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The Spillover Effects of Real-Time Social Comparison Information on Water and Energy Use: Experimental Evidence Using In-Home Displays

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Abstract

In this field experiment, we investigate the spillover effects of real-time social comparison information provided via in-home displays on residential water and energy consumption. We find that social comparisons targeted at electricity use induce conservation beyond electricity, leading to substantial reductions in energy use for water and space heating. Meanwhile, social comparisons targeted at water use induce little or no effects on electricity, water, and space heating consumption. We argue that the differences in the direct and spillover effects of the two treatments can be explained by the differences in preexisting social norms and moral dissonance. The analysis of the heterogeneity of spillover effects reveals that the observed effects are more pronounced among households at the higher percentiles of resource use. Overall, our results suggest that spillover effects on resource use could be as large as the direct effects of behavioral interventions if there are strong, preexisting social norms to conserve the targeted resource.

Keywords Comparison information · Electricity · In-home displays · Natural field experiment · Heating · Social norms · Spillover effects · Water

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1 Introduction

The field of behavioral economics has brought attention to promising ways of encouraging people to make better choices for themselves and society as a whole. The findings in this field have inspired a wide array of environmental policies in multiple areas, including energy, water, and food consumption; transportation and car choice; waste management and resource efficiency; compliance with environmental regulations; and participation in voluntary schemes.[1] The widespread deployment of digital innovations, such as in-home displays and mobile applications, eases and speeds up the implementation of behavioral interventions that trigger socially desirable resource use decisions. Digital instruments enable the provision of granular and easily accessible social comparison information in real time (Tiefenbeck et al. 2019). This facilitates optimal resource use behavior by reducing cognitive biases and socially undesirable decisions.

Social (or peer) comparisons, which allude to social norms, are among the most popular behavioral interventions widely used to induce resource conservation actions, particularly for energy and water resources. A large body of literature provides evidence that social comparisons are effective in reducing residential energy and water consumption, and that the capacity to deliver relevant comparison information at the right time can further enhance the effectiveness of these interventions (Callery et al. 2021). Most of these studies have focused on evaluating the effects of behavioral interventions on targeted resource outcomes. However, it is very likely that the intended social comparisons affect not only the targeted resource domain but also extend (spill over) beyond the targeted outcome to other resource domains, changing the cost-effectiveness and welfare implications of the intervention (see, e.g. Jessoe et al. 2021).

This paper employs a novel field experiment design and data from smart meters for electricity and water to study whether a behavioral intervention in the form of real-time social comparisons delivered via real-time in-home displays affects households' energy and water consumption. We conduct two social comparison interventions within a single sample of apartment households in Sweden. This allows us to explore main and cross-domain spillover effects in both resource domains in a comparative manner. In particular, we examine whether social comparisons targeted at electricity use also affects the use of (both hot and cold) water and space heating—and conversely, whether those targeted at water use spill over into the use of electrical and heating energy. To the best of our knowledge, no study has evaluated such cross-domain spillover effects of water and electricity social comparisons in the same experimental setting. Furthermore, it has never been tested in an experimental setting whether behavioral interventions targeting electricity use spill over into the hot water and space heating domains. The heating of space and water is a central resource domain that, for example, accounted for about 79% of total household energy consumption in the European Union (EU) in 2021 and significantly contributed to the EU's carbon footprint (Eurostat 2023). This means that even a small reduction in the use of hot water and heating energy induced by behavioral interventions such as social comparisons could result in substantial environmental and economic benefits. Additionally, no studies investigate spillover effects by providing behavioral interventions in real time through digital means. All other

[1] See Lourenço et al. (2016) for an overview of behavioral policy initiatives and institutional developments regarding the policy application of behavioral interventions in Europe.

studies exploring spillover effects have predominantly used (bi)monthly reports as behavioral interventions, delivered by post or email.

Another unique feature of our experimental setting is that it enables us to investigate whether moral incentives, rather than monetary ones, primarily drive the spillover effects of social comparisons by focusing on energy use that households do not pay for. Unlike previous studies, which primarily feature a pecuniary motive to conserve untargeted resources (see Section 2 for the literature review), our study uniquely tests the spillover effects on both paid (energy for heating water) and unpaid (energy for heating space) energy use. This allows us to differentiate the impacts of monetary versus moral incentives on resource conservation.

Our field experiment began in March 2016 in Umeå, a city in northern Sweden, and the treatments lasted for one year. The treatments were delivered via preinstalled in-home displays, which were salient and updated in real time.[2] We constructed two separate treatment groups—one targeting electricity use for social comparison and another targeting water use. We found that the electricity social comparison treatment not only induced direct electricity savings but also spillover savings in hot water and heating energy. On average, electricity use decreased by 5.6% (or 111 kWh per year), while non-targeted consumption of hot water and heating energy decreased by 9.9% (about 132 kWh per year) and 0.9% (about 90 kWh per year), respectively. Meanwhile, the water social comparison induced neither direct nor indirect effects on the use of water, electricity, or heating energy. We argue that the differences in direct treatment effects and spillover effects between the water and electricity treatments might be explained by differences in preexisting social norms of resource utilization, demonstrating that the social norm for energy conservation is stronger than that for preserving (cold) water in our study area. Furthermore, moral dissonance could help explain the spillover effects from the electricity domain to the water and heating domains.

The rest of the paper is structured as follows: Section 2 presents a brief literature review summarizing the findings of several field-experimental studies that have empirically tested the spillover hypothesis in the context of various behavioral interventions. Section 3 describes our experimental design. In Section 4, we present the experimental data and interpret the results of our empirical analysis. We conclude in Sect. 5.

2 Brief Literature Review

In this section, we briefly review results from previous field experiments conducted to analyze both the direct and spillover effects of various informational behavioral interventions, including social comparisons. It is well established that social comparisons promote household resource conservation behavior, at least in the short run (see, e.g., review studies of Abrahamse et al. 2005; Darby 2006; Fischer 2008; Ehrhardt-Martinez et al. 2010; Faruqui et al. 2010; Clò et al. 2024). Psychologists argue that peer or social comparisons may activate social norms—descriptive and injunctive—that lead people to change their

[2] The dwellings of the participating households were already equipped with real-time displays prior to the experiment's start. Thus, we avoid the "new-gadget effect," that is, the effect that people pay attention to and play around with their new appliances.

behavior (Cialdini et al. 1991; Reno et al. 1993).[3] However, whether social comparisons 'spill over' into untargeted resource domains is less well understood, presumably due to a lack of opportunities to perform such types of analysis.

To the best of our knowledge, there are only few studies that examine cross-domain spillover effects of social comparisons (Carlsson et al. 2021; Goetz et al. 2021; Jessoe et al. 2021; Bonan et al. 2023). All of these studies investigate spillover effects on energy use stemming from water use reports, not other way round. Two of these studies (Goetz et al. 2021; Bonan et al. 2023) find evidence for significant spillover effects, i.e. that providing water use reports affects not only targeted resource domain (water use) but also an untargeted resource domain for the whole samples.

Several other studies have investigated spillover effects using different types of informational interventions. Alacevich et al. (2021) found that the introduction of a new policy that requested households to engage in waste separation by providing information about the benefits and pro-environmental consequences of organic waste recycling had a positive spillover effect (8%) on treated individuals' total waste production in Sweden. In a similar setting Ek and Miliute-Plepiene (2018) evaluated the spillover effect of a food waste collection policy on the amount of packaging waste collected for recycling. They found a positive SATE of 8%. Tiefenbeck et al. (2013) studied the spillover effect of weekly water consumption feedback on electricity consumption in the U.S. They found that the treatment reduced water consumption but increased electricity consumption by 5.6%. They argued that the negative spillover could be due to moral licensing.

Table 1 summarizes the findings of previous studies in terms of targeted and untargeted treatment resource domains; the type of treatment; whether the experiment was designed bidirectionally, going from the targeted resource domain to the untargeted resource domain and vice versa; and whether subjects/households have a pecuniary motive to conserve the untargeted resource or not. It also accounts for the mode of treatment provision, the duration of the treatment, the frequency of measurement, direct average treatment effects (ATE), the type (positive, negative, or no effect) and size of average treatment spillover effects (SATE), the geographical location of the experiment, and the sample size of the control and treatment groups.

Unlike the previous studies summarized in Table 1, our paper aims to expand the existing literature in two unexplored directions. First, our field experiment allows us to examine the cross-domain spillover effects of water and electricity social comparisons in the same experimental setting. By analyzing spillover effects of electricity and water social comparisons on two types of resource domains (energy and water) in the same social context, we can determine whether preexisting, resource-specific social norms of resource use led to different spillover effects. Second, our experimental setting allows us to explore whether non-monetary (moral) incentives primarily drive the spillover effects of social comparison by analyzing the spillover effects on the energy use that households do not need to pay for. One common feature of all the studies summarized in Table 1 is the presence of a pecuniary motive to conserve the untargeted resource. As households are required to pay for the use of the untargeted resource directly, attention-increasing information might motivate them

[3] Descriptive norms specify "what most people do in a particular situation, and they motivate action by informing people of what is generally seen as effective or adaptive behavior there. Injunctive norms … specify what people approve and disapprove within the culture and motivate action by promising social sanctions for normative and counter-normative conduct" (Reno et al. 1993, p. 104).

Table 1 Summary of the field-experimental studies on spillover effects

Study [1]	Treatment resource domain	Untargeted (spill-over) resource domain(s)	Type of treatment	Experiment designed bidirectionally?	Is there a pecuniary motive to save the untargeted resource?	Mode of treatment provision	Duration of treatment	Direct average treatment effect (ATE)	Type and size of average treatment spillover effect (SATE)	Location	Sample size [2]
1	2	3	4	5	6	7	8	9	10	11	12
Our study	Electricity	Cold and hot water, indoor temperature	Social comparison	Yes	Yes, for water heating. No, for space heating	In-house displays	12 months	−5.6%	Positive on hot water (−9.9%), positive on indoor temperature (−0.9%)	Umeå, Sweden	100 (T) 315 (C)
	Cold and hot water	Electricity, indoor temperature	Social comparison					No effect	No effect		110 (T) 315 (C)
Tiefenbeck et al. (2013)	Water	Electricity	Own feedback with saving tips [3]	No	Yes	Weekly flyers	6 weeks	−6.0%	Negative (5.6%)	Lynnfield, Massachusetts	686 (T) 676 (C)
Ek and Miliute-Plepiene (2018)	Food waste collection	Amount of packaging waste collected for recycling	Introduction of a food waste collection policy	No	Yes	Policy shift	5 years natural experiment	37%	Positive (−13%)	Sweden	244 (staggered)
Alacevich et al. (2021)	Waste separation	Waste production	Introduction of a waste separation policy	No	Yes	Mailed brochure	4 years natural experiment	Not estimated	Positive (−8%)	Partille, Sweden	4,324 (staggered)
Carlsson et al. (2021)	Water	Electricity	Social comparison	No	Yes	Monthly letters	12 months	−6.2%	No, but positive for efficient water users pre-treatment (−9.1%)	Jerico, Colombia	379 (C) 389 (T)
Jessoe et al. (2021)	Water	Electricity	Social comparison with saving tips	No	Yes	Bi-monthly letters by post and email	12.5 months	−4.9% in the whole treatment time and–2.9% in the summertime	No. but positive in summer months (−2.2%)	City of Burbank, Los Angeles	4,559 (T) 2,782 (C)
Goetz et al. (2021)	Hot water	Cold water	Social comparison and other	No	Yes	Email	4 months	−6.02%	Positive (−2.57%)	Switzerland	3,814 (T) 961 (C)
		Room heating							Positive (−5.44%)		
Bonan et al. (2023)	Water	Electricity	Social comparison and other	No	Yes	Bi-monthly reports by emails	24 months	−1.4%	Positive (−0.5%)	Italy	108,980 (T+C)
		Gas							None		

[1]The studies are listed in chronological order

[2](T) refers to the number of households (subjects, manucipalities) in the treatment group. (C) stands for the number of households (subjects, manucipalities) in the control group

[3]By tips, we mean the treatment also includes general or customized advice on how to conserve the targeted resource

to save the secondary resource for monetary gains rather than moral incentives. Our study differs from the aforementioned studies in that we can test the spillover effects for energy use that households pay for (energy for heating water) and for energy that households do not pay for (energy for heating space).[4]

3 Design of the Experiment

The field experiment was implemented in collaboration with a municipality-owned rental housing company, Bostaden Ltd, which is based in Umeå, Sweden. Bostaden Ltd owns and manages over 15,000 apartments and is in this respect the biggest actor in Umeå's rental housing market, with a market share of about 50% (60% if including student housing).

The field experiment included 525 newly built residential rental apartments equipped with in-home displays (IHDs) connected to water and electricity smart meters. These devices provide tenants with real-time information on their electricity and water usage, as well as indoor temperature. The IHDs are placed on the side of the front door and updated almost in real-time. The sampled households were divided into two treatment groups—one for electricity and one for water, comprising 100 and 110 apartments, respectively—and a control group of 315 apartments. We avoided having separate treatments for hot and cold water for mainly two reasons. First, we were constrained by sample size, and additional treatment arms would have further reduced the statistical power of our study. Second, having comparisons for cold water but not for hot water might have raised questions or even complaints from households. The housing company did not want that and preferred having water treatments combined.

The apartments were assigned to the different groups as follows: One 'block batch' (a block of eight buildings) was assigned to the two treatment groups, and three block batches were assigned to the control group. Each of the eight buildings in each treated block batch was then randomly assigned to one of the two treatments. The contiguous block group approach, i.e., random selection of buildings rather than individual apartments, was applied for two reasons. First, to minimize the risk of treatment spillover contaminating the control group, which can occur if subjects in the control and treatment groups are in close proximity (Heckman and Smith 1995; Harrison and List 2004). Second, our housing company preferred to randomize at the building level to reduce the risk of tenant complaints about inconsistencies in apartment amenities within the same building.

Ideally, we would have liked to establish a randomized trial setting that was as 'clean' as possible. However, due to the strong preferences of our research partner, Bostaden Ltd., regarding how to cluster the treatment and control groups, we could not conduct an ideal randomized control trial (RCT). Our experiment arguably resembles an RCT, but we consider it to be more of a 'natural field experiment' in line with the taxonomy of Harrison and List (2004). In the absence of a completely clean RCT, we must resort to natural experimental methods that attempt to mimic the randomized allocation setting under reasonable conditions. A major concern is that the control and treatment groups might differ in ways that could be correlated with the outcome variables (electricity, water, and heating energy use).

[4] Our field experiment participants have to pay for their smart meter-measured use of electricity, cold water, and hot water but not for space heating. Space heating costs are included in the price of apartment rents that are regulated by the state of Sweden.

In principle, many unobservable characteristics that might confound causal identification are those that vary across households or apartments but remain fixed over time. A common method of controlling for time-invariant unobserved heterogeneity is to use difference-in-differences (DID) models, which we specify in Sect. 4.2.[5]

The decision to create two separate treatment groups was based on our objective to test whether the direct and spillover effects of providing social comparison information on different resources vary. The treated households were informed about the changes to their IHDs through printed letters distributed on March 1, 2016. The participating households were observed for 24 months—12 months before and 12 months after the introduction of the treatment.

The key features of the IHD designs for the three groups (two treatments and one control) are shown and summarized in Fig. 1. Before the experiment was introduced, all selected households had been exposed to the control IHD (top IHD in Fig. 1), which displays the household's current electricity and water (cold and hot) consumption in real-time ("Actual consumption") and cumulative 24-hour electricity and water use ("Last 24 hours"). The displays also show outdoor and indoor temperatures and have indicators of positive or negative consumption changes over time, based on the household's past electricity and water consumption.

The middle and bottom IHD displays in Fig. 1 illustrate the new information provided by the treatment IHDs. As can be seen, three horizontal bars have been added to these displays. The top two bars, labeled "Idag and Du", provide information about the household's consumption of the respective resource in the current 24-hour period (i.e., since midnight) and as a 7-day moving daily average, respectively. Electricity and water consumption are measured in kWh and liters, respectively. The third bottom bar, labeled "Andra", shows the 7-day moving daily average consumption recorded for all other IHD-equipped households in apartments of similar size. This new information enables treated households to compare their own average consumption of electricity or water with the average consumption of similar households.

The experiment was not preannounced, and participation was nonvoluntary for the sampled households. Consequently, no monetary incentives were offered to the participants. We chose not to preannounce the experiment to the households to avoid the so-called social desirability bias—that is, the tendency for treated subjects to behave in line with the implicit objectives of the experiment, even if these objectives are not explicitly communicated. During the year following the treatment, not a single household contacted the landlord to express concerns or a desire to revert to the old IHD design at any point during the experimental period.

When interpreting the results, it is important to understand some features of the participating apartments. First, the participating tenants are subject to individual metering and billing of electricity and water. The costs of heating and other utilities, such as garbage management and lighting of common areas, are included in the apartment rent. This means that households are neither aware of individual nor building-level heating costs but

[5] Our experiment was not pre-registered and therefore did not include a pre-analysis plan or power analysis. This is due to the reason that at the time we designed this experiment (year 2015), preregistration was not a common practice for field experiments. Among the similar studies summarized in Table 1 of our manuscript, only two recently designed field experiments (Goetz et al. 2021; Bonan et al. 2023) were pre-registered, while the other five were not.

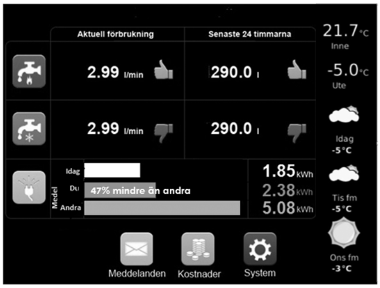
	IHD front screen	Key features on the front screen
IHD, control group		*Aktuell förbrukning* (current consumption): the household's current electricity and water (hot and cold) consumption in real time *Senaste 24 timmarna* (last 24 hours): a household's total electricity and water (hot and cold) consumption in the last 24 hours *Inne*: current indoor temperature
IHD, electricity treatment		Information on current electricity consumption and electricity consumption in the last 24 hours is replaced with 3 bars: *Idag* (today): the household's total electricity consumption since midnight *Du* (you): the household's 7-day moving daily average of electricity use *Andra* (others): the 7-day moving daily average of electricity use of other households in apartments of similar size
IHD, water treatment		Information on current consumption of hot and cold water and the consumption of hot and cold water in the last 24 hours is replaced with 3 bars: *Idag* (today): the household's total consumption of hot and cold water since midnight *Du* (you): the household's 7-day moving daily average consumption of hot and cold water *Andra* (others): the 7-day moving daily average consumption of hot and cold water recorded for other households in apartments of similar size.

Fig. 1 IHD designs for the control group and the two treatment groups

can increase or decrease their indoor temperatures as desired by adjusting each dwelling's thermostats. Apartment-specific indoor temperatures are displayed on the IHD (see Fig. 1). Second, housing company provides all its tenants with fixed electric appliances, such as refrigerators, freezers, dishwashers, and kitchen ranges. These appliances are the same or very similar across all new apartments in terms of energy performance and functions. Third, there is no obvious mechanical link between the consumption of hot water, electricity, and heating since the heating system is based on district heating. The main mechanical link between electricity and (cold) water consumption is through cooking. In the study area, district heating is primarily produced from biofuels and solid waste combustion by a local district heating plant.

It is also important to note that the main objective of our experiment is to test the effect of descriptive norms, and it does not include injunctive norm messages. While most studies have clear injunctive messages in their treatments, this study stands out for avoiding such messages, and the results of this study are not directly comparable with other studies that use the injunctive messages. The displays in our study also had the thumbs-up and thumbs-down icons, which had been available since the installation of these displays by the housing company (see the screen of the control group in Fig. 1). However, the indication of these displays' thumbs-up or thumbs-down icons was based on a within-household comparison (not on peer comparison). Thus, the risk that it contaminated our treatment of descriptive social norms is small.

4 Results

4.1 Descriptive Statistics

Table 2 presents the descriptive statistics for the control group and the two treatment groups for electricity, water usage, and indoor temperature before and after the treatments were delivered. The control group consists of 315 apartments, while the treatment groups include 100 apartments targeting electricity use and 110 apartments targeting water use. We observed these groups for two years—one year before and one year after the treatment was delivered.

Our experiment collects real-time data from smart meters and indoor sensors (measuring indoor temperature). For research purposes, we aggregate the hourly data daily. Our main outcome variables are electricity consumption, cold and hot water use, and daily indoor temperature over two years, with 365 daily observations per year for most apartments.

We removed obviously flawed observations, such as abnormal electricity or water readings (exceeding 1,000 kWh/day or 500 l/day) from the analysis, as well as daily observations with missing data for some hours. We also excluded observations of daily electricity consumption when electricity was reported as switched off (zero consumption), but water was reported as positive consumption. These dropped observations correspond to less than 2% of the total daily observations. Table 2 also reports the exact number of observations for each group during the pre-treatment and post-treatment periods, along with other relevant descriptive statistics.

Table 2 indicates that the average daily electricity use in the electricity treatment group decreased by 0.22 kWh (from 4.52 kWh to 4.30 kWh), while in the control group, it decreased by only 0.11 kWh (from 4.61 kWh to 4.50 kWh). Conversely, daily electricity use in the water-targeted treatment group increased slightly (from 4.9 kWh to 5.0 kWh). The average hot water use in both the water-targeted treatment and control groups remained practically unchanged (around 64–65 liters per day). However, hot water use in the electricity-targeted treatment group decreased slightly (by 2.3 liters per day). The average indoor temperature slightly increased in all groups, which could be due to the fact that our panel data is not balanced, with proportionally more observations in the warmer months of the post-treatment period. Overall, when examining the descriptive statistics of targeted and untargeted resource use, it is not clear whether there is evidence of spillover effects. To test for spillover average treatment effects, we will employ regression analysis.

Table 2 Descriptive statistics

	Pre-treatment			Post-treatment		
	No. of daily observations	Average	Std. dev.	No. of daily observations	Average	Std. dev.
Control group*						
Electricity, kWh/day	75,301	4.61	3.22	113,127	4.50	3.22
Hot water, l/day	73,654	64.05	59.71	109,816	65.24	62.68
Cold water, l/day	73,654	94.48	70.45	109,816	90.28	69.08
No. of rooms**	76,517	2.38	0.71	113,820	2.33	0.72
Apartment size, m^2	76,517	60.41	18.69	113,820	59.13	18.99
Outdoor temperature (^{o} C/day)	76,517	3.41	8.88	113,820	5.34	8.09
Sunlight (radiation intensity)	76,517	73.16	82.38	113,820	91.34	91.16
Precipitation (mm/day)	76,517	1.72	4.04	113,820	1.37	3.77
Indoor temperature (^{o} C/day)	76,517	22.17	1.53	113,820	22.45	1.71
Electricity-targeted treatment group						
Electricity, kWh/day	35,217	4.52	2.69	33,734	4.30	2.51
Hot water, l/day	35,807	53.30	53.45	35,875	50.98	51.63
Cold water, l/day	35,807	73.83	56.38	35,875	73.12	58.46
No. of rooms	36,009	2.28	0.45	36,136	2.28	0.45
Apartment size, m^2	36,009	59.34	9.63	36,136	59.39	9.67
Outdoor temperature (^{o} C/day)	36,009	4.5	8.3	36,136	5.33	8.09
Sunlight (radiation intensity)	36,009	90.80	85.05	36,136	90.89	90.77
Precipitation (mm/day)	36,009	1.70	3.99	36,136	1.38	3.77
Indoor temperature (^{o} C/day)	36,009	22.77	1.29	36,136	22.81	1.40
Water-targeted treatment group						
Electricity, kWh/day	39,636	4.89	3.02	39,894	5.00	2.89
Hot water, l/day	39,125	64.45	58.74	38,959	64.61	58.72
Cold water, l/day	39,125	85.12	63.93	38,959	86.97	64.75
No. of rooms	39,839	2.38	0.59	39,894	2.38	0.59
Apartment size, m^2	39,839	62.37	11.70	39,894	62.29	11.69
Outdoor temperature (^{o} C/day)	39,839	5.06	8.36	39,894	5.36	8.11
Sunlight (radiation intensity)	39,839	90.47	84.69	39,894	91.26	91.03
Precipitation (mm/day)	39,839	1.74	4.11	39,894	1.37	3.76
Indoor temperature (^{o} C/day)	39,839	22.49	1.88	39,894	22.67	1.95

Notes: *The control group has a smaller number of observations before the delivery of the treatment due to the fact that seven buildings containing 185 apartments in the control group were built and fully accommodated between 10 and 2 months before the treatment. **In Sweden, the number of rooms means the number of living space rooms and bedrooms and does not include the kitchen or bathroom. Therefore, a two-room apartment means an apartment with a living room and a bedroom, a bathroom, and a kitchen. In the U.S. or U.K., this apartment would be called a "one-bedroom apartment."

4.2 Spillover Average Treatment Effects

To estimate the direct and spillover average treatment effects, we run the following difference-in-differences regression model:

$$y_{it} = \beta_1 TREAT_i + \beta_2 POST_t + \beta_3 TREAT_i * POST_t + \mu X_{t'} + \alpha_i + \varepsilon_{it}, \qquad (1)$$

where y_{it} represents our outcome variables: daily electricity use (in kWh), hot or cold water use (in liters), and indoor temperature (in ºC) in household *i* at time *t*; $TREAT_i$ is a dummy variable indicating whether household *i* is in the water- or electricity-targeted treatment group or the control group; $POST_{it}$ is a dummy variable indicating the pre- and post-treatment periods; $X_t^{'}$ is a set of the time-varying covariates (year-monthly fixed effects, Monday-to-Sunday fixed effects, and weather controls, such as outdoor temperature, sunlight, and precipitation); α_i represents household fixed effects; and ε_{it} is an idiosyncratic error term (unobserved household-specific shocks). This model is estimated in OLS using the standard fixed-effects estimator with Huber-White standard errors, clustered at the unit of the building to account for serial correlation (Bertrand et al. 2004). The estimated coefficient β_3 measures the direct average treatment effects and the average treatment spillover effects of provision of social comparison information on our outcome variables.

It should be noted that we estimate the SATEs of the water and electricity treatments on apartments' indoor temperatures by applying Equation 1 to the heating period only. In our study area, the heating season includes all months except June, July, August, and September. Therefore, for this analysis, we have eight heating months before the treatment and eight heating months after the treatment.

The results from the estimation of the DID model are presented in Table 3. We find that the water social comparison was ineffective in reducing targeted cold and hot water consumption and did not spill over into the electricity and heating domains (see Columns 1–3 in Table 3). Meanwhile, the electricity social comparison not only had a direct positive effect on electricity conservation (see Column 7 in Table 3) but also a positive spillover effect on hot water consumption and space heating (see Columns 5 and 8 in Table 3). On average, treated households reduced their electricity use by 0.306 kWh per day and hot water consumption by approximately 6.5 liters per day. It should be highlighted that the spillover effect of the electricity treatment on hot water use is stronger than the direct effect of the water treatment itself, which is not significantly different from zero (see Columns 1 and 5 in Table 3). We find that the electricity treatment, unlike the water treatment, had a significant spillover effect on apartments' indoor temperatures. On average, the electricity-targeted treatment group reduced their indoor temperature by 0.202 °C (see Column 8 in Table 3).

4.3 Inference

In our main DID model (see Eq. 1), we rely on building-level clustered robust standard errors to account for the correlation within buildings, as our treatment was assigned at the building level. However, the consistency of the clustered robust estimation depends on conditions such as an infinite number of clusters and equal size of clusters. Since we have a limited number of clusters and an unequal number of observations within each building-level cluster, the standard errors estimated using the clustered robust approach may not be consistent (see, e.g. Mackinnon and Webb 2017). Therefore, we use randomization inference (RI) to test for the causal effects of our treatment. Originally developed by Fisher (1953) and later advanced by Rosenbaum (2002), RI imposes no distributional assumptions on the errors and is valid even in small samples.

RI computes the empirical distribution of the DID estimate for a large number of randomly generated placebo treatments under the null hypothesis of no effect using a simulation method. The critical value of the treatment spillover effect to be used for the inference

Table 3 ATEs and SATEs on daily electricity consumption (in kWh), water use (in liters), and indoor temperatures (in °C)

	Water-targeted treatment				Electricity-targeted treatment			
	Hot water	Cold water	**Electricity**	**Indoor temperature**	**Hot water**	**Cold water**	Electricity	**Indoor temperature**
Variables	(1)	(2)	**(3)**	**(4)**	**(5)**	**(6)**	(7)	**(8)**
TREAT*POST	−3.744	4.505	**−0.048**	**−0.086**	**−6.534*****	**1.446**	−0.306**	**−0.202*****
	(3.959)	(4.113)	**(0.223)**	**(0.070)**	**(1.326)**	**(1.988)**	(0.130)	**(0.065)**
POST	4.162***	−2.329	**0.167***	**0.195*****	**4.116*****	**−2.327**	0.166*	**0.202*****
	(0.934)	(1.813)	**(0.092)**	**(0.032)**	**(0.931)**	**(1.822)**	(0.093)	**(0.032)**
Outdoor temperature	−0.219***	−0.132**	**−0.014*****	**0.022*****	**−0.201*****	**−0.132****	−0.013***	**0.021*****
	(0.035)	(0.049)	**(0.002)**	**(0.002)**	**(0.038)**	**(0.059)**	(0.002)	**(0.002)**
Sunlight	−0.006***	0.005	**−0.002*****	**0.003*****	**−0.006****	**0.005**	−0.002***	**0.003*****
	(0.002)	(0.003)	**(0.000)**	**(0.000)**	**(0.002)**	**(0.003)**	(0.000)	**(0.000)**
Precipitation	−0.022	−0.066**	**0.002**	**−0.004*****	**−0.034**	**−0.079*****	0.005***	**−0.003*****
	(0.025)	(0.030)	**(0.002)**	**(0.001)**	**(0.023)**	**(0.026)**	(0.001)	**(0.001)**
Constant	69.252***	98.606***	**5.623*****	**21.214*****	**65.688*****	**94.799*****	5.479***	**21.320*****
	(0.964)	(1.293)	**(0.099)**	**(0.049)**	**(0.864)**	**(1.042)**	(0.098)	**(0.049)**
Fixed effects	Yes	Yes	**Yes**	**Yes**	**Yes**	**Yes**	Yes	**Yes**
No. of obsv.	261,554	261,554	**267,958**	**184,463**	**255,152**	**255,152**	257,379	**179,770**
No. of apartments	425	425	**425**	**425**	**415**	**415**	415	**415**

Notes: The estimated spillover effects on indoor temperature are for an 8-month heating period. Standard errors clustered at the building level are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Sectoral spillover effects are in bold style test can be determined from a large number of simulations. We randomize the assignment of buildings to treatment and control groups, and we use the DID coefficient (the interaction term in Eq. 1) as the test statistic. Our null hypothesis is that our water and electricity social comparison treatments had no effect on water consumption, electricity, and/or heating energy use, or β3 = 0 in Equation 1. We conduct the RI test using 1000 replications in the "ritest" Stata command developed by Hess (2017). The results from the RI test confirm our initial results that electricity social comparison treatment significantly reduced not only targeted electricity consumption, but also hot water consumption and apartments' indoor temperatures (see Table 4).

4.4 Spillover Quantile Treatment Effects

Motivated by recent impact evaluation studies that document the relevance of measuring the distributional effects of an intervention (see, e.g. Havnes and Mogstad 2015; Bedoya et al. 2018; Byrne et al. 2018), we estimate the spillover quantile treatment effects (SQTE) of our social comparisons. This allows us to explore how the spillover effects vary among households with different levels of resource use.[6]

Following Rios Avila (2019) we estimate the following model to get the SQTEs.[7]

$$RIF\left(y_{it}; v\left(F_{y/TREAT,POST}\right)\right) = \beta_1 TREAT_i + \ \beta_2 POST_t + \ \beta_3 TREAT_i * POST_t + \mu \ X_t' + \alpha_i + \varepsilon_{it}, \tag{2}$$

where $RIF\left(y_{it}; v\left(F_{y/TREAT,POST}\right)\right)$ represents the recentered influence function (RIF) of the outcome variable; y_{it} is the daily hot water use in liters and indoor temperature in degrees of Celsius in household i at time t; $F_{y/TREAT,POST}$ is the cumulative distribution function; $TREAT_i$ is a dummy variable indicating whether household i is in the electricity treatment group or the control group. The remaining variables are the same as in the main DID model (see Eq. 1). The estimated coefficient β_3 measures SQTEs.

As we did not find any significant spillover effects of water social comparison, we present below the SQTEs of electricity social comparison for hot water and indoor temperatures with 95% confidence intervals (see Fig. 2). We find that the SQTEs of electricity treatment on hot water consumption are significant at the higher percentiles of the hot water consumption distribution. Compared to the SATE (see Table 3), significant and larger reductions in hot water use are observed for households with hot water consumption levels above the 45th percentile. Conversely, for hot water consumption levels below the 60th percentile, the SQTEs are smaller (and insignificant below the 45th percentile) than the SATE, implying that the spillover effects of electricity social comparison on hot water conservation are heterogeneous and driven by households that consume hot water above the median level.

On the other hand, the SQTEs of electricity treatment on heating energy use are significant at the tails of the heating energy use distribution. As one can see from the lower panel of Fig. 2, a higher and statistically significant reduction in indoor temperature is found for

[6] We follow the specification of Firpo et al. (2009), which was extended to panel data application by Rios-Avila (2019). We use the Stata command developed by Rios-Avila (2019) to estimate the SQTEs.

[7] See Rios-Avila (2019) for a detailed explanation of the approach.

Table 4 ATEs and SATEs on daily electricity (in kWh), water (in liters), and winter season indoor temperature (in ºC) using RI method

	Water-targeted treatment				Electricity-targeted treatment			
	Hot water	Cold water	Electricity	Heating season indoor temperature	Hot water	Cold water	Electricity	Heating season indoor temperature
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
12 months post-treatment								
TREAT*POST	−3.744	4.505	**−0.0484**	**−0.086**	**−6.534★★★/☆☆☆**	**1.446**	−0.306★/☆☆	**−0.202★★/☆☆☆**
	(3.959)	(4.113)	**(0.223)**	**(0.044)**	**(1.326)**	**(1.988)**	(0.130)	**(0.065)**
	[0.257]	[0.263]	**[0.8060]**	**[0.216]**	**[0.001]**	**[0.587]**	[0.100]	**[0.027]**
Controls	Yes	Yes	**Yes**	**Yes**	**Yes**	**Yes**	Yes	**Yes**
Fixed effects	Yes	Yes	**Yes**	**Yes**	**Yes**	**Yes**	Yes	**Yes**
No. of obsv.	261,554	261,554	**267,958**	**184,463**	**262,435**	**262,435**	257,379	**179,770**
No. of apartments	425	425	**425**	**425**	**415**	**415**	415	**415**

Notes: Randomization inference and clustered error methods were conducted to obtain alternative p-values. ★★★/☆☆☆ $p<0.01$, ★★/☆☆ $p<0.05$, and ★/☆ $p<0.1$ indicate significance levels, where filled stars ★ indicate significance levels preserved under randomization inference, while empty stars ☆ indicate significance levels that are sustained by the cluster-robust standard errors. The standard error clustered at the building level is in parentheses, and the p-value obtained using randomization inference is provided in squared brackets. Sectoral crossover effects are in bold style households with heating energy use levels below the 10th percentile and above the 90th percentile.[8]

4.5 Persistency of the SATEs

To examine the persistency of the SATEs induced by electricity social comparison treatment, we estimate the SATEs for hot water use and indoor temperature for each month of the experiment. The monthly SATEs are generated by estimating the following DID model:

$$y_{it} = \gamma_0 TREAT_i + \ \gamma_1 POST_{it} + \sum_{m=1}^{18} \beta_m \left(MONTH_m {*} TREAT_i \right) + \mu \ X_t^{'} + \alpha_i + \varepsilon_{it}, \quad (3)$$

where y_{it} represents the daily hot water use in liters and indoor temperature in degrees of Celsius in household i at time t; $TREAT_i$ is a dummy variable indicating whether household i is in the electricity treatment group or the control group; and $MONTH_m$ are the dummy variables representing a specific month (m = 1, …, 18) in the post-treatment year. The remaining variables are the same as in the main DID model (see Eq. 1). The estimated coefficients of the interaction terms between the monthly dummies and the treatment variable, β_m, yield the monthly average spillover effects. As before, the model is estimated by using OLS with household fixed effects and clustered standard errors at the building level. We plot the monthly SATEs for hot water and indoor temperature with 95% confidence intervals in Fig. 3.

Figure 3 demonstrates that the electricity treatment led to a reduction in hot water use during the first four months of the experiment (March–June 2016), and similar effects returned after the summer vacation, with statistically significant effects observed in January and February. In the case of indoor temperature, the monthly SATEs (Standard Average Treatment Effects) were significant for four of the eight heating months (May–December 2016).

4.6 Interpreting the Results

Here, we aim to better understand the reasons behind the spillover effects of the electricity social comparison treatment by answering four questions. First, what drives the spillover effects of the electricity treatment—is it a mechanical link between electricity use and hot water and heating use, or behavioral changes? Second, why did we find positive spillover effects by targeting electricity use but not water use? Third, what actions underlie the energy savings (both direct and indirect) induced by the electricity social comparison treatment? Finally, we want to determine whether the overall spillover effect is larger than the direct effect in terms of energy use.

4.6.1 What Can Explain Spillover Effects?

In previous studies, spillover effects induced by social comparisons are generally explained either by mechanical complementarities between appliances or other housing services that

[8] We also conduct heterogeneity analysis based on baseline electricity consumption for electricity-targeted treatment groups. The results are consistent with our main findings and are presented in Table A5 in the Appendix.

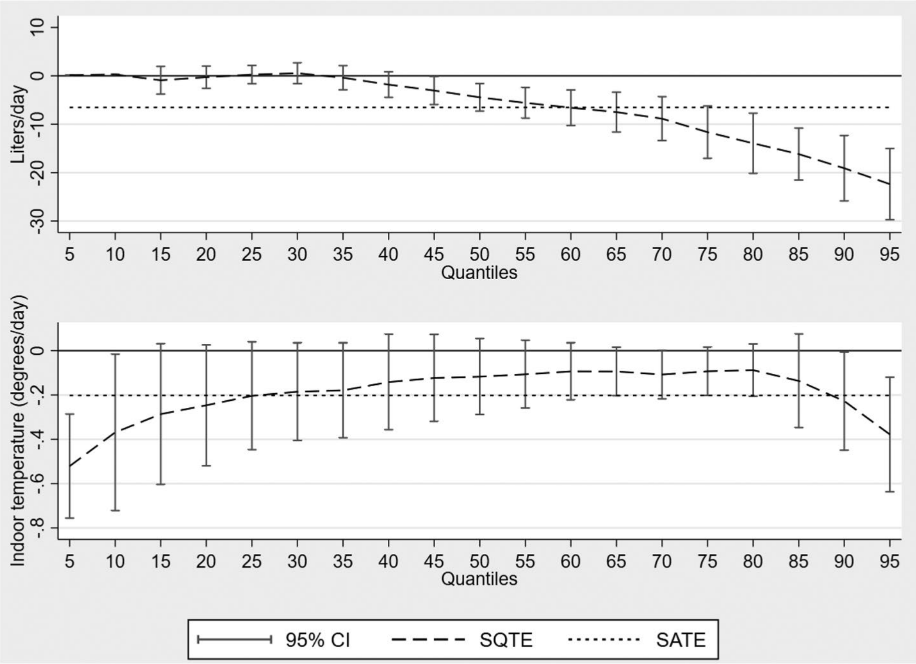


Fig. 2 SQTEs of electricity social comparison on hot water consumption and apartments' indoor temperature

use both energy and water, or by changes in treated households' behavior (see, e.g. Jessoe et al. 2021). One exception is Carlsson et al. (2021), who demonstrate how cognitive dissonance facilitates the positive spillover effect of social comparison information provision. In our case, we posit that behavioral factors drive the spillover effects we observed, since there is no obvious mechanical link between the treatment-targeted electricity use and the use of hot water or indoor temperature in our study area. Participating households live in apartments provided with hot water and space heating by centralized district heating, while electricity is mainly used for lighting, cooking, and running kitchen and other appliances. Hot water is primarily used for showering. Thus, unlike in other studies, we can rule out mechanical complementarities among these resources and should instead focus on behavioral drivers that could explain the observed spillover effects.

As noted in Section 2, participating households did not have direct pecuniary motives to save energy used for space heating, unlike in other studies (see Table 1 for examples), but they had one for energy used to heat their water. In our study area, space heating expenses are included in the apartment rent payments that do not change over winter or summer months, and the state regulates these rents. Thus, only a non-monetary motive to save energy can explain the actions taken to reduce indoor temperatures. Specifically, we draw from the theory of moral dissonance. According to this theory, individuals want to avoid inconsistency in their beliefs and behaviors to reduce moral costs. Due to this, a strong correlation between behaviors in different domains is likely to exist (Festinger 1962). Failure to maintain their primary resource domain consumption behavior in the secondary domain will result in a behavioral inconsistency. To avoid this inconsistency, individuals who reduce

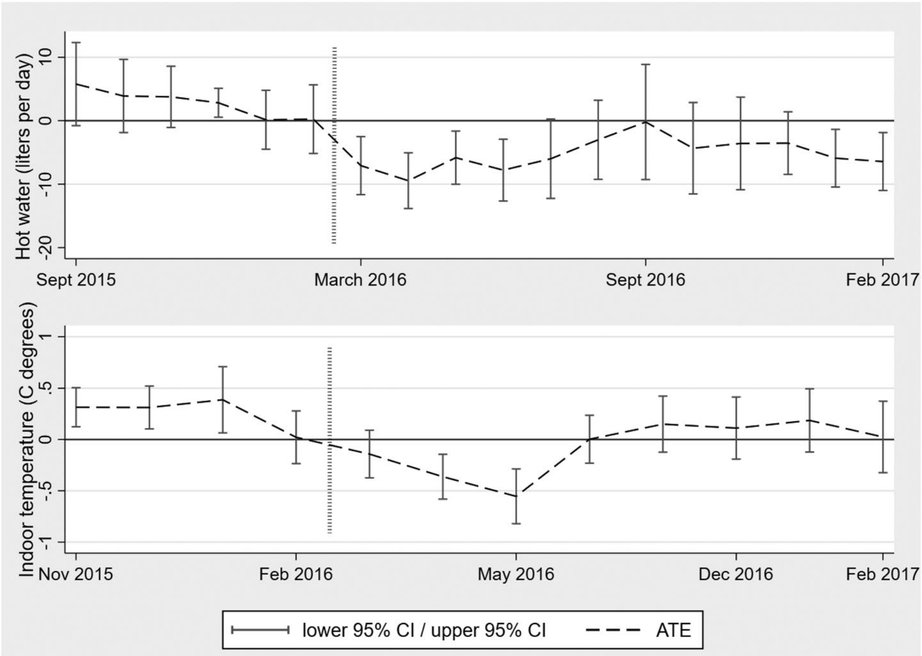


Fig. 3 SATEs of electricity-targeted treatment on hot water use and indoor temperatures for each month over the period of the treatment and pre-treatment (CI 95%)

their primary resource use will also reduce their consumption of the secondary resource. We argue that, in our case, participating households' internal motivations to conserve electricity might translate into internal motivation to consume less energy for water and apartment heating in order to reduce behavioral inconsistencies.

Besides this intuitive explanation, we investigate the estimated quantile spillover treatment effects presented in Section 4.4 to find some supportive evidence for our claims. If the mechanism behind the spillover effects relates to individuals' ambition to be consistent in their behavior, we expect that households who reduced their hot water use or indoor temperature due to electricity-targeted treatment also reduced their electricity consumption. As can be seen in Fig. 2, we find the significant spillover quantile treatment effects of electricity-targeted treatment on hot water consumption for households with hot water consumption above the 45th percentile. Therefore, we estimate the direct treatment effects on electricity use by splitting the sample into two groups. The first group consists of households above the 45th percentile, for which we find a significant spillover effect of electricity-targeted treatment on hot water. The second group contains households below the 45th percentile, for which we find no significant spillover effect on hot water consumption due to the electricity-targeted treatment. The results reveal that on average households who reduce their hot water consumption due to electricity-targeted treatment also reduce their electricity consumption (see Table A2 in the Appendix). Likewise, consistent with the cognitive dissonance theory, on average, we do not find a significant effect on electricity use for households in this subsample of households with no significant spillover effect on hot water. The corresponding results for heating are not as clear. While households who do not reduce the use of heating energy also do not save electricity, for households with significant spillover effects we find a larger but insignificant effect on electricity use (see Tables A3 in the Appendix). Overall, these results provide supporting evidence for cognitive dissonance as the underlying mechanism.

4.6.2 Why Did Positive Spillover Effects Results from Targeting Electricity but Not Water Use?

The differences in the SATEs of the electricity and water treatments can be explained by differences in social norms regarding electricity and water use that prevail in our study area. Kažukauskas et al. (2021) argue that in Sweden there is no social or political pressure to save water, as this resource is abundant and inexpensive throughout the country. However, this is not the case in other countries where water shortages are prevalent; for instance, see the study by Jessoe et al. (2021) in California. Hence, there is reason to believe that people in Sweden are less concerned than those in many other places about the environmental impacts of water use, and that social norms therefore do not provide a very effective tool for reducing residential water use in Sweden.

However, the same cannot be said about residential electricity consumption, since households in Sweden associate electricity use with various environmental problems, including climate change. The results from an Organization for Economic Cooperation and Development (OECD) survey, which asked respondents about the seriousness of six specific environmental issues facing the world, show that Swedish respondents were aware of the negative environmental impact of energy use and perceived climate change as the most serious problem (OECD 2014). The same survey also reports that Swedes were the second most likely to believe that climate change is partly caused by human activity, such as burning coal or gas for power generation. Recently, the Eurobarometer survey on Europeans' attitudes towards climate change asked respondents to identify the single most serious problem facing the world from a list of 11 issues. The results reveal that Swedish respondents ranked climate change as the most serious global problem (41% of respondents– highest among the EU member states). Meanwhile, "poverty, hunger and lack of drinking water" was considered the most serious global problem by 15% of the Swedish respondents, which was below the EU average. Additionally, when asked about individual actions taken to address climate change, 25% of the Swedish respondents (the highest share among the EU member states) had switched to an energy supplier with a greater share of energy from renewable resources (European Commission 2023). Thus, we think that these preexisting differences in social norms about the utilization of electricity and water are the reason the spillover effect was induced by the electricity social comparison treatment.

4.6.3 What Actions Can Explain Positive Direct and Spillover Effects on Energy Use?

The literature suggests two main explanations for energy conservation resulting from the provision of social comparison information. The first is investments in energy-efficient household equipment, and the second is behavioral changes such as habit formation (see, e.g. Allcott and Rogers 2014). We argue that the first explanation does not account for our findings, since all apartments in our study are equipped with very similar kitchen appliances, including refrigerators, dishwashers, and kitchen ranges, provided by the rental company.

This means that households' interest in investing in energy-efficient appliances is negligible. Instead, we contend that behavioral changes explain the observed electricity savings. For instance, to reduce electricity consumption, households might switch off the lights when they leave home and unplug various electronics when not in use. To reduce hot water use, households might shorten shower times and use cold water instead of hot for other activities. Finally, households might reduce heating energy use by adjusting their thermostats and closing off unused rooms in their homes.

4.6.4 Could the Spillover Effects Be Larger than the Direct Effect in Terms of Energy Use?

Another important aspect of our results involves checking whether the energy savings from the spillover effects exceed those from the direct effect. To better understand the total energy savings from both the direct and spillover average treatment effects induced by electricity social comparison, we use back-of-the-envelope calculations to compare the energy savings from the direct effect to those from the spillover effects.[9] We find that the energy savings from the untargeted resource domains (hot water and space heating) are twice as large as those from electricity. We estimate that the energy savings from the reduction in hot water consumption and space heating are about 132 kWh per year and 90 kWh per year, respectively. In comparison, the energy savings from the directly induced reduction in electricity consumption amount to 111 kWh per year (0.306 kWh/day multiplied by 365 days).

4.7 Robustness Tests

4.7.1 Parallel Trends and Placebo Tests

The identification of the DID model relies on the fulfillment of the parallel trends assumption, which states that outcome variables should have similar trends for the treatment and control groups in the pre-treatment period. We test this assumption by following three procedures. First, we visually inspect the trends of our outcome variables (electricity, hot and cold water, and heating energy) for the treatment and control groups before and after the treatment delivery (see Figure A1 in the Appendix). It is evident that our outcome variables have similar pre-treatment trends, providing initial evidence for the validity of the parallel trends assumption.

Second, we also check the pre-treatment balance of the variables by calculating the normalized differences and find that all the normalized differences between the treatment and control groups are less than 0.25, except for indoor temperatures and cold water (see Appendix Table A1). Generally, a difference in average means greater than 0.25 standard deviations is considered substantial. This statistically substantial difference in indoor temperatures between control and treatment groups could have occurred due to our 'batch' randomization approach and the fact that individual actions to control indoor temperature within apartment blocks are somewhat limited.

Third, to conduct a 'placebo' test, we apply randomization inference (RI), as previously discussed in Section 4.3. The results from the RI test confirm our main findings. Further-

[9] We do not aim to measure the welfare effects as is done in other similar studies (Allcott and Kessler 2019) since it is not possible to elicit the demand curve for the social comparison information provision.

Table 5 "Placebo" ATEs and SATEs on daily electricity, cold water, hot water, and heating energy use

	Water-targeted treatment				Electricity-targeted treatment			
Variables	Hot water	Cold water	Electricity	Indoor temperature	Hot water	Cold water	Electricity	Indoor temperature
TREAT*POST	2.405	3.500	**0.283**	**−0.040**	**3.419**	**2.589**	−0.068	**0.025**
	(3.770)	(5.048)	**(0.301)**	**(0.077)**	**(3.877)**	**(5.027)**	(0.301)	**(0.074)**
	[0.556]	[0.303]	**[0.203]**	**[0.716]**	**[0.108]**	**[0.416]**	[0.653]	**[0.641]**
Controls	Yes	Yes	**Yes**	**Yes**	**Yes**	**Yes**	Yes	**Yes**
Fixed effects	Yes	Yes	**Yes**	**Yes**	**Yes**	**Yes**	Yes	**Yes**
Number of observations	97,321	97,321	**98,780**	**99,111**	**70,441**	**70,441**	70,934	**71,278**
Number of apartments	150	150	**150**	**150**	**109**	**109**	109	**109**

Notes: Randomization inference and clustered error methods were conducted to obtain alternative p-values. The standard error clustered at the apartment level is in parentheses, and the p-value obtained using randomization inference is provided in squared brackets. Sectoral crossover effects are in bold style

more, we test for a placebo effect by extending our data with an additional year and considering a 'fake' treatment delivery date. Specifically, we hypothetically consider 2014 as a pre-treatment year and 2015 as a treatment year. The results from this exercise, presented in Table 5, reveal that our outcome variables do not indicate a statistical difference between the treated and control groups in 2014–2015.[10]

4.7.2 Balanced Sample

So far, our analysis is based on an unbalanced panel data sample (see Table 2). Thus, we estimate our main model using a balanced sample to check how this affects our results reported above. As seen in Table 6, the ATEs and SATEs remain robust for the balanced data sample as well.

5 Conclusions

The behavioral environmental economics literature suggests that behavioral interventions may be part of a cost-efficient strategy to encourage households to act in more prosocial ways. While studies have primarily focused on measuring the direct effects of behavioral interventions, the effects of a particular intervention may extend beyond the targeted resource domain, and failing to account for such indirect effects can lead to underestimations of their welfare implications.

Despite the generally reported benefits of using digital real-time feedback to nudge consumers to reduce their energy consumption, none of our reviewed studies use real-time feedback to assess the spillover effects on other resource domains. In this paper, we present new results from a natural field experiment that contribute to the understanding of whether behavioral interventions provided in real-time in the form of social comparisons spill over beyond the targeted resource domains. We estimate the spillover effects of the provision of

[10] We conduct additional analysis using machine learning techniques to account for potential nonlinearities. Specifically, we employ a double-debiased machine learning approach on the full sample. The results remain consistent with our main results and are presented in Appendix Table A4.

Table 6 ATEs and SATEs on daily electricity, cold water, hot water, and heating energy use using the balanced sample

	Water-targeted treatment				Electricity-targeted treatment			
Variables	Hot water	Cold water	**Electricity**	**Indoor temperature**	**Hot water**	**Cold water**	Electricity	**Indoor temperature**
TREAT*POST	-3.253	2.757	**-0.054**	**-0.039**	**-6.066★★★/☆☆**	-0.265	-0.311☆	**-0.147★/☆☆☆**
	(3.235)	(3.589)	**(0.203)**	**(0.048)**	(2.753)	(3.390)	(0.184)	**(0.041)**
	[0.454]	[0.516]	**[0.821]**	**[0.600]**	**[0.007]**	**[0.919]**	[0.145]	**[0.068]**
Controls	Yes	Yes	**Yes**	**Yes**	**Yes**	**Yes**	Yes	**Yes**
Fixed effects	Yes	Yes	**Yes**	**Yes**	**Yes**	**Yes**	Yes	**Yes**
Number of observations	167,356	167,356	**172,640**	**115,815**	**160,954**	**160,954**	162,061	**111,122**
Number of apartments	240	240	**240**	**240**	**230**	**230**	230	**230**

Notes Randomization inference and clustered error methods were conducted to obtain alternative p-values. ★★★/☆☆☆ $p<0.01$, ★★/☆☆ $p<0.05$ and ★/☆ $p<0.1$ indicate significance levels, where filled stars ★ indicate significance levels preserved under randomization inference, while empty stars ☆ indicate significance levels that are sustained by the cluster-robust standard errors. The standard error is in parentheses, and the p-value obtained using randomization inference is provided in squared brackets. Sectoral crossover effects are in bold style social comparison information on the consumption of two resources—energy and water—in the same experimental setting. This enables us to contribute to the existing literature by investigating whether social comparisons targeting resources with presumably different preexisting social norms regarding conservation induce different spillover effects.

We find that only electricity-targeted social comparison is effective in reducing electricity consumption and that it induces conservation beyond electricity, leading to reductions in energy used for heating water and space. Water-targeted social comparison does not induce effects on either the targeted water domain or energy resource domains. We argue that the differences in direct treatment and spillover effects from the water and electricity treatments might be explained by differences in preexisting social norms of resource utilization. We reason that in the case of our study area (northern Sweden), there could be a relatively stronger social norm for the conservation of energy than for the preservation of cold water. This potentially explains why our social comparison treatment is successful in affecting energy-intensive resource domains such as electricity, hot water, and space heating. Our findings suggest that behavioral interventions like social comparisons could bring significant energy savings beyond the targeted resource domains if society has strong preexisting social norms supporting the conservation of the targeted resource.

Furthermore, we find evidence that the positive and significant spillover effects observed in our study could be explained by other nonmonetary incentives such as moral dissonance. Our electricity-targeted social comparison treatment induced behavioral consistency—a reduction in all energy-intensive resource domains except cold water—among treated households. This claim is further strengthened by the significant spillover effect on lower indoor temperatures, even though there was no pecuniary incentive to save energy for heating.

While our study documents important findings on the role of social norms in resource conservation, some aspects warrant future studies. The mechanisms underlying the spillover effects of social comparison information require further investigation. Our study was not primarily designed to address this phenomenon, leading us to offer mainly intuitive explanations for observed spillover effects based on secondary data. A dedicated study specifically examining why normative feedback produces stronger spillover effects in energy-intensive resources would significantly advance this field.

Appendix

Table A1 Covariate balance check before the treatments

	Control		Electricity-targeted treatment			Water-targeted treatment		
	Mean	Std. dev.	Mean	Std. dev.	Normalized differences	Mean	Std. dev.	Normalized differences
Electricity, kWh/day	4.61	3.22	4.53	2.69	0.03	4.89	3.02	−0.09
Hot water, l/day	64.05	59.71	53.3	53.45	0.19	64.46	58.74	−0.01
Cold water, l/day	94.48	70.45	73.83	56.38	0.31	85.12	63.94	0.14
No. of rooms	2.38	0.71	2.28	0.45	0.16	2.38	0.59	−0.00
Apartment size, m^2	60.41	18.69	59.34	9.63	0.06	62.27	11.70	−0.11
Outdoor temperature (°C/day)	3.41	8.88	4.99	8.37	−0.18	5.06	8.36	−0.19
Sunlight (radiation intensity)	73.16	82.38	90.8	85.05	−0.21	90.48	84.69	−0.21
Precipitation (mm/day)	1.72	4.04	1.70	3.99	0.01	1.74	4.11	−0.00
Indoor temperature (°C/day)	22.17	1.53	22.77	1.29	−0.42	22.49	1.88	−0.19

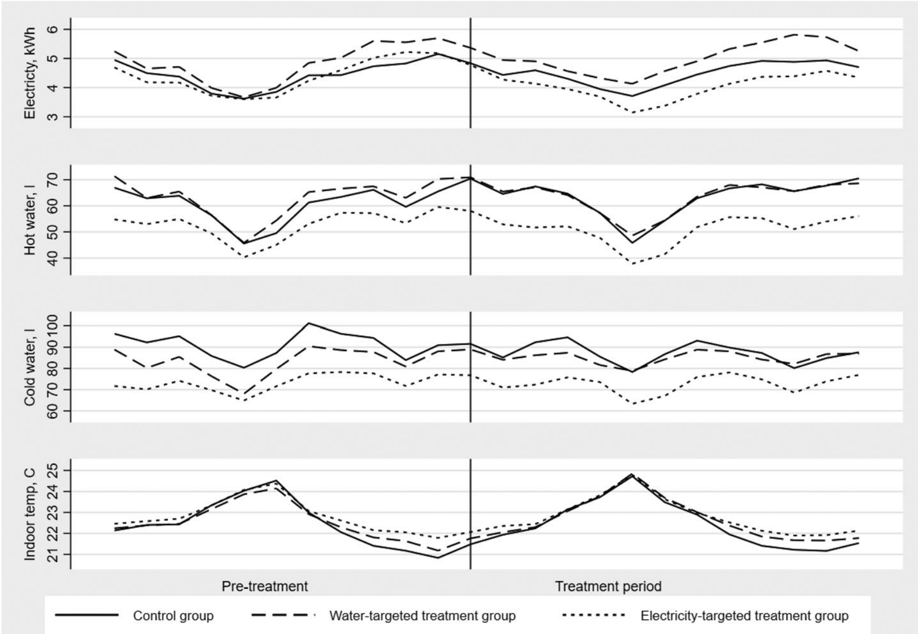


Fig. A1 Dynamics of the treatment-untargeted monthly daily average electricity, water use and indoor temperature before and after treatment delivery (March 2015 -February 2017)

Table A2 Treatment effects on electricity consumption for the sub-sample with and without the significant spillover treatment effects on hot water

Variables	Subsample with significant SQTEs	Subsample without significant SQTEs
TREAT*POST	−0.381**	−0.124
	(0.148)	(0.143)
Controls	Yes	Yes
Fixed effect Controls	Yes	Yes
No. of obs.	147,639	116,997

Notes: Standard errors clustered at the building level are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

Table A3 Treatment effects on electricity consumption for the sub-sample with and without the significant spillover treatment effects on indoor temperature

Variables	Subsample with significant SQTEs	Subsample without significant SQTEs
TREAT*POST	−0.341	−0.185
	(0.369)	(0.143)
Controls	Yes	Yes
Fixed effect Controls	Yes	Yes
No. of obs.	37,554	138,704

Notes: Standard errors clustered at the building level are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

Table A4 ATEs and SATEs on daily electricity consumption (in kWh), water use (in liters), and indoor temperatures (in °C) by using double debiased machine learning

	Water-targeted treatment				Electricity-targeted treatment			
	Hot water	Cold water	Electricity	Indoor temperature	Hot water	Cold water	Electricity	Indoor temperature
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TREAT*POST	−1.394	1.978	**−0.005**	**−0.051**	**−2.601*****	**0.665**	−0.116**	**−0.102*****
	(2.310)	(2.163)	**(0.118)**	**(0.038)**	**(0.594)**	**(0.473)**	(0.058)	**(0.034)**
Controls	Yes	Yes	**Yes**	**Yes**	**Yes**	**Yes**	Yes	**Yes**
Fixed effects	Yes	Yes	**Yes**	**Yes**	**Yes**	**Yes**	Yes	**Yes**
No. of obsv.	261,554	261,554	**267,958**	**184,463**	**255,152**	**255,152**	257,379	**179,770**
No. of apartments	425	425	**425**	**425**	**415**	**415**	415	**415**

Notes: The estimated spillover effects on indoor temperature are for an 8-month heating period. Clustered standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Sectoral spillover effects are in bold style

Table A5 SATEs on water use (in litres), and indoor temperatures (in °C) for electricity targeted treatment group based on baseline electricity consumption

	Hot Water		Cold Water		Heating	
	(1)		(2)		(3)	
Variables	High	Low	High	Low	High	Low
TREAT*POST	−8.702**	−5.666	0.798	4.047	−0.196***	−0.135**
	(4.281)	(3.871)	(5.769)	(4.482)	(0.0489)	(0.0645)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	114,762	147,673	114,762	147,673	77,172	102,598
No. of apartments	161	254	161	254	161	254

Notes: The estimated spillover effects on indoor temperature are for an 8-month heating period. Clustered standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

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Authors Contributions Andrius Kažukauskas: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing, Supervision, Project administration, Funding acquisition. Fissha Asmare: Formal analysis, Writing- Original draft preparation, Writing - Review & Editing. Thomas Broberg: Conceptualization, Investigation. Jūratė Jaraitė: Conceptualization, Writing- Reviewing and Editing, Writing - Review & Editing.

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Data Availability This manuscript uses confidential household-level data owned by a housing rental company AB Bostaden. Any further requests about this data should be directed to AB Bostaden. AB Bostaden's contact details for correspondence are as follows: AB Bostaden Box 244, 901 06 Umeå Phone: +46-90-17-75-00 E-mail: ab.bostaden@bostaden.umea.se

Declarations

Competing Interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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