Journal of Environmental Economics and Management 127 (2024) 103022

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

Non-price energy conservation information and household energy consumption in a developing country: Evidence from an RCT☆,☆☆,☆☆☆

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ARTICLE INFO

JEL classification:
D12
D83
D91
Q40
Q41

Keywords:
Energy efficiency
Electricity consumption
Field experiment
Non-price information
Social norms

ABSTRACT

We use a randomized controlled trial in Bangladesh to test three types of non-price energy conservation strategies that influence electricity consumption of households: (*i*) advice on electricity conservation methods (knowledge treatment); (*ii*) (median) electricity consumption of others in the suburb (suburb comparison); and (*iii*) (median) electricity consumption of neighbors (neighbor comparison). We find that providing advice on saving energy could reduce households' electricity consumption and bills significantly. The effects are stronger for advice on electricity conservation methods than neighbor and suburb comparisons. The effects of providing information about own electricity consumption relative to neighbors' electricity consumption is similar to the effects of giving information about own electricity consumption relative to electricity consumption of households in the same suburb. The effects among households who were *inefficient* users in neighbor and suburb comparison groups are almost as strong as those in the knowledge treatment group. The effects across all treatment groups become stronger over time as they receive repeated information.

1. Introduction

Globally, countries are increasingly adopting different energy efficiency and sustainability programs to address supply shortages, increasing energy demand, and their respective commitments to reduce emissions under the United Nations Framework Convention on

☆ We received funding support from International Growth Centre and Monash University.☆☆ The authors declare no financial benefits received for the purpose of conducting this research.☆☆☆ We acknowledge funding support from the International Growth Centre (IGC) and Monash Business School at Monash University. We also thank conference participants at the Advances in the Field Experiments conference in Chicago, the CDES conference on Sustainable Development in Prato, the conference in environmental economics at Monash University, the IGC conference in Dhaka as well as seminar participants at North South University for their valuable comments and suggestions. The usual disclaimer applies.

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https://doi.org/10.1016/j.jeem.2024.103022
Received 22 January 2023; Received in revised form 14 May 2024; Accepted 3 June 2024
Available online 6 June 2024

Climate Change (UNFCCC) framework. Such programs are traditionally focused on relative prices as the primary force for managing energy demand (Allcott 2011). However, enactment and enforcement of energy policies, such as setting up the carbon tax and energy subsidy, can be expensive, and measuring their effectiveness is difficult (e.g., Hahn and Metcalfe 2021). Moreover, such policies may also be subject to political opposition and scrutiny (Brent et al. 2015). On the other hand, non-price interventions are typically inexpensive relative to subsidies (Bertrand et al. 2010) and carefully crafted psychological cues can have demand effects that are similar to effects of large changes in relative prices (e.g., Allcott and Mullainathan 2010; Allcott 2011; Allcott and Rogers 2014; Andor et al. 2020; Hahn and Metcalfe 2016).

For developing countries that are flogged with shortages of energy supply, non-price energy conservation programs can be a short-term yet cost-effective and politically feasible approach to increase energy efficiency, to manage growing electricity demand in the face of high economic growth and increasing population, and also to combat the climate emergency (Allcott 2011). Moreover, residential electricity accounts for 40% of global energy-related CO_2 emissions and is projected to grow (Rasul and Hollywood 2012), especially in developing countries (IEO 2016). As of 2013, electricity and heat production emitted 50% of CO_2, a fifth of which is the residential source and in an increasing trend (IEA 2015). More recently, the post Covid-19 pandemic recovery of world economies has contributed to a six percent rise in CO_2 emissions, more than the reduction in 2020 due to the Covid-19 pandemic, with 46% of increase attributed to global electricity and heat production (IEA 2021). Therefore, testing and understanding the effects of non-price energy conservation strategies on residential electricity usage in a developing country will provide important insights and policy implications.

In this paper, we compare two non-price mechanisms: *information campaign* that improves knowledge and induces moral appeals and concern (Hastings et al. 2004; Davis and Metcalf 2016) and *social norms marketing* as exogenous factors diffusing certain behaviors (Schultz et al. 2007). We utilize a randomized controlled field experiment to examine the relative effectiveness of energy conservation information in influencing residential energy consumption in three districts in Bangladesh. We assess the role of information on electricity consumption by testing the effects of the following treatments: (1) information about own electricity consumption relative to neighbors; (2) information about own electricity consumption relative to others in the same suburb; and (3) expert advice (knowledge-based) on electricity conservation.

In collaboration with IPDC Bangladesh and with supports from Dhaka Power Distribution Company (DPDC Ltd.) officials[1], we provided information to a subset of 2394 households three times and surveyed all households four times in 2017 to examine the short-term impacts of the treatments on electricity usage and bills. We also revisited the households several months after the intervention ended to examine the longer-term impacts of the treatments. To understand the role of energy conservation tips, we provided pre-printed suggestions for conserving energy. To understand the role of social norms, households received descriptive normative information about the actual energy consumption of the median neighbor or of the median household in their suburb. Social norms play an important role on saving behaviors in developing countries (Fromell et al. 2021) while social comparison may lead to conformity if individuals use the behaviors of others as a reference point for decisions (Cialdini 1993; Cason and Mui 1998; Messick 1999). The conformity behaviors of treated households may differ between the neighbor and suburb groups if neighbors and the wider community members in the suburb are viewed as different social groups. As groups with social ties are likely to be more influential (Zafar 2011), we may expect social comparisons with neighbors to be more effective than social comparisons with others in the wider community.

We identify statistically significant reduction in electricity consumption of 23–43 kWh (i.e., 6.6%–12.2%) for the knowledge treatment group, 14 to 27 kWh (i.e., 3.7%–7.4%) for the neighbor treatment group, and 9 to 21 kWh (i.e., 2.6%–5.9%) for the suburb treatment group during the intervention period. The statistical significance and relative effect sizes are similar when we examine the effects of treatments on electricity bills. Our results indicate that providing advice on saving energy could reduce households' energy consumption significantly. In particular, advice on electricity conservation yields stronger effects than neighbor and suburb comparisons do. The effects of providing information about own electricity consumption relative to neighbors' electricity consumption is similar to the effects of giving information about own electricity consumption relative to electricity consumption of households in the same suburb. The similarity between the two groups implies that individuals in an urban setting are likely to view neighbors and the wider community in the area or suburb as similar social reference groups for consumption norm formation. The effects across all treatment groups became stronger over time as they received repeated information. Consistent with the related literature (e.g., List et al. 2017), these estimates also vary by the respective pre-baseline consumption type and energy efficiency type in each treatment group. The effects among households who were *inefficient* users in the neighbor treatment group become almost as strong as those in the knowledge treatment group six months after the intervention. Such effects are less pronounced for inefficient users in the suburb treatment group. The results suggest that social norm marketing can be as effective as knowledge treatment in the longer term for individuals whose behaviors are more likely to be disapproved socially by those they have social ties with.

We also find evidence that the reductions in electricity usage and bills become even larger 12 months after the intervention ended. We also demonstrate that our results are robust to potential scrutiny effects due to the verification of electricity consumption and bills, as well as potential information spillovers. Overall, our estimates suggest that neighbor, suburb, and knowledge treatments can potentially reduce total urban residential electricity consumption in Bangladesh by 179.55, 157.00, and 277.81 gWh per month, which are equivalent to 11%, 10% and 17% reduction in energy use, respectively. Our results have important implications for meeting growing household energy demand, especially in the context of current global energy crisis.

Our paper contributes to the literature on household energy saving behavior. To the best of our knowledge, we are the first to study both the role of knowledge of electricity conservation and social norms-based home energy reports (HER) on electricity consumption

[1] We particularly thank Mr. Tariqul Hoque, Chief Engineer (Development) of DPDC Ltd. for providing useful energy saving tips in the process.

using a randomized controlled experiment in Bangladesh. Existing experimental studies on HER interventions tend to focus on developed countries and separately examine the effectiveness of information of energy conservation and social norms-based HER on electricity consumption (see, for example, Allcott 2011; Allcott and Rogers 2014; Andor et al. 2020; McAndrew et al. 2021). Our experimental design allows us to evaluate the relative effectiveness of electricity conservation information and social norm-based HER in influencing residential electricity consumption.

As previous research shows that contexts matter for electricity consumption (Andor et al. 2020), examining the relative effectiveness of knowledge of electricity conservation and social-norm based HER is particularly policy relevant in a developing country context for several reasons. First, frequent power outages together with less than universal access to electricity makes the case of developing countries different from those in developed countries given that the problems of demand-supply mismatch and inequality of electricity access are more prevalent in developing countries (Kaygusuz, 2012; Balarama et al. 2020). In addition, lower educational attainment has been linked to greater electricity consumption (Piao and Managi 2023), while IEA (2022) argues that the largest energy efficiency opportunities are in emerging and developing countries. As developing countries generally have lower average educational attainment than developed countries, improved knowledge of electricity conservation methods among the population can help developing countries improve energy efficiency. Developing countries may address increased energy demand by not only increasing energy production but also better energy conservation. Increasing efficiency by reducing electricity consumption might free up some electricity that can then be distributed to improve electricity access for all.

Second, by testing the effectiveness of different types of non-price interventions, this paper adds to the broader literature on using price versus non-price intervention to increase energy consumption efficiency (e.g., Reiss and White 2008; Jessoe and Rapson 2014). Given the extent of government subsidies allocated to the energy sector in developing countries (Lin and Jiang 2011; Solarin 2020), our focus on non-price intervention is particularly important from a public finance perspective for developing countries. As some governments use energy subsidies as a form of social policy (Uddin et al. 2021), non-price interventions may be used in conjunction with these subsidies to increase energy consumption efficiency. This paper sheds light on the relative effectiveness of different forms of relatively low-cost non-price interventions on household electricity consumption in a developing country context. Given that the Bangladeshi government heavily subsidizes the energy sector (Hosan et al. 2023) and has been financing its budget deficits through domestic and foreign sources for years (Rana and Wahid 2017), our findings also suggest that the government can implement energy information campaign to help improve its fiscal situation.

Third, social norms play an important role on saving behaviors in developing countries (Fromell et al. 2021) where social networks function as an important safety net (Chuang and Schechter 2015). Given the important role of social norms in a developing country context, social norms related to the consumption of others in the community can potentially be more effective in influencing the electricity consumption of households than knowledge of electricity conservation methods. Despite the importance of social norms in a developing country context, our findings demonstrate that the effect of giving information of electricity conservation methods on electricity consumption is greater than the effect of giving information of electricity consumption of others in the community, especially in urban settings. From a cost-benefit perspective, our findings highlight the value of providing households with information of energy conservation methods to help improve energy efficiency in developing countries.

We also add to the growing number of recent studies examining how reference to social norms can change a whole range of behaviors, particularly in energy or resource use (Ayers et al., 2013; Costa and Kahn 2013; Allcott 2011; Ferraro and Price 2013). We study two different types of social norms to understand whether consumers are responsive more to a social norm type intervention based on a geographically closer group of consumers (neighbors) than that based on a larger, more diversified, geographically farther group of consumers (suburb-based or area-based social comparison). Independently, we test the impact of energy saving tips in a context where consumers have not been made aware of by an external agency of how to conserve energy.

Brandon et al. (2017) provides a meta-analysis of 38 natural field experiments to conclude that technology adoption and habit formation can result in persistent reductions in energy consumption. However, some other studies offer a mixed result on the effects of social norm on behavior changes. One strand of studies reports that social marketing produces no substantial changes in behavior (Granfield 2005; Peeler et al. 2000; Russell et al. 2005). Some studies even suggest that social norms marketing sometime increases the undesirable perception and behaviors they set out to reduce which is termed as the boomerang effect in literature (Schultz et al. 2007).[2] Hence, we combined both descriptive and injunctive norms.[3]

While there exists debates with respect to the efficacy of social norm-based intervention in reducing undesirable actions, there is a vast strand of literature that shed light in favor of using it to influence alcohol consumption, drug use, disordered eating, gambling, littering, recycling (Donaldson and Dunfee, 1994; Larimer and Neighbors 2003; Schultz 1999; Schultz et al. 2007), charitable giving (Frey and Meier 2004; Croson and Shang 2008), voting (Gerber and Rogers 2009), retirement savings (Duflo and Saez 2003; Beshears et al. 2009), and employee effort (Fehr et al. 1998; Bandiera et al. 2010). On energy consumption, Fanghella et al. (2022) found that technological renovation and energy-saving competition were effective in reducing electricity consumption in the Italian banking

[2] In our context, households using less energy (efficient users) might turn out to be more energy intensive once they know their average usage is lower than other households in their neighborhood or in the suburb.

[3] Injunctive norms refer to perceptions of what should or should not be done by individuals (i.e., approved, or disapproved behavior). Descriptive norms refer to perceptions of what is commonly done in a given situation. They signal mainstream behavior. This is similar to visual messages which are effective in reducing energy consumption (e.g., Papineau and Rivers 2022). We drew a happy face and thumbs-up, an injunctive normative message implying approval, on a flyer delivered to households whose energy use was lower than the neighborhood median or suburb median. We drew a frowning face and thumbs-down, implying disapproval, on a flyer delivered to households whose energy use was higher than the median.

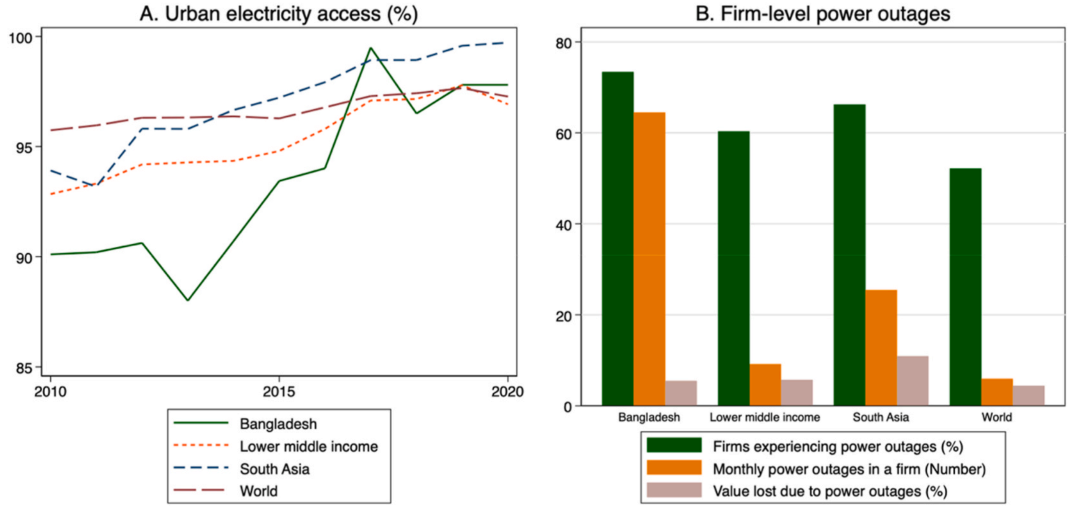

Fig. 1. Access to and scarcity of electricity.
Notes. Fig. 1A plots the percentage of urban households with access to electricity for years 2010-20 in the World, South Asia, lower middle-income countries, and Bangladesh. Fig. 1B plots the respective firm-level power outages. All data comes from the World Development Indicators (World Bank 2022).

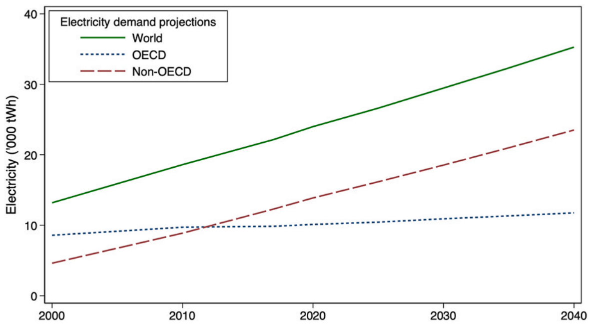

Fig. 2. Electricity demand projections.
Notes. Fig. 2 plots electricity demand projections for the World, OECD, and non-OECD countries for the years 2010–20. All data comes from ExxonMobil (2019).

sector, while Andor et al. (2022) found significant conservation effects of information campaigns.

The paper proceeds as follows. Section 2 describes the background of electricity demand and supply situation in Bangladesh. Section 3 describes the experimental design. Section 4 contains our main results. Section 5 provides additional results and robustness analysis. Finally, section 6 summarizes our research findings and concludes.

2. Background

The United Nations have identified "ensure access to affordable, reliable, sustainable and modern energy for all" as the energy-related sustainable development goals (SDGs). Globally, countries have pledged to achieve the SDGs including energy related goals and targets (i.e., SDG7). There are seven specific targets embedded in SDG7, which have different degrees of priorities and relevance for countries at different stages of development. For example, while the transition to cleaner and sustainable energy sources is critical to credible climate actions and sustainable development since over 90% of global CO_2 emissions are associated to the energy sector (IEA 2019), developing countries are prioritizing universal access to energy (Chen et al. 2022; Eskander 2022).

Over the last decade, global access to electricity has increased considerably. Fig. 1 shows urban access to electricity. Apparently, moderate improvement in global access to electricity comes from drastic improvements in lower middle-income countries including South Asian countries like Bangladesh. Despite these improvements, more than 50% of firms still experience frequent power outages, resulting in considerable losses in their production. This is more prevalent for Bangladesh and other lower-middle income countries: around 70% of firms experience frequent power outages with more than 65 such monthly incidences per firm in Bangladesh.

As of 2021, there were still 675 million people without electricity, most of them from developing countries, and the number is projected only to go down to 660 million in 2030 based on the current trend (United Nation, 2023). Moreover, almost 2.3 billion people still use inefficient and polluting cooking systems. In addition to failure to curb consequent emissions, such trends also contribute to health hazards, among others. The underlying heterogeneity in energy transition status necessarily reinforces the importance of energy efficiency improvement as an interim measure to curb the consequent emissions.

On the other hand, energy demands are ever increasing, and projected to grow further (Fig. 2). According to the demand projections by Exxonmobil (2019), global population will reach 9.2 billion in 2040 with a significant increase in working-age population in many non-OECD countries. This population pressure, together with pressure from economic expansion, will further increase energy needs in those countries. Currently, household electricity consumption accounts for 40% of global energy related CO_2 emission and is expected to grow, especially in developing countries. Altogether, the supply-demand mismatch in developing countries will only worsen further requiring both immediate measures such as improving energy efficiency and long-term measures such as adoption of renewables.

The relative failure of energy efficiency improvement can partly be attributed to the so-called energy-efficiency paradox (Van Soest and Bulte 2001). However, improvement in energy efficiency is one of the energy targets related SDGs.[4] The signatory countries have pledged to double the global rate improvement in energy efficiency by 2030. However, as of 2019, countries were able to improve energy efficiency by 1.9% only, requiring them to speed up the improvement rate to 3.2% over 2020–30 (United Nation, 2023). Considering this dismal trend, we investigate effective ways to increase energy efficiency in a developing country.

3. Experimental design

Below we explain our experimental design and the collection of data.

3.1. Recruitment

The experiment was conducted in three districts, Dhaka, Khulna, and Jashore, in Bangladesh.[5] To find out households who have the potential to reduce electricity consumption, we located ten areas or suburbs in these districts and multiple neighborhoods within each suburb with relatively better socio-economic condition (Fig. S1 and Table S1). We have eight suburbs or areas within Dhaka district, which are traditionally known to local people in Bangladesh as areas within Dhaka. For example, the current Badda area was originally a village many years ago before being incorporated within Dhaka city. Currently, this is a part of Dhaka, but people still recognize it by its original area name. Within each suburb, we then consider a residential road as a "neighborhood". Those living in the same neighborhood are considered as neighbors to each other. We have included up to 10 neighborhoods from a single area. Some roads may have many sections where many apartment complexes are located, therefore providing us the opportunity to randomly choose our subjects and minimize any potential information spillover.

Many households in these districts have very low income and low or no usage of electricity. Hence, we target apartments or areas that are more likely to use air conditioner and generator during hot summer temperature, and therefore, have the potential to reduce electricity use if treated. Specifically, the targeted households must be located in an urban location, having electricity connections, and owning and using at least one energy-intensive appliances (e.g., refrigerator, freezer, washing machine, air conditioner, heater, television, computer, and microwave oven).

With the help of the official bodies that supply residential electricity and distribute bills in these areas and information from different suburbs to locate the appropriate households, we approached many households in January–February 2017. When we recruited households, we ensured not to recruit more than one household from the same floor of an apartment complex, and also not from two consecutive floors. These were done to reduce the possibility of participating households discussing information related to the treatments. Among those we approached, 2394 agreed and provided informed consent to participate in our experiment over multiple survey rounds. Their participation was voluntary, and they did not receive any monetary compensation for their participation. During the recruitment round (i.e., round 0), we collected self-reported data on electricity use and various demographic and socioeconomic attributes of the enlisted households.

We use data from round 0 (January–February 2017), and divide households based on the following characteristics: (1) self-reported electricity use; (2) daily air conditioner (AC) or cooler use; (3) number of power outages (in the last 3 days); and (4) number of rooms. Households were then randomly assigned into four treatment and control arms to make sure they are balanced in these four dimensions. We followed these households over four rounds between May and December 2017, and then again in May 2018 (half of the households) and September 2018 (all households). Note that the treatments were delivered in round 1, round 2 and round 3, but not in round 4, round 5, and round 6. We treat data collected in round 1 as baseline data because treated households had not had the opportunity to respond to the treatment in round 1. We term the data collected in round 0 as pre-baseline data to differentiate it from the data collected in round 1. Thus, both pre-baseline (round 0) and baseline (round 1) data are pre-treatment data.

3.2. Treatment assignment

The treatments are.

[4] SDG target 7.3: By 2030, double the global rate of improvement in energy efficiency (https://sdgs.un.org/goals/goal7).

[5] In addition to the capital city Dhaka, we choose two other major metropolitan cities in Bangladesh, Khulna and Jashore, as we were able to collaborate with local electricity supply authorities in these cities.

Fig. 3. Knowledge and feedback flyers.
Notes. Knowledge (Panel A) and energy use feedback flyers (Panels B–D) were distributed to respective treatment groups during survey rounds 1–3.

(i) Control (T0). Each household receives information about how much energy, in kWh/month and monthly electricity bill, the household had used in the previous month. T0 serves as the control group. All households in treatment groups (i.e., T1, T2 and T3) also receive this information.
(ii) Neighbor comparison treatment (T1). Each household receives information about how own electricity consumption is relative to the median electricity consumption of comparable neighbor households. Neighbors are basically those living in the same neighborhood as defined in section 3.1. The information is provided with an injunctive message that shows a happy face for those whose consumption is in the bottom 40-percentile, a frowning face for those whose consumption is in the top 30-percentile, and a neutral message for those whose consumption is in the middle of the distribution.
(iii) Suburb comparison treatment (T2). Each household receives information about how own electricity consumption is relative to the median electricity consumption in the suburb. Similar to T1, the information is provided with an injunctive message that shows a happy face for those whose consumption is in the bottom 40-percentile, a frowning face for those whose consumption is in the top 30-percentile, and a neutral message for those whose consumption is in the middle of the distribution.
(iv) Knowledge/information treatment (T3). In addition to providing information about own electricity consumption, we provide expert advice on electricity conservation methods. We emphasize six tips given by the city electricity distribution company experts to help households conserve electricity and reduce electricity expenditure (Fig. 3A). To keep the information visible, households were asked to place stickers showing these tips at obvious places in the house, so all household members know them and are reminded of them on a regular basis.

The control group was not aware of the various treatment arms, while the treatment groups were only aware of their own treatment.

3.3. Injunctive messages

For injunctive messages, T2 and T3 households are randomly divided into the following three sub-groups based on their electricity use compared to their respective comparison group.

Table 1
Timeline of survey.

Round	Month of Survey	Billing cycle	Verified?	Treatment delivered?	Expected treatment effects?	Sample size
0	January–February 2017	December 2016	No	No	No	2394
1	May 2017	April 2017	Yes	Yes	No	2248
2	July 2017	June 2017	Yes	Yes	Yes (short term)	2248
3	September 2017	August 2017	Yes	Yes	Yes (short term)	2248
4	December 2017	November 2017	Yes	No	Yes (short term)	2248
5	May 2018	April 2018	Yes	No	Yes (longer term)	1250
6	September 2018	August 2018	Yes	No	Yes (longer term)	2248

Notes. We initially recruited 2394 households, of which 2248 remained throughout the intervention and post-intervention periods. Both round 0 and round 1 provide pre-treatment data. We refer round 1 data as baseline data and round 0 data as pre-baseline data. We surveyed 1250 randomly selected households and surveyed them in round 5 to test for potential scrutiny effects in round 6.

Table 2
Baseline characteristics by treatment status.

Variables	Control [T0]	Neighbor [T1]	Suburb [T2]	Knowledge [T3]	T1 – T0	T2 – T0	T3 – T0
Electricity use (kWh)	322.820 [117.479]	325.339 [125.548]	319.405 [114.819]	320.602 [110.405]	2.519 (7.273)	−3.415 (6.950)	−2.218 (6.837)
Electricity bills (taka)	1726.325 [671.282]	1727.076 [690.082]	1715.954 [733.486]	1692.806 [668.063]	0.750 (40.733)	−10.371 (42.030)	−33.519 (40.150)
Daily AC use	0.829 [0.377]	0.822 [0.383]	0.838 [0.369]	0.835 [0.372]	−0.007 (0.023)	0.009 (0.022)	0.006 (0.022)
Number of power outage (last 3 days)	1.156 [0.990]	1.155 [0.975]	1.146 [0.987]	1.124 [1.003]	−0.001 (0.059)	−0.010 (0.059)	−0.032 (0.060)
Number of rooms	3.497 [0.956]	3.459 [0.928]	3.520 [0.924]	3.554 [0.967]	−0.038 (0.057)	0.022 (0.057)	0.057 (0.058)
No. of obs.	550	567	568	563			

Notes. Randomization was done after pre-baseline (Round 0) data were collected in January–February 2017. Baseline (Round 1) data were collected in May 2017 when electricity use and bills from April 2017 were reported and verified. Standard deviations are reported in brackets "[]". Standard errors are reported in parentheses "()". Reported results are for 2248 households that remained throughout the intervention period.

(i) *Good/efficient users* whose electricity bills are at the bottom 40-percentile. They are provided flyers with a "thumbs up and happy face" norm sign which indicates appreciation for their good use (Fig. 3B).
(ii) *Bad/inefficient users* whose electricity bill is in the top 30-percentile. They received flyers with a "frowning face and thumb-down" sign (Fig. 3C).
(iii) *Average users* whose electricity bills are in the middle 30-percentile. They received flyers showing a neutral message encouraging them to improve (Fig. 3D).

Note that T3 differs from T2 mainly in terms the comparison group. Instead of suburb-wide median dweller in T3, a household electricity bill is compared with the median neighbor's electricity bill in T2.

3.4. Intervention

The main intervention started in May 2017 (round 1, R1) when the temperature started to rise (following a mild to mild/medium temperature in February and March). In R1, we verified electricity use (baseline use) and electricity bills (baseline bills) of enlisted households. We were able to follow 2248 households throughout from R1 to R4 (December 2017). We lost 6% of households who were either relocated or not willing to participate in the experiment over a four-month period. There is no significant difference in attrition across treatment groups. R2 and R3 were conducted in July and September, respectively. In each round, we surveyed them and verified their electricity use and bills before we provided information. Note that R3 was the final round of treatments, even though we continued to follow up with households in R4, R5, and R6 (see Table 1).

4. Main results

4.1. Pre-treatment characteristics

Before we present the main results, we first use pre-treatment characteristics to demonstrate successful randomization of households into treatment and control groups. Table 2 compares baseline (round 1) characteristics across control and treatment households for the 2248 households that remained throughout the intervention period. Table 3 compares baseline characteristics between the control group and each treatment group for several sub-samples categorized by baseline median electricity use status, baseline

Table 3
Baseline characteristics by treatment status for various sub-samples.

Variables	Electricity use	Electricity bills	AC	Outages	Rooms	Electricity use	Electricity bills	AC	Outages	Rooms
	A. Below median of neighbor sample					B. Above median of neighbor sample				
Neighbor	5.925	7.221	0.006	0.048	−0.037	−5.631	−31.214	−0.022	−0.056	−0.042
	(8.154)	(48.033)	(0.031)	(0.082)	(0.078)	(10.836)	(64.266)	(0.032)	(0.086)	(0.083)
Suburb	0.154	−6.109	−0.001	0.042	−0.009	−12.098	−42.199	0.019	−0.067	0.052
	(8.161)	(48.075)	(0.031)	(0.082)	(0.078)	(10.818)	(64.157)	(0.032)	(0.086)	(0.083)
Knowledge	3.529	−11.991	0.008	−0.008	0.052	−10.176	−65.919	0.003	−0.061	0.061
	(8.091)	(47.665)	(0.031)	(0.081)	(0.078)	(10.963)	(65.015)	(0.033)	(0.087)	(0.084)
No. of obs.	1171	1171	1171	1171	1154	1077	1077	1077	1077	1069
	C. Below median of suburb sample					D. Above median of suburb sample				
Neighbor	6.417	5.938	−0.001	0.066	−0.041	−4.505	−20.809	−0.013	−0.071	−0.035
	(7.691)	(42.713)	(0.031)	(0.083)	(0.079)	(11.030)	(67.225)	(0.032)	(0.084)	(0.082)
Suburb	−1.154	−30.664	−0.019	0.033	−0.035	−9.409	−9.695	0.038	−0.054	0.080
	(7.704)	(42.788)	(0.031)	(0.083)	(0.079)	(11.002)	(67.052)	(0.032)	(0.084)	(0.082)
Knowledge	2.088	−20.438	−0.010	−0.068	0.060	−7.257	−49.465	0.023	0.007	0.053
	(7.645)	(42.460)	(0.031)	(0.083)	(0.078)	(11.139)	(67.891)	(0.033)	(0.085)	(0.083)
No. of obs.	1162	1162	1162	1162	1147	1086	1086	1086	1086	1076
	E. Inefficient users relative to neighbor sample					F. Average users relative to neighbor sample				
Neighbor	−1.437	−7.220	0.025	−0.013	0.023	−4.283	−48.099	−0.018	−0.075	−0.111
	(15.543)	(93.620)	(0.043)	(0.115)	(0.107)	(9.898)	(56.468)	(0.036)	(0.097)	(0.098)
Suburb	−3.092	−7.178	0.073*	0.114	0.106	−12.558	−66.727	−0.022	−0.202**	−0.021
	(15.468)	(93.167)	(0.043)	(0.114)	(0.106)	(10.022)	(57.176)	(0.037)	(0.099)	(0.100)
Knowledge	−2.275	−25.251	0.036	0.088	−0.016	−7.981	−73.842	−0.009	−0.162	0.112
	(15.594)	(93.930)	(0.043)	(0.115)	(0.107)	(10.046)	(57.312)	(0.037)	(0.099)	(0.100)
No. of obs.	614	614	614	614	609	799	799	799	799	791
	G. Efficient users relative to neighbor sample					H. Inefficient users relative to suburb sample				
Neighbor	11.098	48.577	−0.024	0.066	−0.014	8.785	61.842	0.040	−0.056	−0.020
	(9.689)	(57.427)	(0.038)	(0.098)	(0.092)	(14.911)	(90.215)	(0.041)	(0.108)	(0.103)
Suburb	4.374	36.785	−0.011	0.073	−0.002	−6.170	−14.123	0.082**	−0.041	0.091
	(9.581)	(56.792)	(0.037)	(0.097)	(0.091)	(14.755)	(89.267)	(0.041)	(0.107)	(0.102)
Knowledge	4.406	5.024	−0.005	−0.005	0.056	−1.558	−14.617	0.058	0.054	0.063
	(9.559)	(56.657)	(0.037)	(0.097)	(0.091)	(15.055)	(91.085)	(0.042)	(0.109)	(0.104)
No. of obs.	835	835	835	835	823	664	664	664	664	659
	I. Average users relative to suburb sample					J. Efficient users relative to suburb sample				
Neighbor	−2.268	−55.945	−0.030	−0.096	−0.054	4.887	18.126	−0.029	0.106	−0.037
	(10.658)	(64.993)	(0.039)	(0.105)	(0.107)	(8.821)	(48.408)	(0.037)	(0.096)	(0.088)
Suburb	−3.853	−7.347	−0.038	−0.116	0.025	−0.455	−8.191	−0.014	0.091	−0.034
	(10.700)	(65.251)	(0.039)	(0.105)	(0.107)	(8.851)	(48.572)	(0.037)	(0.096)	(0.089)
Knowledge	−7.803	−82.253	−0.026	−0.154	0.048	6.506	17.852	−0.013	−0.005	0.060
	(10.603)	(64.661)	(0.039)	(0.104)	(0.107)	(8.841)	(48.517)	(0.037)	(0.096)	(0.089)
No. of obs.	700	700	700	700	692	884	884	884	884	872
	K. Dhaka sample					L. Jashore and Khulna sample				
Neighbor	8.246	17.429	0.015	0.064	0.005	−19.624	−66.127	−0.091*	−0.255*	−0.190*
	(7.638)	(45.983)	(0.025)	(0.063)	(0.066)	(16.561)	(92.303)	(0.049)	(0.146)	(0.098)
Suburb	−1.793	−10.945	0.020	0.002	0.049	−12.191	−23.832	−0.035	−0.090	−0.055
	(7.660)	(46.112)	(0.025)	(0.063)	(0.067)	(16.371)	(91.247)	(0.048)	(0.145)	(0.097)
Knowledge	0.282	−20.454	0.027	0.003	0.092	−14.732	−97.242	−0.071	−0.198	−0.036
	(7.691)	(46.297)	(0.025)	(0.063)	(0.067)	(16.312)	(90.914)	(0.048)	(0.144)	(0.097)
No. of obs.	1753	1753	1753	1753	1728	495	495	495	495	495

Notes. Each coefficient in Table 3 represents the average difference of a baseline characteristic between a treatment group and the control group. Robust standard errors clustered at the household level reported in parentheses. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

electricity use efficiency level, and district (Table 3).

Table 2 shows that in comparison to the control group, all three treatment groups have similar characteristics at the baseline: differences in baseline electricity use, electricity bills, daily AC use, number of power outages in the last 3 days, and number of rooms between treatment groups and the control group are not statistically significant. Table 3 shows that differences in baseline characteristics are also not statistically significant between the control group and each treatment group for various sub-samples categorized by baseline median electricity use status, baseline electricity use efficiency level, and district. Together, these results confirm that randomization was successfully implemented for the full sample and various sub-samples.

Since we randomized households into control and treatment arms and collected two rounds of pre-treatment electricity usage data, we can also further compare whether the pre-treatment trends in electricity usage are similar across control and treatment groups. Note that as pre-baseline data was self-reported by households without verification, we confine this comparison only to self-reported electricity use.[6] Table 4 reports the differences in pre-treatment trends between each treatment group and the control group by different sample restrictions.[7]The results confirm that before the treatment started, control and treatment groups do not exhibit any statistically significant differences in electricity use over time. The similar trends in electricity use are also robust across different sample restrictions.

4.2. Short-term treatment effects

Before we present regression estimates, we first plot average electricity usages and electricity bills for each treatment and control group in round 1 to round 4 in Fig. 4. By inspecting whether the 95% confidence interval of the mean of one group contains the mean of another group in a survey round, we can infer whether the treatment previously delivered had a significant effect on electricity use or bill in that round. For example, baseline electricity usages (April 2017) do not differ across control and treatment groups, confirming the randomization of treatments. After the treatments were delivered in round 1, differences across control and treatment groups started to emerge. While average electricity usages and bills started to rise the control group, they tend to decrease in the treatment groups. In the control group, average electricity consumption rose from 323 kWh in round 1 to 347 kWh in round 2 and round 3, while average electricity bill rose from 1726 Taka (Tk) in round 1 to 1847 Tk in round 2 and to 1872 in Tk.[8] By round 4, average electricity consumption and bill in the control group reached 353 kWh and 1985 Tk, respectively. Interestingly, different treatments took different durations to become statistically different from the control group. For example, one month after the intervention started, the average electricity consumption and bill in the knowledge treatment group remained at around 322 kWh and 1700 Tk (in round 2, June 2017). As average electricity consumption and bill rose significantly in the control group while they remained relatively unchanged in the knowledge group, the knowledge treatment effectively helped treated households prevent their electricity consumption and bills from rising. In contrast, it took households in the neighbor and suburb treatment groups three months to start experiencing significantly lower average electricity consumption and bills than the control group (in round 3, August 2017). The average differences in electricity consumption and bills between the control and treatment groups widened further in the fourth round of survey (November 2017).[9] However, the decreases in average electricity consumption and bills are always similar between the neighbor and suburb groups and they are never as large as those in the knowledge treatment group.

As Table 4 demonstrates that the pre-treatment trends across the control and treatment groups are statistically similar as a result of successful randomization, we will further provide complementary regression estimates on the basis of a differences-in-differences specification that combines the four rounds of data. To estimate the impact of each treatment and to test for differential effects across three treatments, we adopt the following differences-in-differences specification that models household's electricity use or electricity bill as a function of treatment group indicator T_{ki}, survey rounds indicator R_t, and district fixed effects d_i:

$$Y_{it} = \alpha + \sum_{k=1}^{3}\sum_{t=2}^{4}\beta_{kt}T_{ki}R_t + T_{ki} + R_t + d_i + \epsilon_{it}$$

where Y_{it} denotes electricity use (kwh) or electricity bill (TK) of household i in round t. T_{ki} denotes the treatment $k \in [0,1,2,3] =$ [control, neighbor, suburb, knowledge]. R_t denotes survey rounds ($t = 1,2,3,4$), and d_i denotes the district of residence (i.e., Dhaka, Jashore, and Khulna). All other omitted factors are captured by the error term ϵ_{it}. We report the Huber-White "robust" standard errors, clustered at the household level. According to Bertrand et al. (2004), these standard errors are consistent in the presence of any correlation in the errors ϵ_{it} within a household over time. We are interested in the coefficient β_{kt}, as it reflects the causal effect of treatment k in post-treatment round t (i.e., R2, R3, or R4).[10]

Table 5 reports the differences-in-differences estimates by round. Overall, we observe the strongest effects among households in the knowledge treatment group. The reduction in electricity use relative to the control group is 23 kWh in June (R2), 32 kWh in August (R3) and 43 kWh in November (R4). These statistically significant effects represent a reduction in electricity use of 6.6% in R2, 9.2% in R3, and 12.2% in R4, as the average electricity use in the control group is 347 kWh in R2, 347 kWh in R3, and 353 kWh in R4. Similarly, average electricity bills also reduced statistically significantly by 113 Tk in June, 161 Tk in August, and then 259 Tk in November. These effects represent a reduction in electricity bills of 6.1% in R2, 8.6% in R3, and 13% in R4, given that the average electricity bill in the control group is 1847 Tk in R2, 1872 Tk in R3, and 1985 Tk in R4.

Table 5 also shows that the neighbor and suburb treatments led to reduced electricity use and bills relative to the control group. However, statistically significant reductions in electricity consumption of households in neighbor and suburb treatment groups first

[6] Appendix Fig. S2 confirms that reported and verified electricity bills from round 1 are comparable.

[7] Appendix Table S2 reports the differences in baseline characteristics across treatment and control groups for different sub-samples in Dhaka city, whereas Appendix Table S3 reports the differences in pre-treatment trends across treatment and control groups for different sub-samples in Dhaka city.

[8] Note that electricity prices increased between round 2 and round 3.

[9] Fig. S4 and Fig. S5 also confirm these results.

[10] We may also interpret this effect as the intention to treat effect of treatment k if some household members in the treatment do not receive or read the respective information despite the main respondent being presented the information.

Table 4
Differences of pre-treatment trends in electricity consumption.

Variables	All households	Relative to pre-baseline electricity consumption of neighbors		Relative to pre-baseline electricity consumption of suburb		Relative to pre-baseline electricity consumption of neighbors			Relative to pre-baseline electricity consumption of suburb		
		Below median	Above median	Below median	Above median	Inefficient users	Average users	Efficient users	Inefficient users	Average users	Efficient users
Round 1 ×											
Neighbor	−44.453	−44.937	−7.873	−51.431	−14.780	−90.283	−6.042	−36.676	−21.583	−92.964	−51.966
	(56.436)	(56.045)	(93.815)	(55.749)	(93.356)	(146.464)	(62.771)	(68.659)	(138.608)	(64.511)	(65.091)
Suburb	−20.477	13.324	−16.013	−34.827	21.982	−77.676	7.924	1.052	−68.386	27.455	−29.675
	(59.510)	(63.717)	(95.490)	(51.780)	(103.006)	(152.636)	(68.066)	(72.963)	(138.871)	(85.058)	(61.816)
Knowledge	−56.380	−8.325	−98.710	−7.772	−108.266	−214.926	−11.855	5.804	−213.081	−77.237	30.080
	(57.724)	(55.186)	(97.502)	(53.248)	(97.714)	(152.306)	(61.811)	(65.265)	(142.523)	(62.222)	(64.207)
No. of obs.	4496	2342	2154	2324	2172	1228	1598	1670	1328	1400	1768
R-squared	0.002	0.097	0.024	0.119	0.023	0.060	0.016	0.136	0.059	0.028	0.152
Round FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Treatment FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
District FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes. Each treatment group's coefficient represents the average difference between the change (baseline minus pre-baseline) in self-reported electricity consumption (kWh) of a treatment group and the change (baseline minus pre-baseline) in self-reported electricity consumption (kWh) of the control group. Robust standard errors clustered at the household level are in parentheses. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

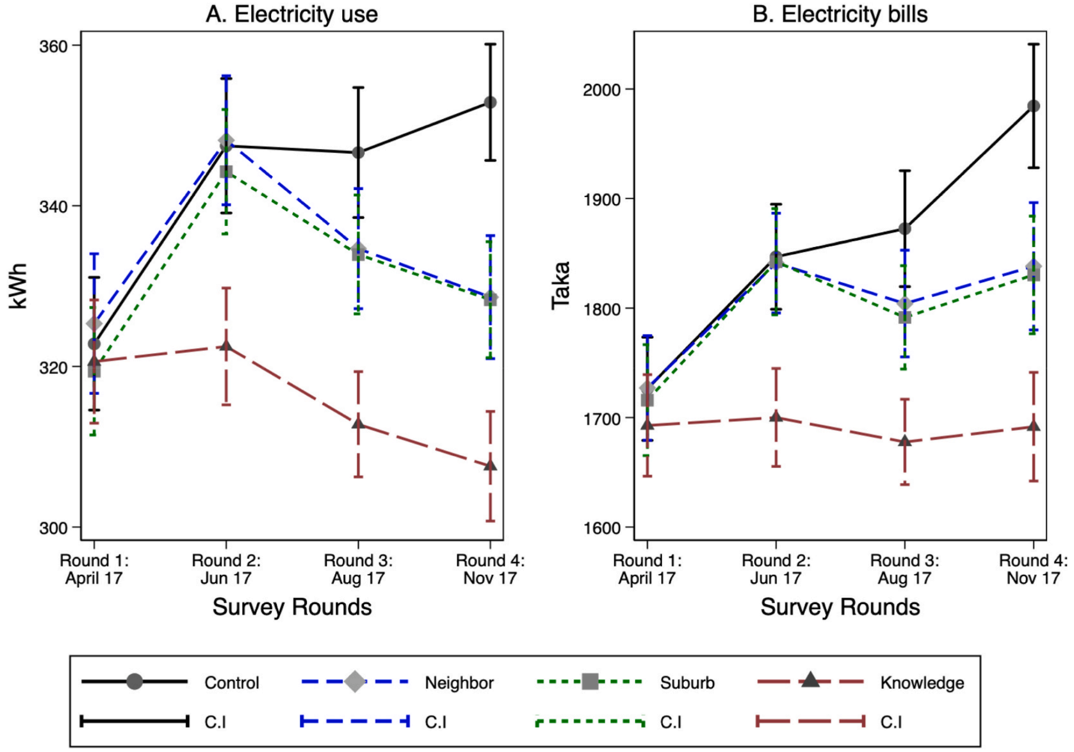

Fig. 4. Electricity use and bills over survey rounds.
Notes. Fig. 4 plots average electricity use (Panel A) and electricity bills (Panel B) for each treatment group over survey rounds 1–4.

appeared in August (R3). The estimated effect of the neighbor treatment on electricity use is −14 kWh in August (R3) and −27 kWh in November (R4). These effects represent a reduction in electricity use of 4% in R3 and 7.6% in R4. The estimated effect of the neighbor treatment on electricity bill is −69 Tk in August (R3) and −147 Tk in November (R4), which translate to a reduction of 3.7% in R3 and 7.4% in R4. Similarly, households in the suburb treatment group were able to reduce electricity use significantly by 9 kWh in August (R3) and 21 kWh in November (R4). These reductions are equivalent to 2.6% in R3 and 5.9% in R4. In terms of electricity bills, households in the suburb treatment group were able to reduce them by 70 Tk in August (R3) and 144 Tk in November (R4). These reductions are equivalent to 3.7% in R3 and 7.3% in R4, respectively. A direct comparison between the neighbor and suburb treatments reveals that these estimated effects are not statistically different from each other (Appendix Table S4), implying that urban households treat neighbors and wider community members in the suburb as socially similar reference groups for consumption norm formation and curtail behaviors. A possible explanation is that urban settings in developing countries are quite different from rural settings where the correlation between geographical distance and social distance tend to be stronger due to the greater social interaction between individuals, lower population density, and higher cost of transportation. To the extent that social ties affect the role of social influence (Zafar 2011), the results also imply that the households in urban Bangladesh tend to have similar, and perhaps also a low level of, social ties with neighbors and individuals in the wider community.

Table 5 additionally reports results for Dhaka district and combined Jashore and Khulna districts separately. Nearly 75% of our surveyed households are in Dhaka, and the estimated results for Dhaka are very similar to those for the entire sample. However, the treatments were generally ineffective in Jashore and Khulna.

Overall, the statistically significant short-term treatment effects reported here appear to be quite large. Delmas et al.'s (2013) meta-analysis indicates that informational interventions typically delivered a 7% reduction in electricity usage, but the reduction dropped to 2% when only high-quality studies with statistical controls were considered. According to a recent systematic review of 100 household energy efficiency interventions that reported a reduction in electricity use, the median measured electricity reduction was 7.9% (McAndrew et al. 2021). Our estimated treatment effect on electricity usage ranges from 2.6% to 12.2% in the short term. Two aspects about Bangladesh can potentially explain why the estimated treatment effects are proportionately larger. First, the average electricity usage in Bangladesh is significantly lower than those in developed countries where prior estimates came from. Given the lower denominator, the effect size is proportionately larger in Bangladesh for the same treatment effect. Second, the larger treatment effects in our study concentrate in the knowledge treatment group, whereas the treatment effects in the suburb and neighbor groups are similar to those reported in past studies. Many households in developing countries are still familiarizing themselves with many modern electronic appliances, their relatively low educational attainment and access to information may hinder them from learning the relevant energy saving information. To the extent that knowledge is lower in Bangladesh, there is more room for the knowledge treatment to influence usage.

Table 5
Short-term treatment effects.

Variables	Electricity use			Electricity bill		
	All cities	Dhaka city	Jashore and Khulna	All cities	Dhaka city	Jashore and Khulna
Neighbor ×						
Round 2	−1.827	−4.045	6.977	−6.520	−10.739	11.107
	(3.727)	(4.070)	(8.699)	(16.528)	(17.419)	(42.993)
Round 3	−14.465***	−19.326***	4.098	−69.070***	−70.288***	−64.102
	(4.298)	(4.622)	(10.541)	(24.402)	(24.142)	(72.665)
Round 4	−26.718***	−35.269***	5.781	−146.718***	−193.685***	31.648
	(6.373)	(5.886)	(20.322)	(42.521)	(39.822)	(134.482)
Suburb ×						
Round 2	0.191	−2.142	10.032	5.830	−7.921	58.820
	(3.351)	(3.621)	(8.016)	(15.793)	(16.787)	(40.480)
Round 3	−9.244**	−12.984***	5.802	−70.428***	−66.185**	−83.476
	(3.893)	(4.194)	(9.466)	(24.572)	(25.935)	(65.785)
Round 4	−21.142***	−30.839***	15.965	−143.757***	−200.473***	70.546
	(5.952)	(5.137)	(19.844)	(40.913)	(38.391)	(126.533)
Knowledge ×						
Round 2	−22.757***	−27.866***	−3.356	−113.273***	−127.718***	−57.675
	(2.972)	(3.187)	(7.270)	(13.510)	(14.230)	(35.483)
Round 3	−31.602***	−35.433***	−16.026*	−161.201***	−168.319***	−135.953**
	(3.943)	(4.271)	(9.473)	(22.638)	(23.180)	(64.411)
Round 4	−43.024***	−54.569***	0.411	−258.888***	−337.560***	28.829
	(5.870)	(5.207)	(18.962)	(39.430)	(35.468)	(125.925)
Control group mean	342.435	338.654	356.752	1857.423	1830.776	1958.322
No. of obs.	8968	6999	1969	8968	6999	1969
R-squared	0.020	0.020	0.006	0.021	0.018	0.008
Round FE	YES	YES	YES	YES	YES	YES
Treatment FE	YES	YES	YES	YES	YES	YES
District FE	YES	NO	NO	YES	NO	NO

Notes. Estimated coefficients of treatment groups over rounds 2–4 are based on the differences-in-differences specification in equation (1). Outcome variables are (verified) electricity consumption (kWh) and bills (Tk). Robust standard errors clustered at the household level are in parentheses. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Table 6
Power outage by city and treatment groups.

Treatment Groups	Dhaka	Khulna and Jashore	Difference
Total	1.06 [0.93]	1.44 [1.13]	0.38*** (0.05)
Control group	1.04 [0.94]	1.58 [1.08]	0.54*** (0.10)
Neighbor group	1.11 [0.92]	1.33 [1.13]	0.22** (0.01)
Suburb group	1.05 [0.92]	1.49 [1.12]	0.45*** (0.01)
Knowledge group	1.05 [0.93]	1.38 [1.17]	0.34*** (0.10)

Notes. This table reports average number of power outages as reported by the surveyed households during the baseline period, with standard deviations in brackets. Standard errors are in parentheses. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

4.3. Why the lack of treatment effects in Jashore and Khulna?

In the previous section, we show statistically significant treatment effects in Dhaka but not Jashore and Khulna. One potential explanation is that power outages are more frequent in places outside Dhaka, especially during hot months, treated households in Jashore and Khulna might not be able to reduce their electricity use significantly relative to the control group when electricity was frequently unavailable for all. Another potential explanation is that many of the households in Jashore and Khulna may be consuming electricity at a more subsistence level in general, leaving them less room to alter their electricity consumption behavior. We now examine whether these explanations can play a role.

Table 6 reports the average frequency of power outages by district and treatment as reported by households in the baseline period. On average, households in Dhaka experienced significantly fewer power outages than households in Jashore and Khulna on average. The results are also consistent with news reports during the intervention period. For example, it was reported that around half the country was experiencing acute power shortages, where southwestern districts where Jashore and Khulna are situated were particularly hard hit, with load-shedding lasted for 6 h every day on average in late April 2017 (Dhaka Tribune 2017). Given the frequent unavailability of electricity in Jashore and Khulna, there is less room for treated households to consume differently from control households in these areas.

To examine whether subsistence level of electricity usage can also play a role, we split the households into those who were in the above average and below average groups according to their baseline (R1) electricity use. Households with below average electricity

Table 7
Short-term treatment effects by baseline consumption type.

Variables	Electricity use			Electricity bill		
	All cities	Dhaka city	Jashore and Khulna	All cities	Dhaka city	Jashore and Khulna
A. Above average electricity use						
Neighbor ×						
Round 2	−5.298	−8.715	12.632	−26.493	−40.277	45.860
	(5.683)	(5.985)	(16.153)	(26.985)	(27.466)	(87.000)
Round 3	−18.232***	−23.703***	10.636	−87.167**	−94.168***	−50.546
	(6.742)	(7.094)	(19.315)	(34.098)	(35.741)	(101.770)
Round 4	−27.866***	−36.279***	16.322	−184.464***	−225.482***	30.248
	(9.934)	(9.283)	(37.117)	(70.085)	(66.844)	(256.436)
Suburb ×						
Round 2	−1.181	−4.450	17.250	−11.920	−30.252	85.488
	(5.214)	(5.354)	(15.849)	(25.627)	(26.042)	(81.635)
Round 3	−11.992*	−17.626***	18.400	−74.981*	−85.221*	−16.720
	(6.294)	(6.606)	(18.331)	(39.395)	(43.538)	(97.810)
Round 4	−27.184***	−32.117***	4.981	−201.494***	−231.457***	−9.617
	(9.306)	(8.178)	(35.715)	(68.252)	(65.610)	(236.059)
Knowledge ×						
Round 2	−22.696***	−27.496***	2.701	−116.678***	−135.444***	−17.280
	(4.470)	(4.579)	(13.734)	(20.749)	(20.968)	(67.765)
Round 3	−34.799***	−39.136***	−10.898	−164.838***	−184.055***	−69.311
	(6.281)	(6.610)	(17.965)	(34.288)	(37.227)	(91.461)
Round 4	−44.082***	−52.883***	5.397	−308.627***	−377.135***	56.772
	(9.188)	(7.956)	(36.188)	(65.266)	(57.764)	(254.472)
No. of obs.	4451	3697	754	4451	3697	754
R-squared	0.026	0.024	0.028	0.021	0.021	0.013
Round FE	YES	YES	YES	YES	YES	YES
Treatment FE	YES	YES	YES	YES	YES	YES
District FE	YES	NO	NO	YES	NO	NO
B. Below average electricity use						
Neighbor ×						
Round 2	1.793	1.655	3.577	13.702	23.741	−9.674
	(4.824)	(5.373)	(10.072)	(19.152)	(20.085)	(45.502)
Round 3	−10.292*	−13.578**	0.155	−48.110	−38.780	−73.025
	(5.315)	(5.620)	(12.343)	(34.609)	(31.455)	(98.731)
Round 4	−25.005***	−33.133***	−1.246	−108.147**	−156.441***	28.143
	(7.891)	(6.664)	(23.140)	(48.265)	(37.834)	(148.197)
Suburb ×						
Round 2	1.600	0.481	5.733	23.400	16.875	43.547
	(4.237)	(4.795)	(8.524)	(18.660)	(20.518)	(41.904)
Round 3	−6.126	−7.480	−1.104	−63.356**	−43.098*	−118.155
	(4.604)	(4.880)	(10.490)	(29.268)	(25.243)	(87.291)
Round 4	−14.362**	−28.457***	25.969	−82.976*	−161.011***	136.967
	(7.202)	(5.609)	(22.122)	(45.191)	(35.110)	(139.486)
Knowledge ×						
Round 2	−22.821***	−28.270***	−6.936	−109.994***	−119.285***	−81.903**
	(3.942)	(4.416)	(8.258)	(17.478)	(19.081)	(39.948)
Round 3	−28.367***	−31.154***	−18.968*	−156.849***	−149.799***	−175.433**
	(4.803)	(5.207)	(10.678)	(29.578)	(26.072)	(87.177)
Round 4	−41.780***	−56.102***	−1.667	−209.216***	−292.229***	16.388
	(7.240)	(6.427)	(20.341)	(44.937)	(38.983)	(128.229)
Observations	4517	3302	1215	4517	3302	1215
R-squared	0.065	0.041	0.017	0.076	0.036	0.026
Round FE	YES	YES	YES	YES	YES	YES
Treatment FE	YES	YES	YES	YES	YES	YES
District FE	YES	NO	NO	YES	NO	NO

Notes. Estimated coefficients of treatment groups over rounds 2–4 are based on the differences-in-differences specification in equation (1). Outcome variables are (verified) electricity consumption (kWh) and bills (Tk). Panel A reports the results for above average baseline users and Panel B reports the results for below average baseline users. Robust standard errors clustered at the household level are in parentheses. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

usage are arguably operating at closer to a subsistence level. We then estimate the treatment effects for the full sample, as well as for Dhaka and Jashore/Khulna separately. To the extent that treatment effects are significant for households in Dhaka and Dhaka is generally less affected by power outages, we expect smaller treatment effects for households with below average usage if there must be a ‘subsistence’ point up till which households are incapable of changing their electricity consumption behavior. The treatment effects are generally larger and more precisely estimated for households with above average usage. Thus, the results in Table 7 provide

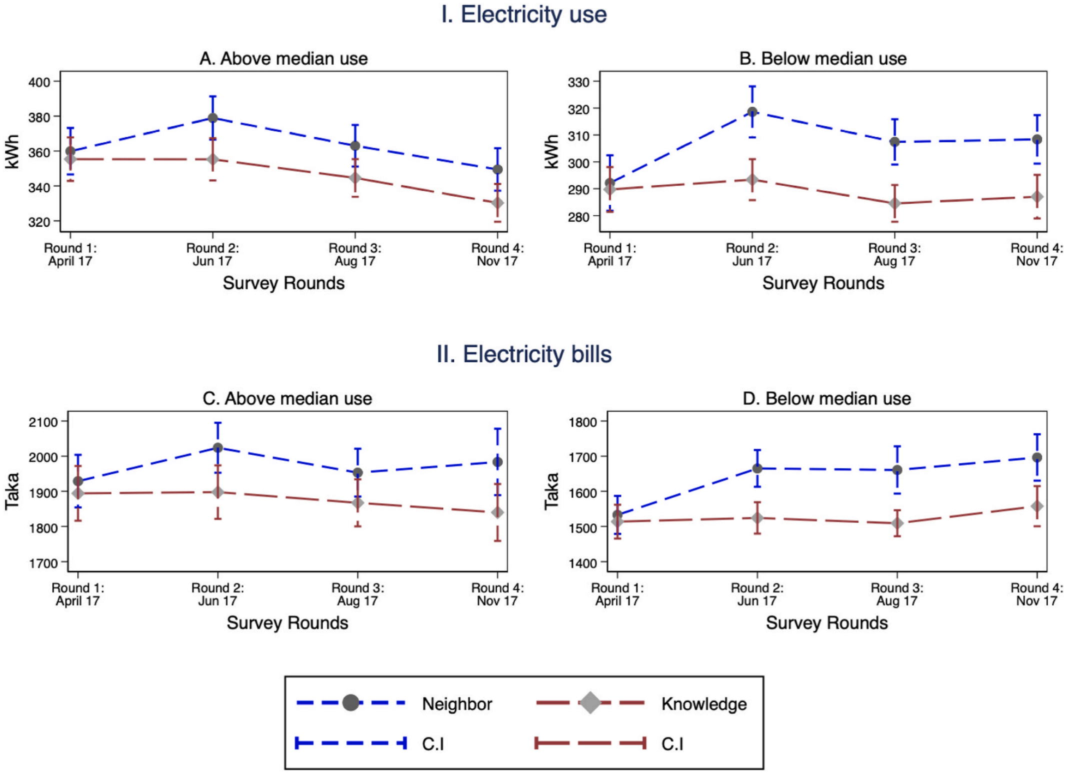

Fig. 5. Neighbor-knowledge treatment comparisons by pre-baseline median electricity use.
Notes. Fig. 5 plots average electricity use (Panels A and B) and electricity bills (Panels C and D) for above and below (pre-baseline) median use groups for neighbor and knowledge treatment groups over survey rounds 1–4.

support for the subsistence consumption explanation for the lack of treatment effects in Jashore and Khulna.

Overall, both greater frequency of power outages and subsistence electricity consumption in Jashore and Khulna than in Dhaka are plausible explanations for the lack of treatment effects in Jashore and Khulna. They can also explain why despite social interactions are likely to be stronger for households in Jashore and Khulna given their relatively less urban-like setting, treatments based on social norms are not effective in Jashore and Khulna. The results also imply that social norm and knowledge treatments are unlikely to be effective for households consuming electricity at a potential subsistence level.

4.4. Heterogeneous short-term effects of treatments: above median versus below median

We examine the relative effectiveness of social norms and knowledge treatments on electricity consumption and bills for households who were in the above median and below median groups according to their pre-baseline (R0) electricity use. As neighbor and suburb treatments differ in their pre-baseline median, we conduct the analysis separately for these social norms treatment groups and compare them with the knowledge treatment group. When using the differences-in-differences specification in equation (1), we drop control and suburb (neighbor) groups when comparing knowledge and neighbor (suburb) groups. For neighbor-knowledge comparison, $\beta_{3t} < \beta_{1t}$ implies that the knowledge treatment is more effective than the neighbor treatment in round *t*, and vice-versa. On the other hand, $\beta_{3t} = \beta_{1t}$ implies no such difference in their respective effectiveness. Similarly, for suburb-knowledge comparison, $\beta_{3t} < \beta_{2t}$ implies that the suburb treatment is more effective, while $\beta_{3t} = \beta_{2t}$ implies no such difference in their respective effectiveness in round *t*.

Fig. 5 plots the average electricity consumption and bills by pre-baseline usage above and below the median for the neighbor treatment and knowledge treatment comparisons. Fig. 6 plots the average electricity consumption and bills by pre-baseline usage above and below the median for the suburb treatment and knowledge treatment comparisons. Clearly, households in the neighbor and suburb treatment groups with pre-baseline usage above and below the median exhibit heterogeneous responses to the treatments. As expected, there is no difference in usage and bills across treatment groups at the baseline in April 2017. Differences started to emerge from R2 onwards. In all the cases, households in the knowledge treatment group generally have lower average electricity use and bills

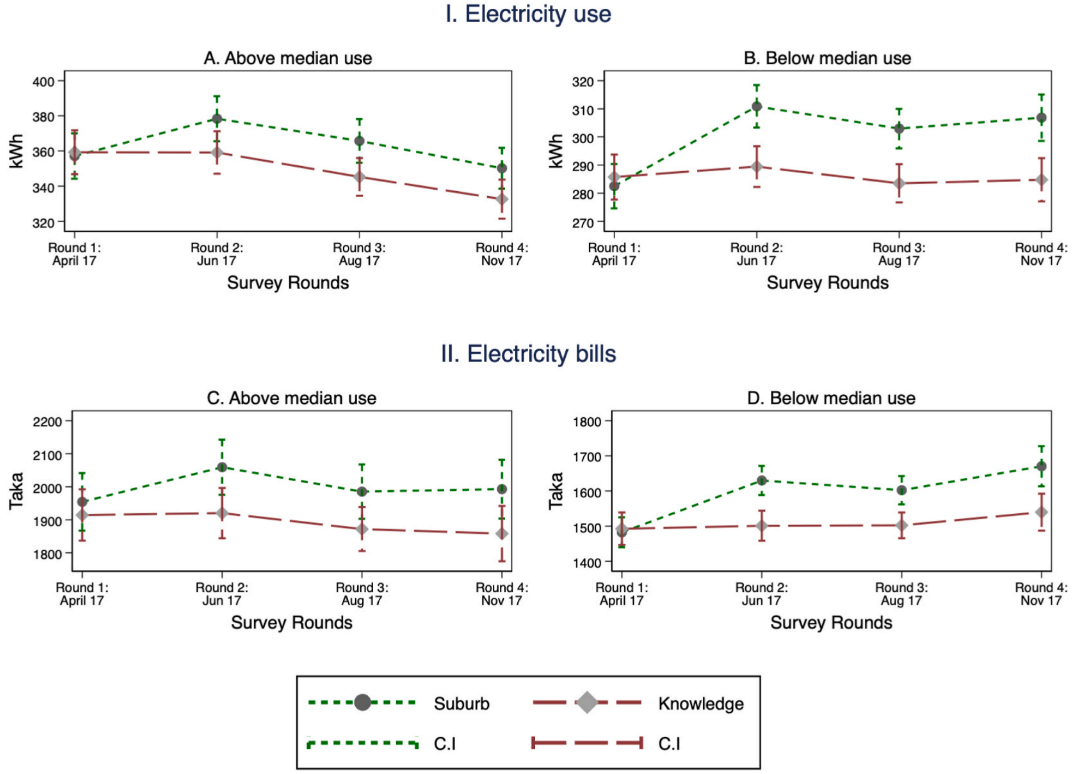

Fig. 6. Suburb-knowledge treatment comparisons by pre-baseline median electricity use.
Notes. Fig. 6 plots average electricity use (Panels A and B) and electricity bills (Panels C and D) for above and below (pre-baseline) median use groups for suburb and knowledge treatment groups over survey rounds 1–4.

than the neighbor and suburb treatment groups.

Table 8 reports the differences-in-differences estimates by pre-baseline usage above and below the median for the neighbor-knowledge comparisons in Panel A and for the suburb-knowledge comparisons in Panel B.[11] For households with pre-baseline usage *above* the median and those with pre-baseline usage below the median, the knowledge treatment is more effective in reducing electricity use and electricity bills than the neighbor treatment (Panel A). However, this relative effectiveness gradually weakens for households with pre-baseline usage above the median; to a point where it becomes statistically similar between the knowledge and neighbor treatment groups in round 4. Therefore, while the knowledge treatment is more effective than the neighbor treatment, this may not always be the case for heavy electricity users who might gradually respond to social comparisons. We observe somewhat more profound differences for the suburb-knowledge comparisons (Panel B). However, we do not observe a gradual weakening in the effectiveness of the knowledge treatment relative to the suburb treatment for households with pre-baseline usage above the median. Thus, for those with pre-baseline usage above the median of the social comparison group, it appears that they are more likely to conform to their neighbors than to the wider community members in the suburb.

4.5. *Heterogeneous short-term effects of treatments: inefficient, average, and efficient users*

We examine the relative effectiveness of the social norms and knowledge treatments on electricity consumption and bills for households who were inefficient users, average users, and efficient users according to their pre-baseline electricity usage. We use their pre-baseline consumption to categorize them as inefficient users (i.e., top 30-percentile), average users (i.e., middle 30-percentile), or efficient users (i.e., bottom 40-percentile) in the following analysis as the majority of households do not switch their status over time.

Fig. 7 plots the average electricity consumption and bills by inefficient, average, and efficient users for the neighbor-knowledge treatment comparisons. Fig. 8 plots the average electricity consumption and bills by inefficient, average, and efficient users for the suburb-knowledge treatment comparisons. As expected, there is no difference in usage across treatment groups at the baseline in April 2017. For both the neighbor-knowledge and suburb-knowledge treatment comparisons, households in the knowledge treatment group generally have lower electricity use and bills than the respective social norms treatment groups. However, differences between the

[11] Appendix Table S5 reports similar differences-in-differences estimates by pre-baseline usage above and below the median for the neighbor-knowledge treatment comparisons (Panel A) and suburb-knowledge treatment comparisons (Panel B) for surveyed households in Dhaka city.

Table 8
Treatment effects by pre-baseline consumption type.

Variables	Electricity use		Electricity bills	
	Above average	Below average	Above average	Below average
A. Neighbor-Knowledge treatment comparisons				
Knowledge ×				
Round 2	−19.116***	−22.820***	−91.567***	−121.634***
	(4.497)	(3.877)	(20.422)	(15.323)
Round 3	−13.884**	−20.479***	−51.201	−132.368***
	(6.275)	(5.142)	(32.011)	(29.608)
Round 4	−14.523	−18.976**	−108.728	−119.858**
	(9.488)	(7.996)	(66.084)	(50.183)
No. of obs.	2169	2336	2169	2336
R-squared	0.014	0.030	0.008	0.035
Round FE	YES	YES	YES	YES
Treatment FE	YES	YES	YES	YES
District FE	YES	YES	YES	YES
B. Suburb-Knowledge treatment comparisons				
Knowledge ×				
Round 2	−21.359***	−24.660***	−98.940***	−138.954***
	(3.649)	(3.336)	(17.872)	(15.205)
Round 3	−22.662***	−22.686***	−74.103*	−110.143***
	(5.924)	(4.201)	(38.433)	(22.092)
Round 4	−19.628**	−25.279***	−94.496	−140.586***
	(9.120)	(7.020)	(65.979)	(44.620)
No. of obs.	2186	2323	2186	2323
R-squared	0.020	0.037	0.014	0.045
Round FE	YES	YES	YES	YES
Treatment FE	YES	YES	YES	YES
District FE	YES	YES	YES	YES

Notes. Estimated coefficients of treatment groups over rounds 2–4 are based on the differences-in-differences specification in equation (1). Outcome variables are (verified) electricity consumption (kWh) and bills (Tk). Robust standard errors clustered at the household level are in parentheses. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

knowledge and social norms treatment groups tend to widen over time for average and efficient users, whereas differences between the knowledge and social norms groups first widen and then narrow for inefficient users. Interestingly, the differences between the knowledge and neighbor treatment groups almost completely disappear by R4 (Fig. 8).

Table 9 reports the differences-in-differences estimates by efficiency type for the neighbor-knowledge treatment comparisons (Panel A) and suburb-knowledge treatment comparisons (Panel B).[12] For the neighbor-knowledge treatment comparisons (Panel A), the knowledge treatment is more effective in reducing electricity use and bills for all efficiency types. We observe similar patterns for the suburb-knowledge comparisons (Panel B). However, the relative effectiveness of the knowledge treatment diminishes over time for inefficient users in both the neighbor-knowledge and suburb-knowledge comparisons. This gradual reduction in relative effectiveness is more pronounced among inefficient users in the neighbor-knowledge comparisons.

Overall, the evidence indicates heterogeneous treatment effects. This is consistent with List et al. (2017) who have found that non-pecuniary interventions disproportionately affect intense users, whereas low users need financial incentives to reduce their energy consumption. The effects of the knowledge treatment are relatively homogenous across households with different pre-baseline electricity consumption. However, the effects of neighbor treatment and suburb treatment generally take longer to realize independent of the pre-baseline electricity consumption of households. The effects, especially the effect of the neighbor treatment, become almost as strong as the knowledge treatment for inefficient users six months after the intervention. Thus, the evidence indicates that knowledge treatment is generally more effective, and the effect is more immediate, whereas social comparison treatment generally takes longer to realize and is likely to be as effective as knowledge treatment only for households that are in the top of the electricity consumption distribution. Importantly, the stronger effects of neighbor treatment than suburb treatment for inefficient users in the longer term suggest that behaving differently from the social comparison groups hurt more when the behaviors are more likely to be disapproved socially and when the comparison group is likely to be geographically closer.

[12] Appendix Table S6 reports similar differences-in-differences estimates by efficiency type for the neighbor-knowledge treatment comparisons (Panel A) and suburb-knowledge treatment comparisons (Panel B) for surveyed households in Dhaka district.

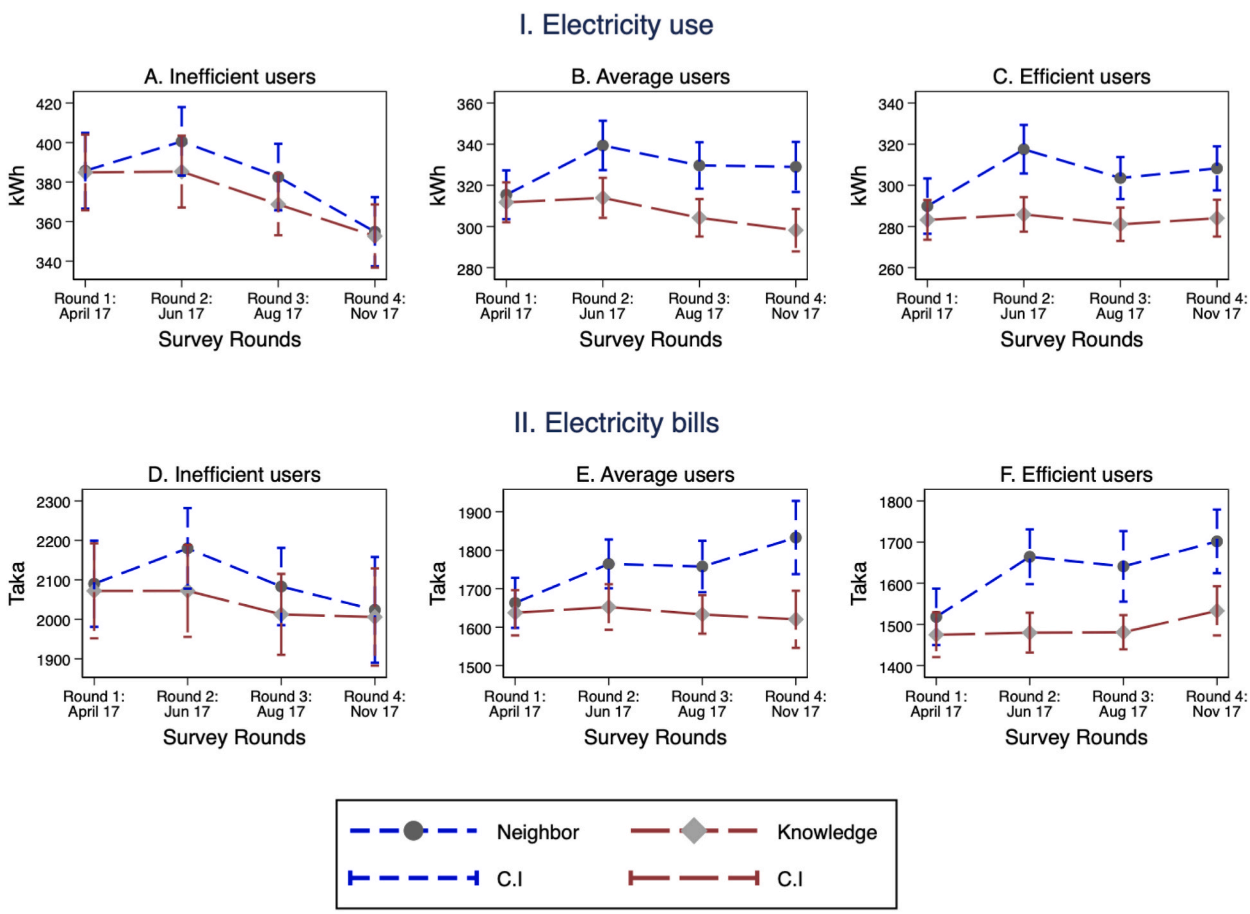

Fig. 7. Neighbor-knowledge treatment comparisons by pre-baseline efficiency type.
Notes. Fig. 7 plots average electricity use (Panels A–C) and electricity bills (Panels D–F) by (pre-baseline) efficiency type for neighbor and knowledge treatment groups over survey rounds 1–4.

5. Additional results

5.1. Potential scrutiny effects

As households were surveyed and their electricity consumption and bills were being verified in the study, one potential concern is that they might behave differently because they received treatments and knowing that they would be scrutinized over time. To investigate whether there exist any scrutiny effects, we randomly selected half of the households and surveyed them in April 2018 (round 5).[13]If receiving treatments while being surveyed and scrutinized about electricity consumption could amplify behavioral changes, then those being surveyed in April 2018 would have lower electricity consumption in August 2018 (round 6) than those not being surveyed in April 2018. However, both the scrutinized and non-scrutinized households have very similar electricity use and electricity bills in August 2018 (Fig. 9I, Panels A and B), and we do not identify any significant differences. Therefore, our results are likely not driven by households' concern of being scrutinized.

5.2. Longer-term treatment effects

Next, we examine whether the treatments continued to be effective 12 months after the intervention ended. Although average electricity consumption and bills are generally higher in round 6 than in round 1, all treatment groups have significantly lower average electricity consumption and bills than the control group (Fig. 9II, Panels C and D). The differences-in-differences estimates reported in Table 10 confirm that across all three treatment groups, the effects were statistically significantly negative 12 months after the intervention ended. These results are consistent with persistent effects of similar interventions on residential water savings in Colombia

[13] Appendix Table S7 confirms that these two groups have similar baseline characteristics.

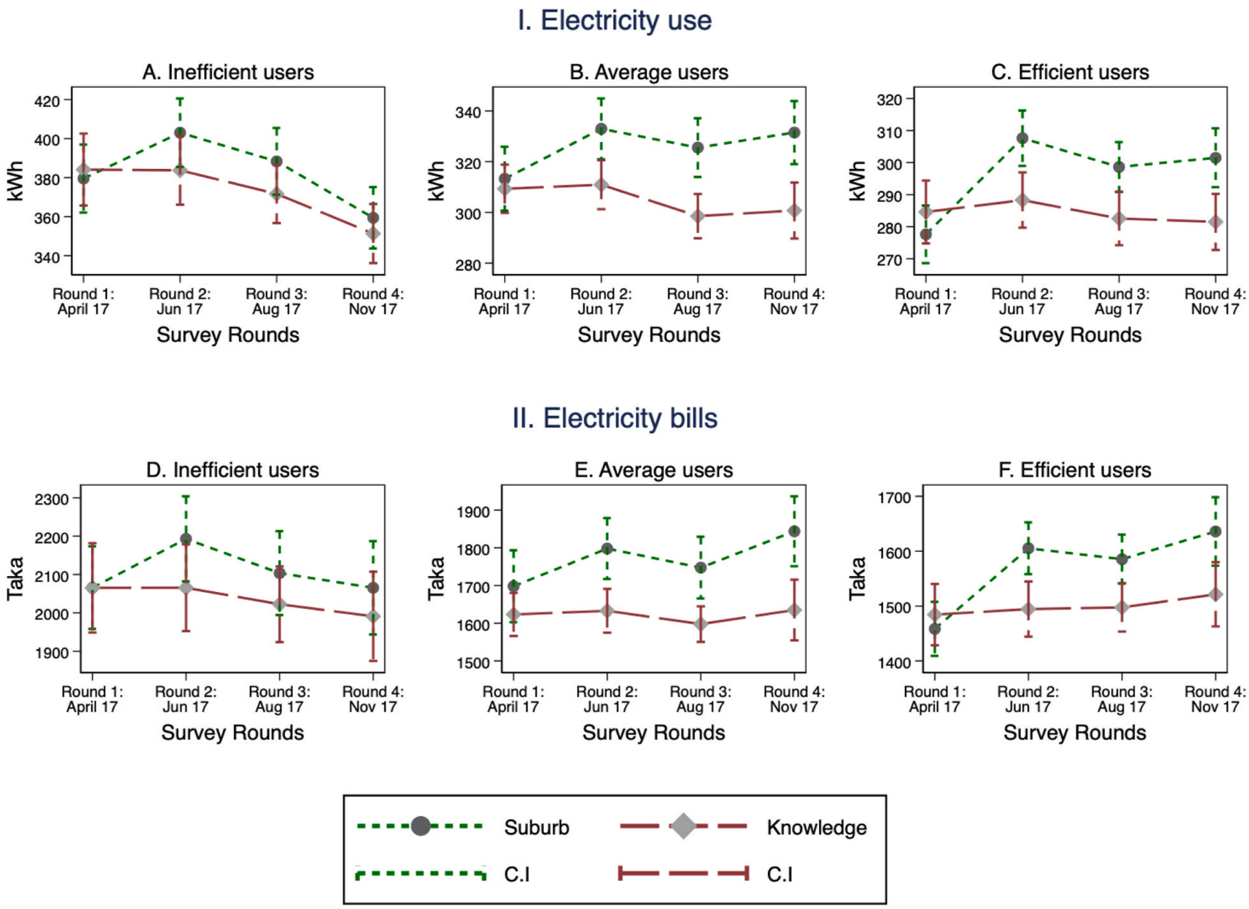

Fig. 8. Suburb-knowledge comparisons by pre-baseline efficiency type.
Notes. Fig. 8 plots average electricity use (Panels A–C) and electricity bills (Panels D–F) by (pre-baseline) efficiency type for suburb and knowledge treatment groups over survey rounds 1–4.

that were identified by Torres and Carlsson (2018). Although the estimated treatment effects (both electricity use and bills) for the knowledge treatment group remain the largest, their 95% confidence intervals (i.e., the mean plus twice the standard errors) contain the estimated treatment effects for the neighbor treatment group. On the other hand, the 95% confidence intervals of the estimated treatment effects for the knowledge treatment group do not contain the estimated treatment effects for the suburb treatment group. Thus, it takes time for social comparison treatments to be as effective as knowledge treatment and neighbor comparison tends to become more effective than suburb comparison in the longer term. Furthermore, both the neighbor treatment and knowledge treatment tend to become similarly effective in Jashore and Khulna in the longer term, suggesting that social comparisons with neighbors are important in settings where population density is lower and individuals are more likely to interact with community members who are geographically closer to them.

5.3. Robustness

We perform two robustness checks. First, although we recruited households located not too closely to one another to participate in the study, it is not possible to completely rule out the potential for the treated households to share information with households in another treatment or control group. Such information or treatment spillovers, especially from one treatment group to the control group, can potentially bias (downward) the estimated treatment effect. To examine whether our estimated treatment effects are biased due to information spillovers, we estimate the effects of treatment intensity (i.e., percentage of total surveyed households receiving a particular treatment within a given neighborhood) on the electricity consumption and bills of households in the control group by round. Note that the estimating sample is restricted to households in the control group only. If information spillovers were present, then the electricity consumption and bills among households in the control group would decrease as treatment intensity in the neighborhood increased. The results in Appendix Table S9 show that the electricity consumption and bills of households in the control group do not respond to treatment intensity in the neighborhood. Second, although all the surveyed households live in urban areas, size of their dwelling, measured in square feet, might potentially affect their ability to reduce electricity consumption. To assess if our

Table 9
Treatment effects by pre-baseline efficiency type.

Variables	Electricity use			Electricity bills		
	Inefficient	Average	Efficient	Inefficient	Average	Efficient
A. Neighbor-Knowledge comparison						
Knowledge ×						
Round 2	−14.459**	−21.778***	−24.996***	−89.712***	−86.333***	−140.815***
	(6.936)	(4.210)	(4.668)	(32.127)	(18.169)	(17.653)
Round 3	−12.989	−21.735***	−15.792***	−52.503	−98.645***	−116.297***
	(9.750)	(5.847)	(6.017)	(51.404)	(32.174)	(32.800)
Round 4	−1.323	−27.114***	−17.524*	0.068	−187.240***	−125.171**
	(14.661)	(8.457)	(9.722)	(100.551)	(61.769)	(57.471)
No. of obs.	1214	1643	1648	1214	1643	1648
R-squared	0.014	0.027	0.032	0.005	0.027	0.039
Round FE	YES	YES	YES	YES	YES	YES
Treatment FE	YES	YES	YES	YES	YES	YES
District FE	YES	YES	YES	YES	YES	YES
B. Suburb-Knowledge comparison						
Knowledge ×						
Round 2	−23.875***	−18.092***	−26.267***	−126.884***	−90.144***	−136.860***
	(5.009)	(4.067)	(3.879)	(22.349)	(21.444)	(17.987)
Round 3	−21.530**	−23.060***	−23.041***	−82.386	−74.962**	−113.869***
	(8.418)	(5.845)	(4.836)	(55.353)	(36.241)	(24.116)
Round 4	−12.452	−26.797***	−26.866***	−72.655	−134.144**	−139.976***
	(13.123)	(8.701)	(8.210)	(93.658)	(65.597)	(50.111)
No. of obs.	1312	1441	1756	1312	1441	1756
R-squared	0.034	0.020	0.047	0.021	0.021	0.056
Round FE	YES	YES	YES	YES	YES	YES
Treatment FE	YES	YES	YES	YES	YES	YES
District FE	YES	YES	YES	YES	YES	YES

Notes. Estimated coefficients of treatment groups over rounds 2–4 are based on the differences-in-differences specification in equation (1). Outcome variables are (verified) electricity consumption (kWh) and bills (Tk). Robust standard errors clustered at the household level are in parentheses. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

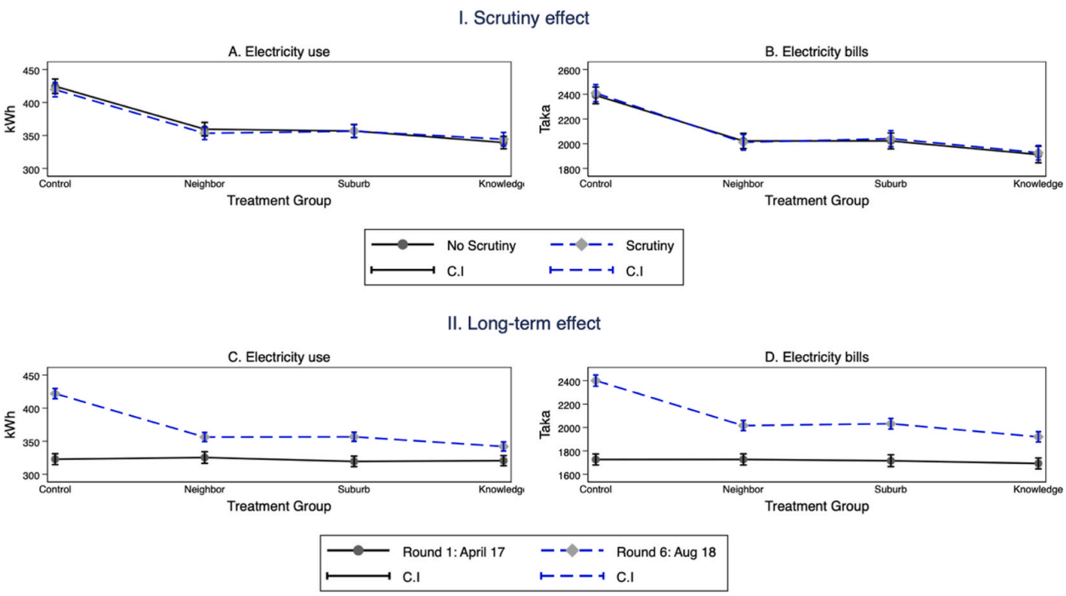

Fig. 9. Scrutiny and long-term treatment effects.
Notes. Fig. 9I plots average electricity use (Panel A) and electricity bills (Panel B) in round 6 by scrutinization status in round 5. Fig. 9II plots average electricity use (Panel C) and electricity bills (Panel D) in round 1 and 6.

Table 10
Long-term treatment effects.

Variables	Electricity use			Electricity bill		
	All cities	Dhaka city	Jashore and Khulna	All cities	Dhaka city	Jashore and Khulna
Neighbor ×						
Round 2	−1.827	−4.045	6.977	−6.520	−10.739	11.107
	(3.727)	(4.070)	(8.701)	(16.528)	(17.419)	(43.004)
Round 3	−14.466***	−19.326***	4.098	−69.076***	−70.288***	−64.102
	(4.298)	(4.623)	(10.544)	(24.402)	(24.143)	(72.684)
Round 4	−26.722***	−35.269***	5.816	−146.753***	−193.685***	31.897
	(6.373)	(5.886)	(20.328)	(42.523)	(39.823)	(134.513)
Round 6	−68.083***	−73.629***	−46.578**	−384.821***	−403.543***	−310.303***
	(6.984)	(6.959)	(19.956)	(41.336)	(41.935)	(114.597)
Suburb ×						
Round 2	0.191	−2.142	10.032	5.830	−7.921	58.820
	(3.351)	(3.621)	(8.018)	(15.793)	(16.787)	(40.491)
Round 3	−9.246**	−12.984***	5.773	−70.450***	−66.185**	−83.682
	(3.893)	(4.194)	(9.464)	(24.572)	(25.936)	(65.828)
Round 4	−21.143***	−30.839***	15.979	−143.767***	−200.473***	70.649
	(5.952)	(5.137)	(19.850)	(40.912)	(38.392)	(126.567)
Round 6	−61.702***	−69.958***	−30.413	−357.818***	−395.269***	−214.614*
	(6.767)	(6.441)	(20.278)	(41.684)	(42.156)	(114.671)
Knowledge ×						
Round 2	−22.757***	−27.866***	−3.356	−113.273***	−127.718***	−57.675
	(2.972)	(3.187)	(7.271)	(13.510)	(14.231)	(35.492)
Round 3	−31.602***	−35.433***	−16.026*	−161.207***	−168.319***	−135.953**
	(3.943)	(4.272)	(9.476)	(22.638)	(23.181)	(64.428)
Round 4	−43.028***	−54.569***	0.458	−258.932***	−337.560***	29.171
	(5.869)	(5.208)	(18.970)	(39.428)	(35.469)	(125.959)
Round 6	−77.684***	−87.165***	−42.245**	−447.111***	−507.840***	−225.799**
	(6.811)	(6.772)	(19.090)	(40.497)	(40.981)	(110.080)
Constant	357.163***	356.640***	357.526***	1952.697***	1939.307***	1994.397***
	(2.957)	(3.182)	(7.189)	(17.682)	(19.325)	(42.087)
No. of obs.	11,149	8692	2457	11,149	8692	2457
R-squared	0.050	0.056	0.024	0.058	0.064	0.030
Round FE	YES	YES	YES	YES	YES	YES
Treatment FE	YES	YES	YES	YES	YES	YES
District FE	YES	NO	NO	YES	NO	NO

Notes. Estimated coefficients of treatment groups over rounds 2–4 and 6 are based on the differences-in-differences specification in equation (1) that includes one additional round of data. Outcome variables are (verified) electricity consumption (kWh) and bills (Tk). Robust standard errors clustered at the household level are in parentheses. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

estimates are robust to this possibility we redefine the dependent variables as electricity use per square feet and electricity bills per square feet. The results in Appendix Table S9 show that the differences-in-differences estimates are similar to those reported in Table 5.

6. Conclusions

We provide the first experimental evidence from a developing country about the relative effectiveness of energy conservation information and social comparisons in influencing residential energy consumption. Our experiment covers Dhaka, Jashore, and Khulna districts in Bangladesh. Dhaka itself accounts for more than 22 million urban population. As a large number of poor households living in these areas do not consume much electricity, we only target households with potential to reduce their electricity consumption. The sampled households are not representative of all the households in Bangladesh, rather represent about 5 million urban households in the Dhaka district.

Overall, consistent with existing literature (e.g., Brülisauer et al. 2020; Myers and Souza 2020), our results suggest that providing simple energy saving tips could be a powerful tool for reducing energy consumption among urban middle-income households in Bangladesh. The results also suggest that households respond to information about electricity consumption of their own neighbor or median of their suburb level consumption. However, these households take more time to respond to information about the consumption level of the social comparison group for there to be an effect. We find that both above and below median users respond similarly, especially for those receiving energy saving tips. Households who were inefficient users reduce their electricity consumption faster and more than those who were efficient users or average users if they receive repeated information about the median consumption of their neighbors or suburb. The reduction in their electricity usages and bills, especially among those in the neighbor comparison group, become as much as those who received the knowledge treatment. The results suggest that these inefficient users did try to find ways to reduce electricity consumption after they were reminded repeatedly of the social norm, especially set by their neighbors. The responses are, however, relatively muted for average or efficient users. Note that these latter households were told they were doing as well as or better than their neighbor or suburb median. Hence, such responses from these households are not unexpected.

The policy conclusion from our results is that social-norm information reduces electricity consumption when repeated feedback is provided and may be as effective as information campaigns in the longer term when the comparison group is formed by those with close social ties.

Our results could also mean that all households could conserve energy as we remind them about their energy usage, but efficient and average users could not cut back their energy as much as those inefficient users as these households were already consuming less. Results can potentially be generalized for urban households, at least for those living in greater Dhaka, with electricity connections. As reported in Table S10, neighbor, suburb, and knowledge treatments can potentially reduce total urban electricity consumption by 179.55, 157.00, and 277.81 gWh, which are equivalent to 11%, 10% and 17% reduction in energy use, respectively in Dhaka alone.

CRediT authorship contribution statement

Ahsanuzzaman: Supervision, Project administration, Data curation, Supervision, Project administration, Data curation. **Shaikh Eskander:** Writing – original draft, Methodology, Formal analysis. **Asad Islam:** Writing – review & editing, Writing – original draft, Project administration, Funding acquisition, Conceptualization. **Liang Choon Wang:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The Authors declare no conflict of interest.

Appendix A. Supplementary data

Supplementary data to this chapter can be found online at https://doi.org/10.1016/j.jeem.2024.103022.

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