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ARTICLE

Two steps forward, one step back: negative spillovers in water conservation

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Abstract
Showering is one of the most water-intensive behaviours in urban households, accounting for 20–30% of water use. Real-time feedback from smart devices has been proven to significantly reduce water consumption in showers. Still, it is not known whether these devices have spillover effects on other water use behaviours. For the first time, we provide empirical evidence for a significant and negative within-domain spillover effect from the use of such devices, showing an increase in water use in other activities by 2.5% per day per household. Up to one-third of conservation effects are eroded by such spillovers, resulting in a two steps forward, one step back situation. Overall, however, net water use is still reduced by 4.7% in the 385 households that were observed. This study points out an important behavioural limit on the use of such smart shower devices and suggests that such use be accompanied by informational or other campaigns to reduce the large negative spillovers.

Keywords: smart shower devices; water conservation; spillover effects; moral licensing; behavioural change

Introduction
Showering accounts for a significant proportion (roughly 20–30%) of water used in residential households (Shahmohammadi *et al.*, 2019; Hoo, 2020), while heating this water to comfortable temperatures also consumes a significant amount of energy (Makki *et al.*, 2013; Binks *et al.*, 2017). Hence, motivating reduced water use during showers is a significant step towards sustainability and conservation efforts.

Given the relatively low price elasticity of water demand, as well as the political risk of raising water prices, research on non-price measures such as nudges is, as a result, particularly useful for policymakers (Bernedo *et al.*, 2014; Smith and Visser, 2014; Brick *et al.*, 2023). While pricing policies remain important for balancing conservation and revenue needs for utilities and authorities, non-price measures are growing in importance and prominence as complementary policy instruments.

There has been a large body of empirical work on nudges – which are defined as a way to reshape the choice architecture to encourage individuals to behave in ways that they *themselves* would prefer over their current actions (Oliver, 2017, 2023) – especially on providing real-time feedback through smart devices. Such smart shower devices have been shown to significantly reduce water use during showers (Willis *et al.*, 2010; Agarwal *et al.*, 2017).

During showers, users are typically more focused on the immediate pleasures derived from showering compared to the volume of water used and may not be conscious of the amount of time and water used in the process. Real-time feedback on water usage helps to mitigate this by transforming water consumption from something 'abstract, invisible and untouchable' to a process that is 'transparent, dynamic and controllable' (Buchanan *et al.*, 2014). Smart shower devices make users aware of how much water they are using at any given time and work to increase the salience of this information (Karlin *et al.*, 2015; Tiefenbeck *et al.*, 2018).

For example, the Hydrao Aloé conveys water use through the changing colours of LED lights in the shower head, while the Amphiro B1 does so through a numerical information display installed in the shower hose (see Supplementary Appendix S1 for more detailed descriptions). Agarwal *et al.* (2017) found a significant reduction in shower water consumption using the Amphiro B1 device in households in Singapore, and Willis *et al.* (2010) found a mean reduction of 27% in shower event volumes using the WaiTEK Shower Monitor.

In general, other studies have shown the effectiveness of devices that provide real-time feedback either through reducing electricity consumption (Jessoe and Rapson, 2014), reducing caloric intake (Bollinger *et al.*, 2011) or increasing online information disclosure (Kehr *et al.*, 2015).

Recent work by Goette and Tiefenbeck captures much of our current understanding of the behavioural aspects of water conservation. First, Goette *et al.* (2019) found that feedback is more likely to reduce water consumption levels among heavy users (confirming earlier work by Tiefenbeck *et al.* (2018)). The influence of feedback not only varies with the type of water consumer but also with other forms of social interventions. Goette *et al.* (2021) showed that the water-conserving benefits of feedback interventions are consistently stronger for high baseline users but only when they are initially presented with an achievable water conservation goal. That is, over-ambitious goals can backfire on water conservation.

Second, Tiefenbeck *et al.*'s (2019) paper is based on nearly a decade of research on how feedback reduces household water use. Both weekly and monthly reports of household water consumption levels have been shown to reduce household water consumption by around 6% (Tiefenbeck *et al.*, 2013; Torres and Carlsson, 2018). Moreover, the amount of water saved through feedback interventions is significant. Tiefenbeck *et al.* (2014) showed that participants who received real-time feedback on the amount of water consumed while showering subsequently reduced their consumption levels by 23%, and this was sustained throughout the two-month study period. They further found that feedback interventions may be more effective among the younger generations. Tiefenbeck *et al.* (2018) found that real-time feedback using the

Amphiro B1 device reduced Swiss household shower resource (water and energy) consumption by 22%. Recently, Tiefenbeck *et al.* (2019) have shown that providing real-time feedback on energy consumed while showering leads to a significant 11.4% reduction in energy use. This promising finding was obtained from hotel guests – volunteers neither aware of nor incentivised to participate in the study.

While these experiments have done much to show that nudging by increasing salience works to constrain water consumption, there remains a gap in our current understanding relating to the possible spillover effects. Spillover effects are interesting because they potentially increase or reduce the effect of a specific intervention or policy (Dietz *et al.*, 2009). Spillover is defined as the effect of an intervention on subsequent behaviours not directly targeted by the intervention (Truelove *et al.*, 2014). Liu *et al.* (2021) found that setting goals to reduce electricity consumption may, in some cases, also lead to a reduction in water consumption. However, negative spillover could also occur in an environmental campaign. Werfel (2017) found that reminding people of their energy-saving actions reduced their support for a carbon tax policy.

The pathways for such spillover effects of behavioural interventions are increasingly receiving attention in the field of environmental psychology (Truelove *et al.*, 2014; Nash *et al.*, 2017; Maki *et al.*, 2019) and environmental economics (Carlsson *et al.*, 2021; Jessoe *et al.*, 2021; Kumar *et al.*, 2023).

Positive spillovers are accounted for by cognitive dissonance and theories relating to identity (Truelove *et al.*, 2014; Nash *et al.*, 2017). Cognitive dissonance theory (Festinger, 1962) suggests that people feel discomfort if they hold contradictory beliefs or behave inconsistently. The inconsistency between what people believe and how they behave motivates people to engage in additional environmentally conscious actions that will help minimize feelings of discomfort.

Negative spillovers (also known as compensatory spillovers), as reviewed by Nilsson *et al.* (2017) and Truelove *et al.* (2014), are posited as the reduction of the likelihood of subsequent pro-environment behaviour after prior engagement in pro-environment behaviour. Some research relates such spillovers to the moral licensing theory, which suggests that after performing a moral behaviour, individuals are more likely to feel entitled or 'licensed' to behave immorally in other aspects (Merritt *et al.*, 2010).

Overall, however, empirical studies on spillover effects tend to be limited. Many studies measure non-targeted behaviours of interventions based on intentions or self-reported data, which is subject to error and bias (Makki *et al.*, 2013; Lanzini and Thøgersen, 2014). Studies are often correlational in nature, making causal inferences difficult (Truelove *et al.*, 2014). At the same time, there are very few studies looking across longer time horizons and only measure the spillover immediately after the initial behavioural action (Maki *et al.*, 2019).

Our study aims to add to empirical research on spillover effects within the water domain. We evaluate whether the real-time feedback from smart shower devices can have spillover effects on other water use behaviours in households using a difference-in-difference approach. We first find that there is a large and significant conservation effect; second water use at other places in the household increases, partly offsetting the gains in shower water conservation.

The outline of this paper is as follows. The section 'Methods' discusses the study design, data collection and estimation of treatment and spillover effects. The section

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'Results' presents the results and findings, juxtaposed against important current research. The section 'Conclusions' sets out our conclusions and how these contribute to the current understanding of water behaviours.

Methods

Study design

Our research was conducted in a randomized control trial in Singapore. Singapore, being a water-stressed, city-state where water is imported from a neighbouring country and where water conservation is high on the national agenda (Tortajada *et al.*, 2013), is constantly exploring new and innovative ways to conserve water. However, more needs to be done. The Smart Shower Programme is a manifestation of the latest approach – a turn towards libertarian paternalism (Thaler and Sunstein, 2003, 2008) by applying nudges (in the form of smart shower devices) to encourage water conservation by individuals and households.

Under the Smart Shower Programme, the Public Utilities Board – Singapore's National Water Agency – started to deploy smart shower devices in 10,000 new homes in 2018. A prior trial on 500 households in 2015 indicated a water savings of 5 L per person per day during showers, which translates to about 3% of their monthly water usage (PUB, 2022).

For this current study, the Hydrao Aloé smart shower devices were installed in the bathrooms of households (NUS ethics approval no. S-18-332) from four high-rise housing estates in Singapore (Keat Hong Mirage and Keat Hong Pride in Choa Chu Kang, and Waterway Cascadia and Waterway View in Punggol), which share very similar characteristics to households in the Smart Shower Programme in terms of flat types and building age but are not within the programme. Each household was observed for a period of three months, with the first month being the baseline period and the next two months as the intervention period. Smart shower device readings were collected between 18 July and 13 November 2020 (due to different start times for different groups of households; see Figure 1).

The four housing estates comprise 4,368 flats in high-rise buildings, which construction was completed in 2015 and 2016. (A gap of a few years after building completion was chosen to prevent overlapping with households' move-in phase, where water use can be more erratic and difficult to interpret.) Limiting our sample households to high-rise buildings also has the benefit of ensuring that there will be minimal fluctuations in water pressure, which is controlled centrally by authorities, ensuring that water usage deviations will not be a consequence of differences in water flow (due to water pressure). Singapore's housing policies limit the combined household monthly incomes of occupants to S$12,000 (about US$9,000) at the time of buying these flats and do not allow selling the flat within five years after purchase. As a result, the typical occupants share very similar profiles – young families, sometimes with living-in elderly parents, with similar household incomes. The flats comprise two or three bedrooms, and all have two bathrooms. These similarities ensure a fair comparison across households in the treatment and control groups. An additional step is to balance the two groups on key characteristics, such as location, household size and household water use during the random assignment process (see Supplementary Appendix S2).

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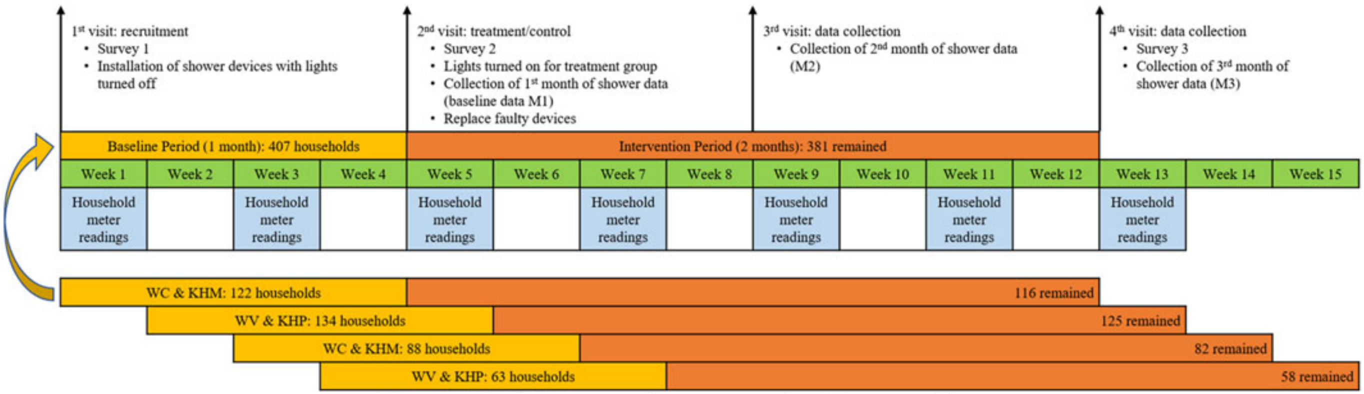

Note: WC refers to Waterway Cascadia, KHM to Keat Hong Mirage, WV to Waterway View, and KHP to Keat Hong Pride

Figure 1. Study timeline and implementation.

Invitation letters to join the study were sent out about 2 weeks before recruitment. During the recruitment, trained surveyors went door-to-door to ask households to participate in the study. Basic information was given: (1) households were informed that the study involved smart shower devices and water conservation, (2) that there would be water data collection and three short surveys over the entire study period and (3) that they would receive a S$20 (about US$15) grocery voucher for participating in each survey. About 10% of the households agreed to participate, and, in total, 407 households were recruited. Participating households were informed that they could keep the smart shower devices at the end of the study.

Once households opted into the research project, the first survey was administered, the water meter was read, and the Hydrao Aloé smart shower devices were installed in both household's bathrooms. The Hydrao Aloé device is powered by water flow during a shower and can record water volume (in whole litres), duration, average temperature and flow rate per shower. A mobile application allows the shower data to be synced to a cloud application to configure the colour of LED lights in the shower head based on pre-set thresholds of water use. Households were only able to access this mobile application after the end of the study. During a shower, around 2 min of soaping time is allowed before the next water flow is recorded as a new shower.

The surveyors visited the recruited households three more times at monthly intervals. Prior to the second visit, households were randomly assigned to either the treatment or control group. The randomization ensured that treatment and control households were balanced on key characteristics such as baseline household water use, household size and selected survey questions.

During the second visit, the surveyors configured the light settings of the devices for treatment households. The shower heads' colour changes were set from green to red with the following thresholds: green (0–10 L), blue (10–14 L), purple (14–18 L) and red (18–20 L). The devices started flashing red when water use exceeded 20 L. The target of 20 L was selected based on an average use of about 25 L per shower event during the baseline period. For control households, the lights remained off throughout the intervention period. Small waterproof posters explaining the meaning of each colour were placed inside the shower cubicles of the treatment households. The researchers also administered the second survey, replaced faulty devices and recorded the water meter readings.

During the third visit, surveyors retrieved the second month of shower data, replaced any faulty devices and read the household water meters. Finally, during the fourth and last visit, households answered the third survey, surveyors retrieved the third month of shower data and read the water meters of the households.

Figure 1 gives an overview of the study timeline and implementation process.

Data collected

Of the 407 households that were recruited, 385[1] remained at the end of the study. Some households dropped out due to personal reasons, long periods of absence

[1]An ex-post power estimation test (Burlig *et al.*, 2020) and an analysis of covariance (ANCOVA) robustness check support the adequacy of the sample size (see Supplementary Appendices 3 and 4).

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from the house or smart shower device inactivity due to personal preferences (for example, finding the showerhead too heavy). There were no indications of systemic differences due to these attrition issues.

The raw dataset included observations of 239,216 measured showers from 768 devices in 385 households. The devices' limited internal memory restricts shower volume records to 240 shower events between data downloads, with older records being overwritten by new ones. This type of limitation is not unique to such smart shower devices; Agarwal *et al.* (2017, p. 17) and Tiefenbeck *et al.* (2018, Supp. Info. p.3) used devices with limits of 672 and 205 shower events, respectively. Imputation was used to replace the missing overwritten records in the shower data (similar to the Agarwal *et al.* (2017) study) to account for time-fixed effects and calculate shower event frequencies. Since all shower events recorded (even overwritten ones) are ordered with a running sequence of numbers, we were able to use the sequence of numbers to determine if there was a gap (missing sequence numbers) that needed to be imputed. The number of showers to impute was the respective average number of showers in each period. The volume inputted was the mean volume of the device used in each period. A total of 21,445 shower values were added through imputation, resulting in a total of 260,661 showers. Imputation of missing data did not affect the robustness of the data – average water consumption per shower event and trends of control and treatment groups remain similar to a parallel analysis without the imputation (see Supplementary Appendix S5).

In the next pre-processing step, 61,470 recorded showers below 5 L were removed as records with very low water use may not indicate showers, but rather water used for other purposes (such as cleaning). While this number appears high, shower heads in Singapore bathrooms are frequently used for cleaning due to closed cubicle designs (Agarwal *et al.*, 2017). The first and last recorded shower event for each time period (between data collection) was also discarded due to noise from field workers installing and syncing smart shower devices, which requires running the shower to power the Bluetooth connection – this resulted in another 2,026 shower events being dropped. Finally, the data were cleaned by filtering out the devices that recorded fewer than 10 shower events during the baseline and the intervention period; 2,510 shower events falling under this category were removed. The final dataset consisted of 194,655 showers from 672 smart shower devices in 381 households (see Table 1).

Water meters for households were read at every fortnightly visit to a recruited household, resulting in four readings for each household. Water consumption for each household was obtained by taking the difference between two consecutive readings and dividing that by the number of days that had passed.

Estimation of treatment and spillover effects

To quantify the treatment effect, we applied a difference-in-difference approach based on the following equation:

$$y_{is} = \alpha_i + \beta_1 T_{is} + \delta_t + \varepsilon_{is}, \tag{1}$$

where y_{is} is the water volume of shower event s from device i, and T_{is} is a binary variable that equals 1 if the shower event s from device i occurs during the intervention

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Table 1. Sample distribution across treatment and control

Group	No. of households	No. of devices	No. of showers recorded	Baseline (M1) Average water use (L) Per shower	Baseline (M1) Average water use (L) Per household	Baseline (M1) Average duration of showers (min)	M2 + M3 Average water use (L) Per shower	M2 + M3 Average water use (L) Per household	M2 + M3 Average duration of showers (min)
Treatment	189	336	94,768	24.90	160.10	3.49	19.75	123.78	3.51
Control	192	336	99,887	25.17	166.88	3.62	25.17	167.61	3.77
Total	381	672	194,655	25.04	163.45	3.55	22.54	145.46	3.64

period and device i is in the treatment group (t represents the percentage point of study completion; the baseline period is defined by $t \leq 33\%$ (i.e. the first month of the three-month study) and the intervention period is defined by $t > 33\%$). The control group serves as the reference group. Thus, β_1 represents the average treatment effect. Furthermore, we control for device-fixed effects, α_i, and time-fixed effects, δ_t, using the study completion variable, t. Finally, ε_{is} represents the shower-specific error term and to account for the correlation among shower events coming from the same device, we cluster standard errors on the devices.

The persistence of the treatment effect was assessed by extending (1) to four time periods based on the fortnightly estate water meter reading collection:

$$\begin{aligned} y_{is} = \alpha_i + \beta_1 T_{is} + \beta_2 T_{is}(\delta_t - a_1) + \beta_3 T_{is}(\delta_t - a_2) \\ + \beta_4 T_{is}(\delta_t - a_3) + \beta_5 T_{is}(\delta_t - a_4) + \delta_t + \varepsilon_{is}, \end{aligned} \tag{2}$$

where a_k are the knots or cutoffs in a spline regression and the terms δ_t–a_k have the value only if the term is positive, and 0 otherwise. In this model, β_1 can be interpreted as the treatment effect immediately at the start of the intervention. The remaining β-coefficients are the slopes for the treatment group at each phase of the intervention period and will provide information on the persistence of the treatment effect.

We also investigated if the overall water use of households was affected by the use of smart shower devices. The household water use derived from the monthly water meter readings was split into shower water use, based on the data downloaded from the smart shower devices, and non-shower use. All amounts were converted to LPD for each household.

The model to assess the spillover effect of water used elsewhere in the household is similar to the model for the shower analysis. However, this time, i refers to a household rather than a device. There are also no subscript s since showers have already been aggregated at the household level; s in T_{is} is replaced by the time subscript t to represent periods. Households and time-fixed effects are present as well. y_i refers to shower, non-shower or overall LPD. Treatment variable $T = 1$ when the observation is recorded from the treatment group during the intervention period.

$$y_i = \alpha_i + \beta_1 T_{it} + \delta_t + \varepsilon_i. \tag{3}$$

Results

Water savings in shower use

A typical shower event during the baseline period used around 25 L and took about 4 min (see Table 1). There was considerable variation in the showering behaviour of households. For instance, while most showers used 10–25 L, some households consumed more than 60 L per shower.

After the intervention, there was an immediate drop in the average water use of the treatment group and no change in the control group (see Figure 2). The immediate effect was around 7 L per shower event (a positive and significant slope of the curve), which stabilized after 2 weeks at about 5 L per shower until the end of the study period.

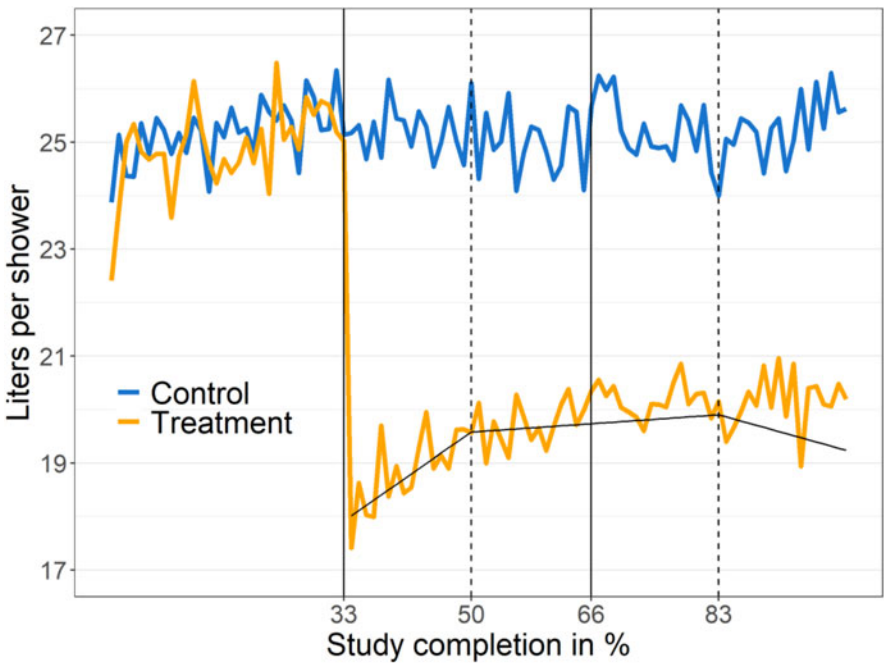

Figure 2. Shower water use over the study period.

The average treatment effect over the intervention period is 5.54 L per shower event and is statistically significant at the 1% level (Table 2). The treatment resulted in a 22% decrease in shower water use, given an average baseline use of 25 L per shower.[2]

The persistence of the treatment effect was analysed by dividing the study period into four parts, with splits at 33%, 50%, 66% and 83% study completion, and estimating a spline regression model. The treatment effect was estimated at 6.99 L per shower immediately after the feedback was switched on. The slope at the first spline is positive and significant, suggesting that households were adjusting to the surprise of the intervention and saving slightly less than the immediate savings observed. The slope at the second spline is not significant and close to zero (the coefficient from Treatment * first spline nearly offsets the coefficient from Treatment * second spline), and the rest of the coefficients are small and non-significant. This implies that the treatment effect had stabilized after the initial drop-off at least for the remaining weeks of the study, although whether the treatment effect will remain stable over the longer term cannot be determined without further follow-up longitudinal studies.

[2]Compared to about 2–4 L with a baseline of 20 L in the Agarwal *et al.* (2017) study (about 10% decrease) and around 9.5 L per shower with a baseline of 44 L in the Tiefenbeck *et al.* (2018) study (about 22% decrease).

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Table 2. Results of the difference-in-difference estimations for treatment effect

	Dependent variable: volume (L)	
Treatment effect	(1)	(2)
Treatment	−5.541***	−6.987***
	(0.389)	(0.513)
Treatment * first spline (knot = 33)		0.098***
		(0.033)
Treatment * second spline (knot = 50)		−0.088
		(0.055)
Treatment * third spline (knot = 66)		0.000
		(0.048)
Treatment * fourth spline (knot = 83)		−0.049
		(0.047)
Device-fixed effects?	Yes	Yes
Time-fixed effects?	Yes	Yes
Observations	194,655	194,655
Adjusted R^2	0.260	0.260

Note: Standard errors are clustered on devices. *p < 0.1; **p < 0.05; ***p < 0.01.

Negative spillovers

Households used an average of 496 LPD in the baseline period, with no significant difference between treatment and control (see Table 3). Non-shower use averaged 333 LPD, while shower use averaged 163 LPD. Figure 3 shows the change in overall water consumption relative to the baseline periods, and Table 4 shows the regression results. There was a non-significant increase in overall water use in the control group, while the treatment group showed a significant decrease in the overall water consumption of 23.5 LPD or a decrease of 4.7% of the baseline water use. However, the magnitude of this overall decrease in household water consumption was smaller than that of the decrease in shower water use. Specifically, while the control group had a slight non-significant increase in shower LPD, the treatment group had a significant 37 LPD reduction in shower water use. This suggests a negative spillover effect of about 13.5 LPD since the decrease in shower water used per day due to the intervention was offset by an increase in non-shower water used per day.

Overall, some negative spillover is observed across all households, although it is not high enough to completely erode the conservation effects. While the net effect is large (roughly 5% of a household's water use), about one-third of the treatment effect was lost due to negative spillovers.

This finding should be seen against current thinking on spillover effects. Earlier studies suggest that the effects of water savings at the household level are

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Table 3. Water usage and duration per household

Group	Baseline (M1)			M2 + M3		
	Average overall water usage per household (L)	Average shower water usage per household (L)	Average non-shower water usage per household (L)	Average overall water usage per household (L)	Average shower water usage per household (L)	Average non-shower water usage per household (L)
Treatment	494.72	160.10	334.62	476.05	123.78	352.27
Control	497.32	166.88	330.44	502.15	167.61	334.54
Total	496.01	163.45	332.55	488.96	145.46	343.50

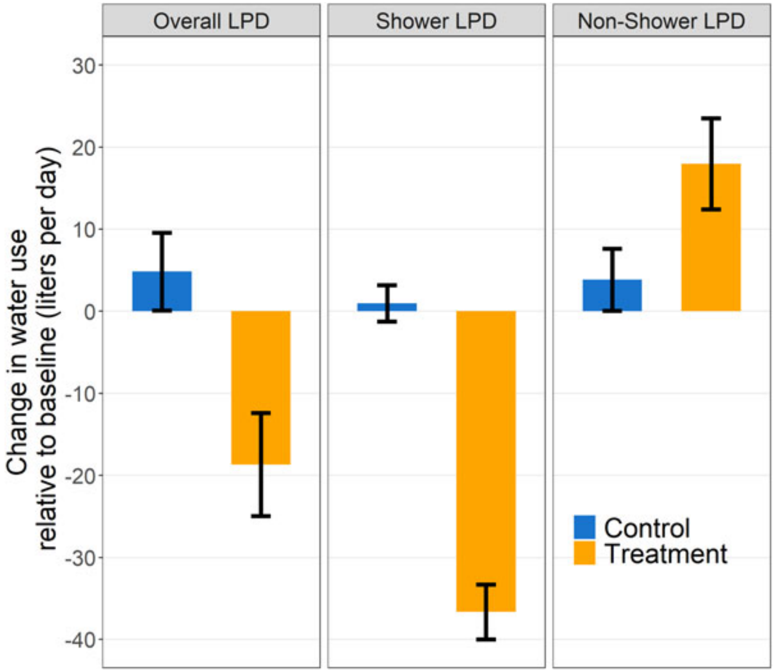

Figure 3. Overall and shower difference-in-difference estimates (household level).

Table 4. Spillover effect

	Spillover effect		
	Dependent variable: water use (LPD)		
	Overall LPD (1)	Shower LPD (2)	Non-shower LPD (3)
Treatment	−23.511***	−37.048***	13.537**
	(7.856)	(3.982)	(6.656)
Household-fixed effects?	Yes	Yes	Yes
Time-fixed effects?	Yes	Yes	Yes
Observations	1,116	1,116	1,116
Adjusted R^2	0.959	0.925	0.948

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

larger than what can be accounted for by the use of smart shower devices (Agarwal *et al.*, 2017), suggesting a positive spillover effect possibly due to increased awareness of resource use. However, as the study had used aggregated secondary data, its results were inconclusive. Our study establishes that the spillover is, in fact, negative and large, at least in the context of Singapore.

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Second, negative spillover in environmental behaviour had earlier been established by Tiefenbeck *et al.* (2013), but this was *across* domains. They reported that households that reduced water use (6.0% on average) simultaneously increased their electricity consumption by a similar proportion (5.6% on average). Our study shows that this effect takes place *within* domains as well.

Third, we were interested in uncovering the mechanism underlying the spillover effects to improve the intervention. Our work finds traction in current thinking on moral licensing.

Figure 4 shows that there is a negative relationship between the change in water use for showering and other water use in the treatment group, while this relationship is positive in the control group. When considering only households that decreased their showerhead usage after the treatment, we notice a small spillover effect, i.e., a decrease in showerhead use led to an increase in non-bathroom use. For every 1 L of water saved through the showerhead treatment, these households increased their non-bathroom usage by about 0.15 L. This spillover effect may be explained by

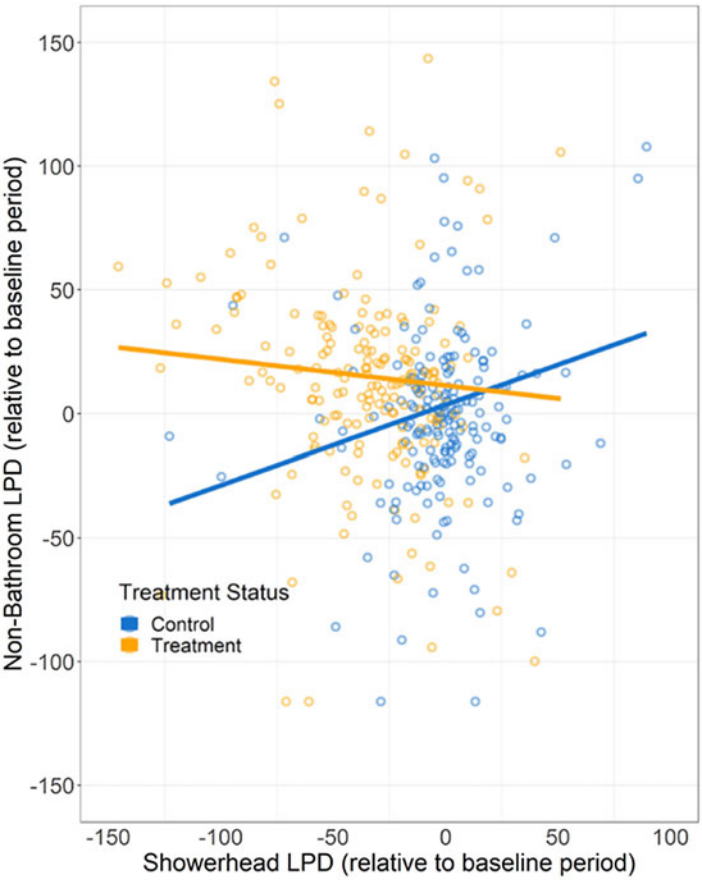

Figure 4. Shower vs non-shower LPD.

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treatment households opting to use other taps within the household rather than the showerhead for their non-bathroom water needs. Yet, consideration of the showerhead treatment only explains about 1% in the variance of non-bathroom usage – there are probably other factors that have a greater impact on the increase in non-bathroom water usage.

This provides *prima facie* support for the moral licensing hypothesis – that users compensate for conservation behaviours in showering by using more in other areas. While this is insufficient to infer a causal relationship, this preliminary finding is worthy of further exploration in future studies.

Additional analysis

The large behavioural response also allows us to examine whether the reaction to real-time feedback differs in subsamples. Previous studies have found that conservation effects are larger for high baseline users than for users who start with more efficient resource use (Allcott, 2011; Ferraro and Price, 2013; Allcott and Rogers, 2014; Brent *et al.*, 2015; Schultz *et al.*, 2016). We checked if the aggregate treatment effect was affected by the baseline use of the shower devices. By splitting and categorizing the observations by the median baseline shower consumption (which was 19 L), we can examine whether the treatment effect differed between high (an average of 33.77 L) and low (an average of 15.45 L) baseline users. While there do not seem to be noticeable differences in the control group between high and low baseline users, the converse is true for the treatment group. On average, in the treatment condition, high baseline users reduced their shower water use by around 5 L more compared to low baseline users.

We also checked whether the number of showers that were taken was influenced by the use of the smart shower devices. Participants in the treatment condition could have taken more showers despite consuming less water per shower event. This could have attenuated water conservation behaviours arising from the use of smart shower devices. However, we found a small decrease in the average number of showers taken per day in the treatment group (from 3.15 to 3.07 showers per day), while in the control group, there was almost no change (from 3.31 to 3.30 showers per day). A difference-in-difference estimation of the shower frequency shows that the decrease is not significant when all devices are included, significant ($p < 0.05$) if two outlier devices are excluded and significant ($p < 0.10$) if further devices with incomplete baseline data are excluded (to remove the potential impact of imputation) (see Supplementary Appendix S6 for more details).

A check of the heterogeneity by regressing the spillover effect to a range of household characteristics and attitudes did not show any clear patterns (such as over time, across different intervention periods or with household size). However, the presence of older household members seems to affect the spillovers; the negative spillovers were significantly ($p < 0.05$) stronger for households with people aged 50 and above (see Supplementary Appendix S7).

The survey examined respondents' attitudes towards showering, conservation and the smart shower device, as well as their water use perception. The results show that both treatment and control group respondents' attitudes towards water conservation and the environment were similar and did not change significantly over the study period. The survey also shows that while the treatment group saw the merits of using smart shower devices, they also experienced some degree of stress using it.

As expected, the treatment intervention increased respondents' awareness of their water use during shower events. In the surveys, respondents were asked to estimate how much water they use during shower events. We then compared their estimates with their actual water use before and after the intervention (see Supplementary Appendix S8). Before the intervention, control and treatment households estimated that they used about 13 L per shower event, which is only around half of the average baseline of 25 L per shower event. After the smart shower devices were switched on, treatment households estimated their shower water use much more accurately, with the mean estimated water use being close to the actual mean water use. Interestingly, despite not receiving any feedback, control households also showed increased awareness of their water use, even though they were still about 9 L off the mark. The exact reason for this cannot be identified from the present study but is worth exploring in future research.

Conclusion

Overall, this study serves as a response to the call for more research on the outcomes of experiments that aim to inform governance (Kivimaa *et al.*, 2017) by highlighting the impact of spillovers in the use of smart water devices for water conservation efforts. There are two main findings in this study – the first confirms existing research and the second provides a novel insight into water use behaviours. First, in line with the behavioural turn among policy scholars to effect policy changes (Leong and Howlett, 2022), including the consumer behaviour and policy sphere (Reisch and Zhao, 2017), we found that the use of nudging through real-time feedback has a large effect on the per-shower water use – on the studied sample, savings are on average 5.54 L per shower. One of the reasons could be due to a more accurate idea of how much water is being used – our surveys find that real-time feedback makes perceptions of water use far more accurate.

Our study design allows us to explore beyond a snapshot view of this nudging effect and examine its impact on a medium term (of —two to three months). Nevertheless, we do need to be wary of extrapolating the results to the longer term. Most of the literature suggests that this type of nudge will decay relatively quickly (Ferraro *et al.*, 2011; Ferraro and Price, 2013; Allcott and Rogers, 2014; Bernedo *et al.*, 2014), and this is evident in our study as well through the drop-off in treatment effect from the initial 7 L per shower to 5 L per shower. However, the effectiveness of nudges in the long run is still not clear in the existing literature (Congiu and Moscati, 2022). Some scholars have suggested that the long-term effectiveness of nudges will depend on whether it is a Type 1 nudge (those targeting automatic behaviour) or a Type 2 nudge (those that educate or persuade at the conscious level) (Lin *et al.*, 2017). Type 2 nudges are expected to lead to long-term changes, but the efficacy of Type 1 nudges in leading to sustained changes is less certain. Our study suggests a stabilization of the treatment effect after the initial drop-off (especially when the nudged behaviour becomes a habit over time), but with smart shower devices being a Type 1 form of nudge, it is equally likely that individuals will start to revert to their old habits once the salience of the devices has worn off.

Second, and more significantly, we demonstrate, for the first time, the existence of a negative spillover from the use of smart meter devices. This is observed across all households, and while this does not completely erode conservation effects, it does provide a cautionary insight into the use of such devices. Whereas in the past, research has only shown the benefits of use, our study shows that as high as one-third of the conservation effects may be cancelled by negative spillovers. That is to say, two steps forward, unfortunately, one step back.

Other than negative spillovers, another important consideration of implementing smart water devices in residential units, based on a systems perspective, is the impact on the amount of wastewater available. While using smart meter devices during showers helps to save water, it also has the lead-on effect of reducing wastewater available, which could subsequently be used for water recycling. This is another important avenue for water conservation in Singapore. As such, from a systems perspective, the efficacy of smart meter showers may be further eroded on a national basis (though it still does lead to savings on a household level).

We also recognize that there is a limit to the mileage smart water devices can have. As we mentioned, showering is a pleasurable activity, so the devices can only reduce water usage to a certain extent without actually prohibiting showers altogether.

While concerns about the potential autonomy-eroding qualities of soft paternalistic interventions such as nudging and smart shower devices need to be paid proper attention (Oliver, 2023), another area of concern revolves around the externalities associated with these interventions (spillovers). Nudge interventions should not be considered in isolation but with consideration of all the 'ripples on a pond', i.e. the behavioural splash as a result of the intervention (Dolan and Galizzi, 2015).

Lastly, we posited that moral licensing could account for this behaviour – that users compensate for their restrictive behaviours in showering by using more water elsewhere. Given this, policymakers will need to systematically evaluate any potential spillovers (positive or negative) (Krpan and Urbaník, 2021) with future research that could focus on further uncovering the mechanism of such spillovers as well as policy implications such as the need to compensate for these negative spillovers by raising awareness of water consumption in non-showering areas. For instance, by tweaking the nudges into socially minded nudges (Van Der Linden, 2018), such as by informing people how many referent others are participating in the same initiative (installing smart water devices in their homes).

Supplementary Material. To view supplementary material for this article, please visit https://doi.org/10.1017/bpp.2024.25.

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References

Agarwal, S., X. Fang, L. Goette, T. F. Sing, S. Schoeb, V. Tiefenbeck, T. Staake and D. Wang (2017), The Role of Goals and Real-Time Feedback in Resource Conservation: Evidence from a Large-Scale Field Experiment. https://www.iame.uni-bonn.de/people/lorenz-goette/goals-and-real-time-feedback [14 November 2022].

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

Allcott, H. and T. Rogers (2014), 'The short-run and long-run effects of behavioral interventions: experimental evidence from energy Conservation', *American Economic Review*, **104**(10): 3003–3037. https://doi.org/10.1257/aer.104.10.3003.

Bernedo, M., P. J. Ferraro and M. Price (2014), 'The persistent impacts of norm-based messaging and their implications for water conservation', *Journal of Consumer*, **37**: 437–452. https://doi.org/10.1007/s10603-014-9266-0.

Binks, A. N., S. J. Kenway and P. A. Lant (2017), 'The effect of water demand management in showers on household energy use', *Journal of Cleaner Production*, **157**: 177–189. https://doi.org/10.1016/j.jclepro.2017.04.128.

Bollinger, B., P. Leslie and A. Sorensen (2011), 'Calorie posting in chain restaurants', *American Economic Journal: Economic Policy*, **3**(1): 91–128. https://doi.org/10.1257/pol.3.1.91.

Brent, D. A., J. H. Cook and S. Olsen (2015), 'Social comparisons, household water use, and participation in utility conservation programs: evidence from three randomized trials', *Journal of the Association of Environmental and Resource Economists*, **2**(4): 597–627. https://doi.org/10.1086/683427.

Brick, K., S. De Martino and M. Visser (2023), 'Behavioural nudges for water conservation in unequal settings: experimental evidence from cape town', *Journal of Environmental Economics and Management*, **121**: 102852. https://doi.org/10.1016/j.jeem.2023.102852.

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

Burlig, F., L. Preonas and M. Woerman (2020), 'Panel data and experimental design', *Journal of Development Economics*, **144**: 102458. https://doi.org/10.1016/j.jdeveco.2020.102458.

Carlsson, F., M. Jaime and C. Villegas (2021), 'Behavioral spillover effects from a social information campaign', *Journal of Environmental Economics and Management*, **109**: 102325. https://doi.org/10.1016/j.jeem.2020.102325.

Congiu, L. and I. Moscati (2022), 'A review of nudges: definitions, justifications, effectiveness', *Journal of Economic Surveys*, **36**: 188–213. https://doi.org/10.1111/joes.12453.

Dietz, T., G. T. Gardner, J. Gilligan and M. P. Vandenbergh (2009), 'Household actions can provide a behavioral wedge to rapidly reduce US carbon emissions', *Proceedings of the National Academy of Sciences*, **106**(44): 18452–18456. https://doi.org/10.1073/pnas.0908738106.

Dolan, P. and M. M. Galizzi (2015), 'Like ripples on a pond: behavioral spillovers and their implications for research and policy', *Journal of Economic Psychology*, **47**: 1–16. https://doi.org/10.1016/j.joep.2014.12.003.

Ferraro, P. J. and M. K. Price (2013), 'Using nonpecuniary strategies to influence behavior: evidence from a large-scale field experiment', *The Review of Economics and Statistics*, **95**(1): 64–73. https://doi.org/10.1162/REST_a_00344.

Ferraro, P. J., J. J. Miranda and M. K. Price (2011), 'The persistence of treatment effects with norm-based policy instruments: evidence from a randomized environmental policy experiment', *American Economic Review*, **101**(3): 318–322. https://doi.org/10.1257/AER.101.3.318.

Festinger, L. (1962), 'Cognitive dissonance', *Scientific American*, **207**(4): 93–106.

Goette, L., C. Leong and N. Qian (2019), 'Motivating household water conservation: a field experiment in Singapore', *PLoS One*, **14**(3), https://doi.org/10.1371/journal.pone.0211891.

Goette, L., H.-J. Han and Z. H. Lim (2021), (rep.). The Dynamics of Goal Setting: Evidence from a Field Experiment on Resource Conservation (Ser. CRC TR 224).

Hoo, R. (2020), 'Managing water demand in Singapore through a systems perspective', *International Journal of Water Resources Development*, **36**(6): 879–887. https://doi.org/10.1080/07900627.2019.1684245.

Jessoe, K. and D. Rapson (2014), 'Knowledge is (less) power: experimental evidence from residential energy use', *American Economic Review*, **104**(4): 1417–1438. https://doi.org/10.1257/aer.104.4.1417.

Jessoe, K., G. E. Lade, F. Loge and E. Spang (2021), 'Spillovers from behavioral interventions: experimental evidence from water and energy use', *Journal of the Association of Environmental and Resource Economists*, **8**(2): 315–346. https://doi.org/10.1086/711025.

Karlin, B., J. F. Zinger and R. Ford (2015), 'The effects of feedback on energy conservation: a meta-analysis', *Psychological Bulletin*, **141**(6): 1205–1227. https://doi.org/10.1037/a0039650.

Kehr, F., T. Kowatsch, D. Wentzel and E. Fleisch (2015), 'Blissfully ignorant: the effects of general privacy concerns, general institutional trust, and affect in the privacy calculus', *Information Systems Journal*, **25** (6): 607–635. https://doi.org/10.1111/isj.12062.

Kivimaa, P., M. Hildén, D. Huitema, A. Jordan and J. Newig (2017), 'Experiments in climate governance – a systemic review of research on energy and built environment transitions', *Journal of Cleaner Production*, **169**: 17–29. https://doi.org/10.1016/j.jclepro.2017.01.027.

Krpan, D. and M. Urbaník (2021), 'From libertarian paternalism to liberalism: behavioural science and policy in an age of new technology', *Behavioural Public Policy*, 1–27. https://doi.org/10.1017/bpp.2021.40.

Kumar, P., H. Caggiano, C. Cuite, F. A. Felder and R. Shwom (2023), 'Analyzing spillovers from food, energy and water conservation behaviors using insights from systems perspective', *Behavioural Public Policy*, **7**(3): 773–807. https://doi.org/10.1017/bpp.2022.41.

Lanzini, P. and J. Thøgersen (2014), 'Behavioural spillover in the environmental domain: an intervention study', *Journal of Environmental Psychology*, **40**: 381–390. https://doi.org/10.1016/j.jenvp.2014.09.006.

Leong, C. and M. Howlett (2022), 'Theorizing the behavioral state: resolving the theory-practice paradox of policy sciences', *Public Policy and Administration*, **37**(2): 203–225. https://doi.org/10.1177/0952076720977588.

Lin, Y., M. Osman and R. Ashcroft (2017), 'Nudge: concept, effectiveness, and ethics', *Basic and Applied Social Psychology*, **39**(6): 293–306. https://doi.org/10.1080/01973533.2017.1356304.

Liu, Y., H. W. Kua and Y. Lu (2021), 'Spillover effects from energy conservation goal-setting: a field intervention study', *Resources, Conservation and Recycling*, **170**: 105570. https://doi.org/10.1016/j.resconrec.2021.105570.

Maki, A., A. R. Carrico, K. T. Raimi, H. B. Truelove, B. Araujo and K. L. Yeung (2019), 'Meta-analysis of pro-environmental behaviour spillover', *Nature Sustainability*, **2**(4): 307–315. https://doi.org/10.1038/s41893-019-0263-9.

Makki, A. A., R. A. Stewart, K. Panuwatwanich and C. Beal (2013), 'Revealing the determinants of shower water end use consumption: enabling better targeted urban water conservation strategies', *Journal of Cleaner Production*, **60**: 129–146. https://doi.org/10.1016/j.jclepro.2011.08.007.

Merritt, A. C., D. A. Effron and B. Monin (2010), 'Moral self-licensing: when being good frees us to be bad', *Social and Personality Psychology Compass*, **4**(5): 344–357. https://doi.org/10.1111/j.1751-9004.2010.00263.x.

Nash, N., L. Whitmarsh, S. Capstick, T. Hargreaves, W. Poortinga, G. Thomas, E. Sautkina and D. Xenias (2017), 'Climate-relevant behavioral spillover and the potential contribution of social practice theory', *WIREs Climate Change*, **8**(6): e481. https://doi.org/10.1002/wcc.481.

Nilsson, A., M. Bergquist and W. P. Schultz (2017), 'Spillover effects in environmental behaviors, across time and context: a review and research agenda', *Environmental Education Research*, **23**(4): 573–589. https://doi.org/10.1080/13504622.2016.1250148.

Oliver, A. (2017), *The Origins of Behavioural Public Policy*. Cambridge: Cambridge University Press. https://doi.org/10.1017/9781108225120.

Oliver, A. (2023), 'A symposium on the behavioural limits of the state', *Behavioural Public Policy*, 1–5. https://doi.org/10.1017/bpp.2023.17.

Public Utilities Board (2022), *Handbook on Application for Water Supply*. https://www.pub.gov.sg/-/media/PUB/PDF/Handbook_on_Application_for_Water_Supply_2022.pdf [14 March 2024].

Reisch, L. A. and M. Zhao (2017), 'Behavioural economics, consumer behaviour, and consumer policy: state of the art', *Behavioural Public Policy*, **1**(2): 190–206. https://doi.org/10.1017/bpp.2017.1.

Schultz, P. W., A. Messina, G. Tronu, E. F. Limas, R. Gupta and M. Estrada (2016), 'Personalized normative feedback and the moderating role of personal norms: a field experiment to reduce residential water Consumption', *Environment and Behavior*, **48**(5): 686–710. https://doi.org/10.1177/0013916514553835.

Shahmohammadi, S., Z. Steinmann, H. King, H. Hendrickx and M. A. J. Huijbregts (2019), 'The influence of consumer behavior on energy, greenhouse gas, and water footprints of showering', *Journal of Industrial Ecology*, **23**(5): 1186–1195. https://doi.org/10.1111/jiec.12858.

Smith, G., and Visser, M. (2014), '*Behavioural Nudges as a Water Savings Strategy. WRC Report No. 2091/1/13*', Water Research Commission. https://www.wrc.org.za/wp-content/uploads/mdocs/2091.pdf.

Thaler, R. H. and C. R. Sunstein (2003), 'Libertarian Paternalism', *The American Economic Review*, **93**: 175–179.

Thaler, R. H. and C. R. Sunstein (2008), *Nudge: Improving Decisions About Health, Wealth and Happiness*. New Haven: Yale University Press.

Tiefenbeck, V., T. Staake, K. Roth and O. Sachs (2013), 'For better or for worse? Empirical evidence of moral licensing in a behavioral energy conservation campaign', *Energy Policy*, **57**: 160–171. https://doi.org/10.1016/j.enpol.2013.01.021.

Tiefenbeck, V., Degen, K., Tasic, V., Goette, L., and Staake, T. (2014). *On the Effectiveness of Real-Time Feedback: The Influence of Demographics, Attitudes, and Personality Traits*. Final Report to the Swiss Federal Office of Energy, Bern.

Tiefenbeck, V., L. Goette, K. Degen, V. Tasic, E. Fleisch, R. Lalive and T. Staake (2018), 'Overcoming salience bias: how real-time feedback fosters resource conservation', *Management Science*, **64**(3): 1458–1476. https://doi.org/10.1287/mnsc.2016.2646.

Tiefenbeck, V., A. Wörner, S. Schöb, E. Fleisch and T. Staake (2019), 'Real-time feedback reduces energy consumption among the broader public without financial incentives', *Nature Energy*, **4**(10): 831–832. https://doi.org/10.1038/s41560-019-0480-5.

Torres, M. M. J. and F. Carlsson (2018), 'Direct and spillover effects of a social information campaign on residential water-savings', *Journal of Environmental Economics and Management*, **92**: 222–243. https://doi.org/10.1016/j.jeem.2018.08.005.

Tortajada, C., J. Joshi and A. K. Biswas (2013), *The Singapore Water Story: Sustainable Development in an Urban City-State*. Oxford: Routledge.

Truelove, H. B., A. R. Carrico, E. U. Weber, K. T. Raimi and M. P. Vandenbergh (2014), 'Positive and negative spillover of pro-environmental behavior: an integrative review and theoretical framework', *Global Environmental Change*, **29**: 127–138. https://doi.org/10.1016/j.gloenvcha.2014.09.004.

Van Der Linden, S. (2018), 'The future of behavioural insights: on the importance of socially situated nudges', *Behavioural Public Policy*, **2**(2): 207–217. https://doi.org/10.1017/bpp.2018.22.

Werfel, S. H. (2017), 'Household behaviour crowds out support for climate change policy when sufficient progress is perceived', *Nature Climate Change*, **7**(7): 512–515. https://doi.org/10.1038/nclimate3316.

Willis, R. M., R. A. Stewart, K. Panuwatwanich, S. Jones and A. Kyriakides (2010), 'Alarming visual display monitors affecting shower end use water and energy conservation in Australian residential households', *Resources, Conservation and Recycling*, **54**(12): 1117–1127. https://doi.org/10.1016/j.resconrec.2010.03.004.

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