coefficients on week, month, public holiday, school holiday, afterhours, weekend and night flow dummies. Robust standard errors clustered on school in parentheses. *** p<0.01, ** p<0.05, * p<0.1

7. Limitations

The study had a restricted timeline and sample size due to budget constraints and the high cost of a randomised control trial. The lengthy time required for meter installation and pre-intervention maintenance restricted the number of schools that could participate in the study. Furthermore, water saving was of paramount concern during the Cape Town water crisis, thus the baseline period had to be curtailed in order to roll out treatment as soon as possible. The drought, the water restrictions, the high tariffs and the heightened awareness of the need to save water meant that our sample was not a blank page: most Cape Town residents were already engaging in water conservation. The already stringent restrictions may have made it difficult for staff and pupils to cut water usage still further in response to the behavioural treatments. The study also suffered from practical hindrances in the form of theft and vandalism of smart water meters – it must be remembered that this study, unlike many in the literature, was set in a developing country. Signal disruptions also affected data quality from the meters. A further limitation was that we had no control over the transfer of information from staff to pupils. Behavioural nudges were applied through text messages and emails to staff to ensure scalability at low cost. Applying the treatment in this group fashion limited our understanding of the effect on individual behaviour.

8. Conclusion

This study used a randomised control trial to investigate the effect of two behavioural interventions in the form of information feedback, one of them with the addition of an interschool social comparison, in improving water conservation in 105 schools across the Western Cape, South Africa. Overall reductions of between 15% and 26% were observed, translating to significant water savings of 380 kilolitres per school per year on average. These savings were also highly cost effective with cost recuperated within ten months, even when excluding savings from the maintenance campaign.

Separate analysis of treatment effects across times of day (school hours, after school hours and night time) revealed differences in the responses of staff and pupils. We observed greater reductions in water use during school hours, when pupils are the main users, when we provided not only feedback but also savings information from other schools for comparison. In contrast, we observed reductions in night time flow, which indicated better water management by staff, when we provided only feedback. The implication is that pupils were responsive to the social comparison, i.e. competition, whereas the staff reacted to it by shifting the responsibility of water saving to the pupils. When only water use feedback was provided, staff who received this information shouldered the water-saving burden themselves by improving leak detection and water management. This finding highlights the signalling effect that different forms of information can have in guiding behavioural change. Analysing the treatment effects month by month showed that water savings increased cumulatively over the four months of the intervention. This highlights the importance of repeated feedback to bring about behavioural change. A longer period of intervention would provide further insight.

This study presents compelling insights into the effectiveness of information feedback and social comparison, along with the power of new technologies such as smart water meters, in promoting water saving in schools. Water conservation research to date has largely overlooked the fact that schools are major water users in a city. The example of Cape Town's narrow escape from being a waterless city is a salutary reminder of the vital role water plays in sustainability.

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Appendix

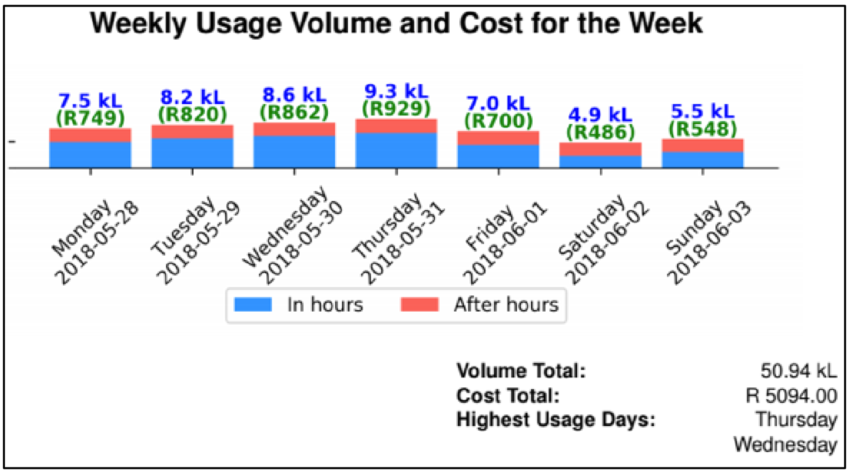

Figure A1: Weekly usage information sent in e-mail feedback reports

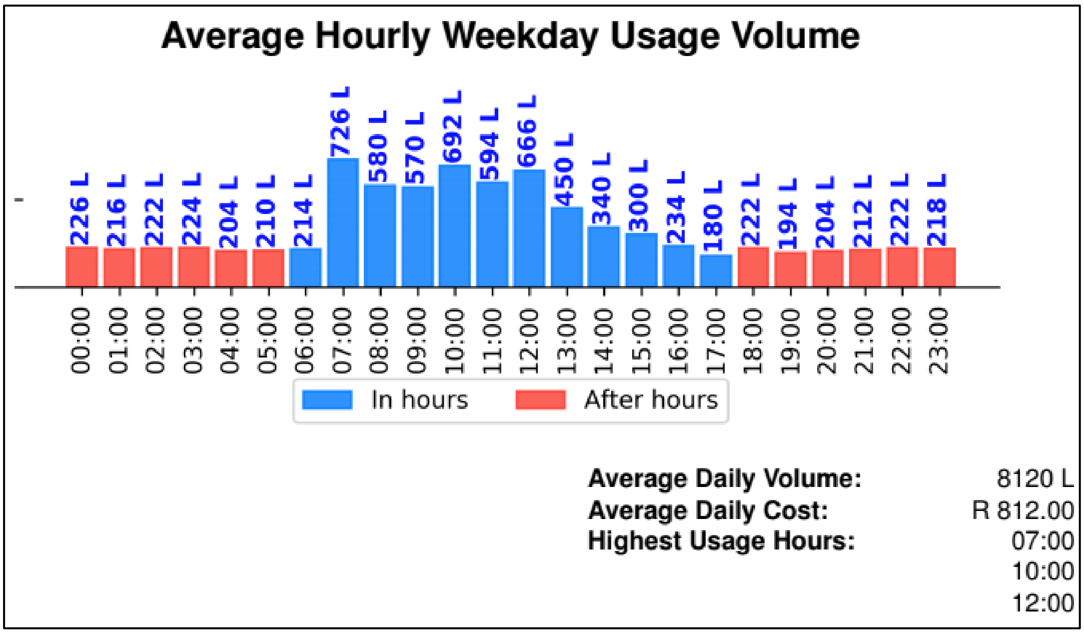

Figure A2: Hourly usage information sent in e-mail feedback reports

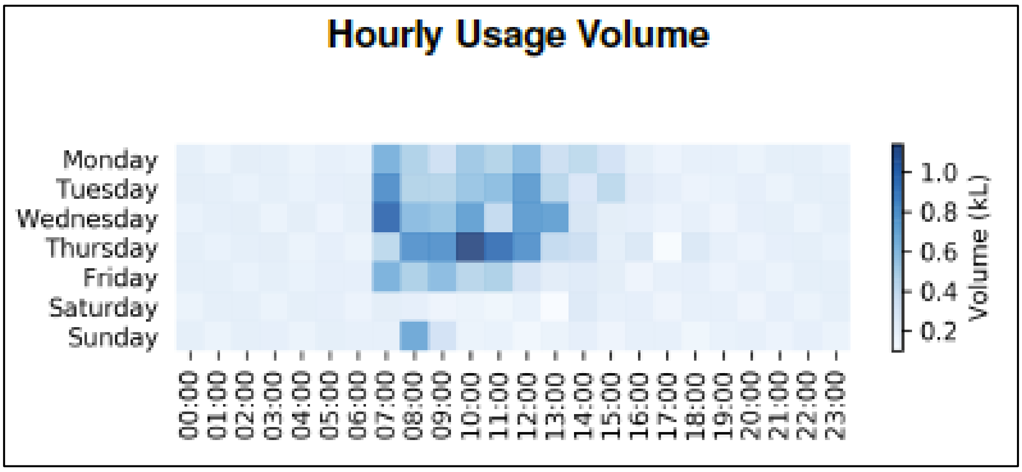

Figure A3: Water volume heat map sent in e-mail feedback reports

DROPULA BY BRIDGIOT

COMPETITION REPORT

De Waveren Primary
Start: 2018-05-28
End: 2018-06-03

Water Savers Score Board:

Your school's water usage change last week:[1]

De Waveren Primary	7.0% decrease

The top three schools' water usage change last week:[2]

School 1	48.0% decrease
School 2	15.1% decrease
School 3	7.0% decrease

Your schools' water usage change in the last month:

Two weeks ago	3.6% decrease
Three weeks ago	6.0% increase
Four weeks ago	14.9% decrease

Schools in Competition:

Beaumont Primary, Belvue Primary, Cornflower Primary, Danie Ackerman Primary, De Waveren Primary, Downeville Primary, Erica Primary, Id Mkhize Secondary Gugs, Impendulo Primary, Isiphiwo Primary, Kleinvlei Sekondêr, Manyano Secondary, Merrydale Primary, Perseverance Sekondêr, Zola Secondary

Figure A4: Comparative information sent in e-mail social comparison reports

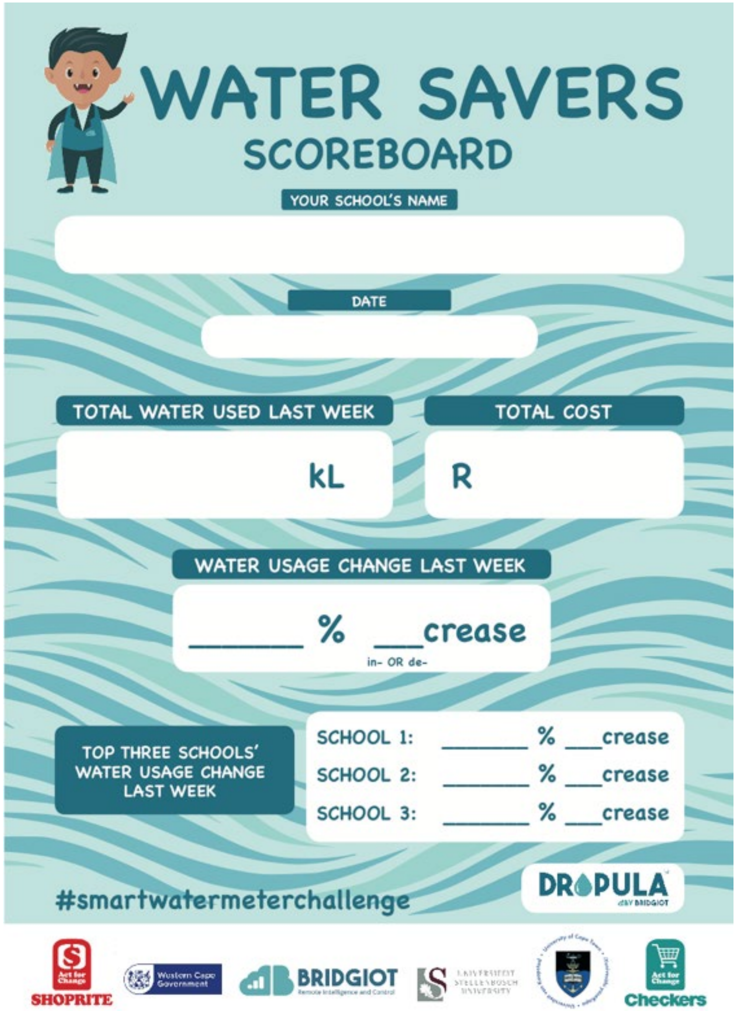

Figure A5: Poster sent to treatment 2 schools

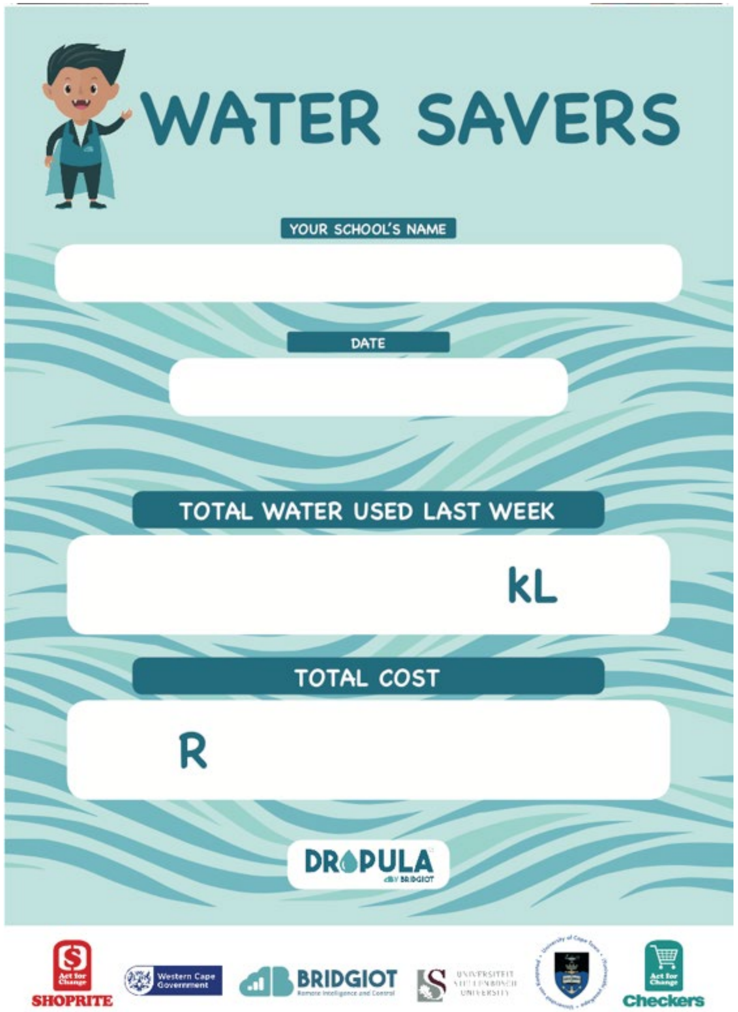

Figure A6: Poster sent to treatment 1 schools

Table A1: Difference-in-differences regressions with dependent variable standardised to per pupil water use

Dependent variable: Water usage volume litres/30min per pupil

	(1) All	(2) Night	(3) School	(4) After
Post	0.0238***	0.0224***	0.0289***	0.0270***
	(0.00833)	(0.00710)	(0.0109)	(0.00816)
Treatment 1 X Post	-0.0301**	-0.0342***	-0.0290**	-0.0351***
	(0.0126)	(0.0115)	(0.0145)	(0.0128)
Treatment2 X Post	-0.0209***	-0.0162**	-0.0311***	-0.0211***
	(0.00702)	(0.00679)	(0.0105)	(0.00718)
Public holiday	-0.0424***	-0.00170		
	(0.00325)	(0.00248)		
School holiday	-0.0461***	-0.00939***		
	(0.00349)	(0.00279)		
After-hours indicator	-0.109***			
	(0.00498)			
Weekend	-0.0485***	-0.000246		
	(0.00241)	(0.00131)		
Major leak	0.855***	1.540***	0.619***	1.303***
	(0.0689)	(0.262)	(0.0374)	(0.123)
Night flow	0.0613***	0.101***	0.0439***	0.0651***
	(0.00649)	(0.00826)	(0.00787)	(0.00640)
Constant	0.202***	0.0348***	0.307***	0.0788***
	(0.0126)	(0.0121)	(0.0154)	(0.0116)
Hours	All hours	Night hours	School hours	After hours
	00:00-24:00	01:00-04:00	07:00-14:00	14:00-07:00
Weekends & holidays	Yes	Yes	No	No
Observations	679,649	99,120	124,964	274,935
R-squared	0.366	0.400	0.236	0.281
No. of schools	105	105	105	105
Baseline mean vol.	0.101	0.0505	0.246	0.0667
Percentage reduction:				
Treatment 1	-29,80%	-67,72%	-11,79%	-52,62%
Treatment 2	-20,69%	-32,08%	-12,64%	-31,63%

Fixed effects regressions. Robust standard errors clustered on school in parentheses. Suppressed coefficients on month, week. *** p<0.01, ** p<0.05, * p<0.1

Table A2: DiD output with sample split by schools with usage above and below the baseline mean usage

Above or Below Baseline Mean	(1) All Below	(2) All Above	(3) Night Below	(4) Night Above	(5) School Below	(6) School Above	(7) After Below	(8) After Above
Post	16.20**	10.60	10.73***	22.29	25.46**	12.79	16.83***	22.64
	(6.913)	(21.76)	(3.730)	(24.30)	(9.939)	(18.10)	(5.387)	(29.98)
Treatment1 X Post	-8.128	-39.48	-9.985*	-70.77**	-5.830	-48.10*	-8.120	-74.15*
	(7.561)	(28.31)	(5.128)	(32.27)	(12.32)	(24.83)	(6.836)	(37.35)
Treatment2 X Post	-15.73**	-4.776	-8.953*	-17.93	-25.39**	-25.46	-15.74***	-15.20
	(6.269)	(19.91)	(4.535)	(24.27)	(11.30)	(15.69)	(5.442)	(27.88)
Constant	146.0***	289.1***	10.99	33.38	213.2***	456.8***	50.65***	109.8***
	(9.455)	(27.65)	(8.058)	(21.95)	(14.59)	(30.19)	(7.973)	(24.41)
Hours	All	All	Night	Night	School	School	After	After
	00:00-24:00	00:00-24:00	01:00-04:00	01:00-04:00	07:00-14:00	07:00-14:00	14:00-07:00	14:00-07:00
Weekends and holidays								
Observations	418,271	261,378	64,463	34,657	73,371	51,593	183,383	91,552
R-squared	0.390	0.405	0.375	0.441	0.228	0.300	0.292	0.283
Number of schools	67	38	72	33	64	41	72	33
Baseline mean vol,	55.41	199.8	15.33	134.8	156.1	420.5	30.46	160.5

Fixed effects regressions. Robust standard errors clustered on school in parentheses. Suppressed coefficients on month, week, major leak, night flow,after-hours, weekends, public holidays and school holidays. *** p<0.01, ** p<0.05, * p<0.1

Table A3: DiD output with high consuming schools systematically dropped

	(1)	(2)	(3)	(4)	(5)	(6)	(10)	(11)	(12)
Outliers dropped		med>=200	med>=150		med>=200	med>=150		med>=200	med>=150
Hours	All hours	All hours	All hours	School hours	School hours	School hours	Night hours	Night hours	Night hours
	00:00-24:00	00:00-24:00	00:00-24:00	07:00-14:00	07:00-14:00	07:00-14:00	01:00-04:00	01:00-04:00	01:00-04:00
Weekends & holidays	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Dependent variable: Water usage (litres/30min)									
Treatment 1 X Post	-27.29**	-25.63**	-11.66*	-26.96*	-21.85	-12.70	-31.23**	-29.71***	-14.29**
	(13.02)	(11.89)	(6.487)	(13.84)	(13.83)	(12.13)	(12.93)	(11.30)	(5.592)
Treatment2 X Post	-16.13**	-19.95***	-22.32***	-28.48***	-28.72***	-29.40***	-11.73	-14.26**	-16.12***
	(7.515)	(6.336)	(6.415)	(9.291)	(9.901)	(10.09)	(8.344)	(5.760)	(5.496)
Observations	679,649	621,560	581,448	124,964	114,682	107,482	99,12	90,643	84,791
R-squared	0.377	0.389	0.403	0.270	0.274	0.283	0.397	0.427	0.474
No. of schools	105	97	92	105	97	92	105	97	92
Baseline mean vol.	106.6	91.97	83.29	255.7	238.8	227.6	53.48	38.85	31.28
% change T1	-25.60%	-27.87%	-14.00%	-10,54%	-9,15%	-5,58%	-58.40%	-76.47%	-45.68%
% change T2	-15.13%	-21.69%	-26.80%	-11,14%	-12,03%	-12,92%	-21.93%	-36.71%	-51.53%
Dependent variable: Water usage per pupil (litres/30min)									
Treatment 1 X Post	-0.0301**	-0.0279**	-0.0151*	-0.0290**	-0.0160	-0.0247*	-0.0342***	-0.0313***	-0.0180***
	(0.0126)	(0.0121)	(0.00767)	(0.0145)	(0.0135)	(0.0148)	(0.0115)	(0.0109)	(0.00625)
Treatment2 X Post	-0.0209***	-0.0235***	-0.0261***	-0.0311***	-0.0313***	-0.0310***	-0.0162**	-0.0172***	-0.0201***
	(0.00702)	(0.00702)	(0.00714)	(0.0105)	(0.0116)	(0.0113)	(0.00679)	(0.00623)	(0.00607)
Observations	679,649	621,560	581,448	124,964	107,482	114,682	99,12	90,643	84,791
R-squared	0.366	0.377	0.389	0.236	0.244	0.238	0.400	0.442	0.474
No. of schools	105	97	92	105	92	97	105	97	92
Baseline mean vol.	0.101	0.0895	0.0819	0.246	0.225	0.234	0.0505	0.0383	0.0317
% change T1	-29.80%	-31.17%	-18.44%	-11,79%	-7,11%	-10,56%	-67.72%	-81.72%	-56.78%
% change T2	-20.69%	-26.26%	-31.87%	-12,64%	-13,91%	-13,25%	-32.08%	-44.91%	-63.41%

med: Median water use L/30min over entire period of study. Fixed effects regressions. Robust standard errors clustered on school in parentheses. Suppressed coefficients on month, week, afterhours, weekends, major leaks, night flow public holidays and school holidays. *** p<0.01, ** p<0.05, * p<0.1