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CDES Working Paper No. 01/23
JANUARY 2023

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

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January 2023

Abstract

We use a randomized controlled trial in Bangladesh to test three types of non-price energy conservation strategies influencing residential energy 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' energy consumption significantly. The effects are stronger for advice on electricity conservation 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 knowledge treatment group. The effects across all treatment groups become stronger over time as they receive repeated information.

JEL Codes: D12, D83, D91, Q40, Q41

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

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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 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). Especially 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).

The issue of conserving energy is particularly important in a developing country context where households suffer from frequent power outages due to the shortage of electricity supply. Moreover, residential electricity accounts for 40% of global energy-related CO2 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 CO2, a fifth of which is the residential source and in an increasing trend (IEA 2015).[1] 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.

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 conducted a randomized controlled field experiment to examine the relative effectiveness

[1] The post-pandemic recovery of world economies has contributed to a six percent rise in CO2 emissions, more than the reduction in 2020 due to the pandemic, with 46% of increase attributed to global electricity and heat production (IEA 2021).

of energy conservation information in influencing residential energy consumption in three cities in Bangladesh. We assess the role of information on electricity consumption by testing the effects of the following treatments: (1) expert advice (knowledge-based) on electricity conservation; (2) information about own electricity consumption relative to others in the same suburb; and (3) information about own electricity consumption relative to neighbors.

In collaboration with IPDC Bangladesh and with supports from Dhaka Power Distribution Company (DPDC Ltd.) officials[2], we provided information to a subset of 2,394 households three times and surveyed all households four times in 2017 to examine the short-term impacts of the treatments on electricity usage. 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. We also revisited the households several months after the intervention ended to examine the longer-term impacts of the treatment. We identify the statistically significant reduction in electricity consumption of 7.1%-14.3% for the knowledge treatment group, 3.5%-8.1% for the neighbor treatment group, and 3.5%-7.9% for the suburb treatment group. Consistent with related literature (e.g., List *et al.* 2017), these estimates also vary by the respective pre-baseline consumption type and baseline efficiency level of households in each treatment group.

Our estimates indicate that providing advice on saving energy could reduce households' energy consumption significantly. 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 effects among households who were *inefficient* users in neighbor and suburb comparison groups are almost as strong as those in knowledge treatment group. The effects across all treatment groups become stronger over time as they receive repeated information. Overall, our estimates suggest that neighbor, suburb and knowledge treatments can potentially reduce total urban electricity consumptions of Bangladesh by

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

206.74, 197.96 and 359.68 gWh, respectively. Our results have important implications in meeting the household energy demand especially in the context of current global energy crisis.

This paper joins 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.* 2009; 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 similar group of consumers (neighbor) than that based on a larger and a more diversified group of consumers (city-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.

While 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, related literature provides a mixed result on the effects of social norm on behavior changes. In fact, 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 2007)[3]. Hence, we combined both descriptive and injunctive norms.[4] 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.

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 *et al.* 1994; Larimer and Neighbors 2003; Schultz 1999; Schultz *et al.* 2007), charitable giving (Frey and Meier 2004; Croson and Shang 2008), voting (Gerber and

[3] 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.
[4] 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).

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 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 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 CO2 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. Figure 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 loss 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.

[Figure 1]

As of 2020, there were still 733 million people without electricity, most of them from developing countries, and the number is projected only to go down to 679 million in 2030 based on the current trend (UN 2022). Moreover, almost 2.4 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 (Figure 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.

[Figure 2]

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 related SDGs.[5] 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 (UN 2022). Considering this dismal trend, we investigate effective ways to increase energy efficiency in a developing country.

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

3. Experimental design

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

3.1. Recruitment

The experiment was conducted in three cities, Dhaka, Khulna, and Jessore, in Bangladesh. To find out households who have the potential to reduce electricity consumption, we located certain areas or neighborhoods in these cities with relatively better socio-economic condition. Many households in these cities have very low income and low or no usage of electricity. Hence, we target apartments or areas more likely to use air conditioner and generator during hot summer temperature. Using information from different suburbs to locate the appropriate households, we enlisted 2,394 households to participate on the experiment in January-February 2017. We then assigned them randomly into four treatment arms. Randomization was done at the household level. We followed these households over four rounds between April and November 2017.

3.2. Treatment assignment

The treatments are:

(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. 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 10 tips given by the city electricity distribution company experts to help households conserve electricity and reduce electricity expenditure (Fig. 5A). 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.

[Table 1]

3.3. Injunctive messages

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

(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. 5B).

(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. 5C).

(iii) *Average users* whose electricity bills are in the middle 30-percentile. They received flyers showing a neutral message encouraging them to improve (Fig. 5D).

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

[Figure 3]

3.4. Intervention

The main intervention started in April 2017 (round 1, R1) when the temperature started to rise (following a mild to mild/medium temperature in February and March). In R1, we conducted a detailed socio-economic survey of households and verified each household electricity bill (baseline bill). We were able to follow 2,248 households throughout from R1 to R4 (November). 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 June and August, respectively. In each round, we surveyed them and verified their bill before we provided information.

4. Main Results

4.1. Baseline characteristics

Table 2 shows that households' electricity usage, electricity expenditure, frequency of air conditioning use, number of rooms, frequency of power outage, and so on are, on average, statistically similar across treatment groups in R1. Note that although the effectiveness of treatments can be different for different utilities (e.g., Andor *et al.* 2022), we did not consider households' gas use as in most cases in Dhaka city the gas-based cooking burners are fixed with two burners.

[Table 2]

In comparison to the control group, all three treatment groups have similar characteristics at the baseline: differences in characteristics between treatment groups and the control group are statistically insignificant (Table 2). Therefore, our samples are randomized at the household level.

4.2. Average effects of treatments

Households receive appropriate treatment from R1 onwards. To retrieve the average treatment effect for each treatment over rounds, we estimate the following ordinary least squares (OLS) model with robust standard errors in each round:

$$y_i = \beta_0 + \beta_1 N_i + \beta_2 S_i + \beta_3 K_i + \epsilon_i \qquad (1)$$

where y_i denotes logged electricity consumption (kwh) of household i. N_i, S_i, and K_i denote the assignment of treatments: 1 if the household i received a treatment and 0 if not. In particular, $N_i = 1$ if household received neighbor treatment, $S_i = 1$ if household received suburb treatment, and $K_i = 1$ if household received knowledge treatment.

In equation (1), $\hat{\beta}_0$ denotes the estimated (logged) electricity consumption of the control group, whereas $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ denote the effect of treatment on electricity consumption in comparison to the control group. We expect $\hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3 > 0$.

Table 3 reports overall results, i.e., average treatment effects, for all households by round, which are also plotted in Figure 4. Baseline electricity usages (April 2017) do not differ across treatments, confirming the randomization of treatments. After intervention started, electricity consumption started to decrease for treatment groups, but the intervention takes different durations to become effective: while it significantly went down for the knowledge treatment group one month after the intervention started (June 2017), it takes neighbor and suburb treatment groups three months to significantly lower their electricity consumptions (August 2017). The differences in electricity consumption between the control and treatment groups widened further in the last round of survey (November 2017).

[Table 3]

[Figure 4]

Overall, strongest effects are observed for households in the knowledge treatment group. The statistically significant reduction in electricity consumption relative to the control group is 7.1% in June, which then grows to 9.7% in August and 14.3% in November. Statistically significant reductions in electricity consumption of households in neighbor and suburb treatment groups first appeared in August. The estimated effect is -3.5% in August and roughly -8% in November for both these groups.

4.3. Heterogeneous effects of treatments: above median versus below median

We next examine the electricity usage for households who were in the above median and below median usage groups according to their pre-baseline electricity usage. As neighbor and suburb treatments differ in their baseline median, we conduct the analysis separately. First, for neighbor comparison, we drop the suburb group and estimate the following OLS model with robust standard errors in each round and for households with above median and below median usages, respectively:

$$y_i = \beta_0 + \beta_1 N_i + \beta_3 K_i + \epsilon_i \qquad (2)$$

We are interested in the estimated coefficients $\hat{\beta}_1$ and $\hat{\beta}_3$ that compare the relative effectiveness of neighbor and knowledge treatments. In particular, $\hat{\beta}_1 > \hat{\beta}_3\ \forall \hat{\beta}_1, \hat{\beta}_3 > 0$ implies that the neighbor treatment is more effective. Similarly, $\hat{\beta}_1 < \hat{\beta}_3\ \forall \hat{\beta}_1, \hat{\beta}_3 > 0$ implies the greater effectiveness of the knowledge treatment, whereas $\hat{\beta}_1 = \hat{\beta}_3\ \forall \hat{\beta}_1, \hat{\beta}_3 > 0$ implies no such difference in their respective effectiveness.

Second, for suburb comparison, we estimate the following OLS model with robust standard errors in each round and for households with above median and below median usages, respectively:

$$y_i = \beta_0 + \beta_2 S_i + \beta_3 K_i + \epsilon_i \qquad (3)$$

The estimated coefficients $\hat{\beta}_2$ and $\hat{\beta}_3$ compare the relative effectiveness of suburb and knowledge treatments. In particular, $\hat{\beta}_2 \gtrless \hat{\beta}_3\ \forall \hat{\beta}_2, \hat{\beta}_3 > 0$ implies the relatively greater effectiveness of suburb and knowledge treatments, respectively; whereas $\hat{\beta}_2 = \hat{\beta}_3\ \forall \hat{\beta}_2, \hat{\beta}_3 > 0$ implies no such difference in their respective effectiveness.

[Table 4]

[Figure 5]

Table 4 and Figure 5 report the results. Clearly, above and below median electricity users from neighbor and suburb treatment groups exhibit heterogeneous effects of the intervention. As expected, there is no difference in usage across treatment groups at the baseline in April 2017.

For households with usage *above* the median for neighbor comparison (Figure 5A), knowledge treatment lowers the electricity consumption by 9.2%, 10.8% and 14.4% in rounds 2-4, respectively (Table 4). On the other hand, differences in electricity consumption between the neighbor treatment and control group also appear in rounds 3 and 4: electricity consumption is 6.2% lower among the neighbor treatment group in round 3 and 9.6% lower in round 4.

For households with usage *below* the median for neighbor comparison (Figure 5B), knowledge treatment significantly lowers the electricity consumption by 5.6%, 8.9% and 14.4% in rounds 2-4; whereas neighbor treatment significantly lowers the electricity consumption by 7.5% only in round 4.

We observe similar patterns for households with usage *above* the median for suburb comparison (Figure 5C). While knowledge treatment lowers electricity consumption by 7.7%, 10%, and 13.4% in rounds 2-4, suburb treatment is effective for rounds 3 and 4: reduced by 5.1% in round 3 and 8.6% in round 4.

Finally, for households with usage *below* the median for suburb comparison (Figure 5D), the difference between households in the knowledge treatment and control group grows as before: electricity consumption decreases by 6.7%, 9.4%, and 15.1% in rounds 2-4. On the other hand, significant differences in electricity consumption between the suburb treatment and control group only appear in round 4: electricity consumption is 7.7% lower among the suburb treatment group in round 4.

4.4. Heterogeneous effects of treatments: Inefficient, average, and efficient users

Finally, we examine the electricity usage 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.

For neighbor comparison, we estimate the following OLS model with robust standard errors in each round and for households with different electricity use efficiency levels:

$$y_i = \beta_0 + \beta_1 N_i + \beta_3 K_i + \epsilon_i \qquad (4)$$

$\hat{\beta}_1$ and $\hat{\beta}_3$ compare the relative effectiveness of neighbor and knowledge treatments: $\hat{\beta}_1 \gtrless \hat{\beta}_3$ $\forall \hat{\beta}_1, \hat{\beta}_3 > 0$ implies the relatively greater effectiveness of suburb and knowledge treatments, respectively; whereas $\hat{\beta}_1 = \hat{\beta}_3$ $\forall \hat{\beta}_1, \hat{\beta}_3 > 0$ implies no such difference in their respective effectiveness.

Similarly, for suburb comparison, we estimate the following OLS model with robust standard errors in each round and for households with different electricity use efficiency levels:

$$y_i = \beta_0 + \beta_2 S_i + \beta_3 K_i + \epsilon_i \qquad (5)$$

$\hat{\beta}_2$ and $\hat{\beta}_3$ compare the relative effectiveness of suburb and knowledge treatments: $\hat{\beta}_2 \gtrless \hat{\beta}_3$ $\forall \hat{\beta}_2, \hat{\beta}_3 > 0$ implies the relatively greater effectiveness of suburb and knowledge treatments, respectively; whereas $\hat{\beta}_2 = \hat{\beta}_3 \ \forall \hat{\beta}_2, \hat{\beta}_3 > 0$ implies no such difference in their respective effectiveness.

Results in Table 5 and Figure 6 show how these messages influence households differently relative to the control and knowledge treatment groups depending on whether they received the suburb or neighbor comparison treatment.

[Table 5]

[Figure 6]

For the inefficient users (top 30-percentile), the neighbor comparison treatment does not have a significant effect on electricity consumption in round 2 and only started to have a significant effect in round 3 onwards (Figure 6A). The treatment leads to roughly 7% and 12% reductions in electricity consumption in rounds 3 and 4 (Table 5). In comparison, knowledge treatment leads to 7%, 10%, and 12% reductions in electricity consumption in rounds 2-4.

Somewhat similar effects are observed for inefficient users in the suburb comparison treatment group (Figure 6D). Suburb treatment becomes significantly effective in round 4, leading to roughly 11% reduction in electricity consumption. On the other hand, knowledge treatment reduces electricity consumption by 6%, 8% and 13% in rounds 2-4, respectively.

For average users (middle 30-percentile), the neighbor comparison treatment does not have a significant effect on electricity consumption in round 2 and only started to have a significant effect in round 3 onwards (Figure 6B). The neighbor treatment leads to roughly 5% and 8% reductions in electricity consumption in rounds 3 and 4, whereas the knowledge treatment leads to 8.7%, 11.4%, and 16.4% reductions in electricity consumption in rounds 2-4.

For average users in the suburb comparison treatment group (Figure 6E), the knowledge treatment leads to 9.1%, 11.8%, and 13.5% reductions in electricity consumption in rounds 2-4. However, although the coefficients are negative, the suburb treatment effects are statistically insignificant and only one-third of the respective knowledge treatment effects.

For efficient users (bottom 40-percentile), the neighbor comparison treatment significantly reduces electricity consumption, by 6.2%, only in round 4, whereas the knowledge treatment leads to immediate and persistently stronger effects: 6%, 8.3% and 13.9% reductions in electricity consumption in rounds 2-4 respectively (Figure 6C).

Efficient users in the suburb comparison group have similar experiences: the suburb treatment reduces electricity consumption only in round 4 by 8%, whereas the knowledge treatment leads to 5%, 8% and 15.2% reductions in electricity consumption in rounds 2-4.

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 knowledge treatment are relatively homogenous across households with different pre-baseline electricity consumption. However, the effects of neighbor comparison treatment and suburb comparison treatment generally take longer to realize independent of the pre-baseline electricity consumption of households. The effects, especially the effect of neighbor comparison 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.

5. Additional Results

5.1. Robustness analysis

We additionally investigate whether there exist any scrutiny effects (Figure 7A) and whether the effects of knowledge and neighbor treatments remain in the long run (Figure 7B).

[Figure 7]

First, half of the households were surveyed in April 2018 (round 5), while the other half were not. If receiving treatment 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). However, we do not identify any significant difference between electricity consumption of scrutinized and un-scrutinized households in round 6. Therefore, our results are not driven by households' concern of being scrutinized.

Next, Figure 7B confirms that although at a lower scale, the estimated effects persist even after 12 months, of which households did not receive an intervention after August 2017. A comparison between electricity consumptions in November 2017 and August 2018 confirms that the effects of treatments persist a year after having no further intervention. These results are consistent with persistent effects of similar interventions on residential water savings in Colombia that were identified by Torres and Carlsson (2018).

5.2. Total potential benefits of treatments

To calculate total number of households that can potentially benefit from social norms marketing and information campaigns, we first determine the households for which our results can be generalized. We set up the following criteria:

1. Living in an urban location,
2. Having electricity connections,
3. Living in a home occupying 1-5 rooms, and
4. Owning and using at least one energy-intensive appliances: refrigerator/freezer, washing machine, heaters, television, VCR/VCP/DVD, Microwave oven, and computer/TV.

We then collect information of households that satisfy all four criteria from the Bangladesh Household Income and Expenditure Survey (HIES) 2016 (BBS 2016), which is a nationally representative survey of households in Bangladesh administered by the Bangladesh Bureau of Statistics (BBS). According to the HIES 2016, 20.76% Bangladeshi households are from urban areas with electricity connections, occupying 1-5 rooms and own and use energy-intensive appliances. The total number of urban households that our study represents were 7,845,371 in 2021.[6]

According to our estimates, neighbor, suburb and knowledge treatments reduce energy consumption by 8.1%, 7.9% and 14.3%, respectively. Baseline average electricity consumption of households in the neighbor, suburb and knowledge groups were 325.339, 319.405 and 320.602 kwh, respectively, for which their verified electricity bills were BDTk 1727.076, 1715.954 and 1692.806, respectively. Therefore, average reduction in energy consumption per household is 26.35 kWh (neighbor treatment), 25.23 kWh (suburb treatment) and 45.85 kWh (knowledge treatment), amounting to total potential savings of 206.74 gWh (neighbor

[6] The total number of household is calculated using the average household size of 4.4 according to BBS (2011).

treatment) 197.96 gWh (suburb treatment) and 359.68 gWh (knowledge treatment) in 2021. These reductions in energy consumption resulted in average reduction in electricity bills per household of BDTk 139.893 (neighbor treatment), 135.56 (suburb treatment) and 242.071 (knowledge treatment), amounting to total potential monetary savings of BDTk 1.467 billion (neighbor treatment), 1.422 billion (suburb treatment) and 2.539 billion (knowledge treatment) in 2021.

6. Conclusions

We provide the first experimental evidence from a developing country about the relative effectiveness of energy conservation information in influencing residential energy consumption. Our experiment covers all major residential areas in Dhaka city and two other major cities in Bangladesh. These three cities account for more than 20 million population. As a large number of poor households living in these cities do not consume much electricity, we only target households with potential to reduce their electricity consumption. Hence, the sampled households are not representative of all the households in Bangladesh, rather represent about 8 million urban households (see Table S2 for details).

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 such information or they need to be reminded repeatedly 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 at the baseline reduce their electricity consumption faster and more than those who were efficient users or average users at the baseline if they receive information about the median consumption of their neighbors or suburb. They reduce their electricity consumption almost as fast as those households belong to knowledge treatment- suggesting that these inefficient users did try to find ways to reduce electricity consumption after they were reminded repeatedly of the social norm. 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.

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 with electricity connections as they constitute around 21% of total population. Overall, neighbor, suburb and knowledge treatments can potentially reduce total urban electricity consumptions by 206.74, 197.96 and 359.68 gWh, respectively (Table S2).[7]

[7] According to Bangladesh Power Development Board (http://www.bpdb.gov.bd/), at present, Bangladesh produces about 12k-13k gWh electricity, though some estimates suggest that the actual production is as low as 5k gWh (see, https://tradingeconomics.com/bangladesh/electricity-production#). Thus, the energy saving information campaign among these 8 million households could potentially save 3-8% of total energy demand of the country. As there are potential to save energy among other household groups, albeit lower, our back-of-the-envelope collection suggests that such information campaign could reduce the energy demand by about 10%.

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Figures

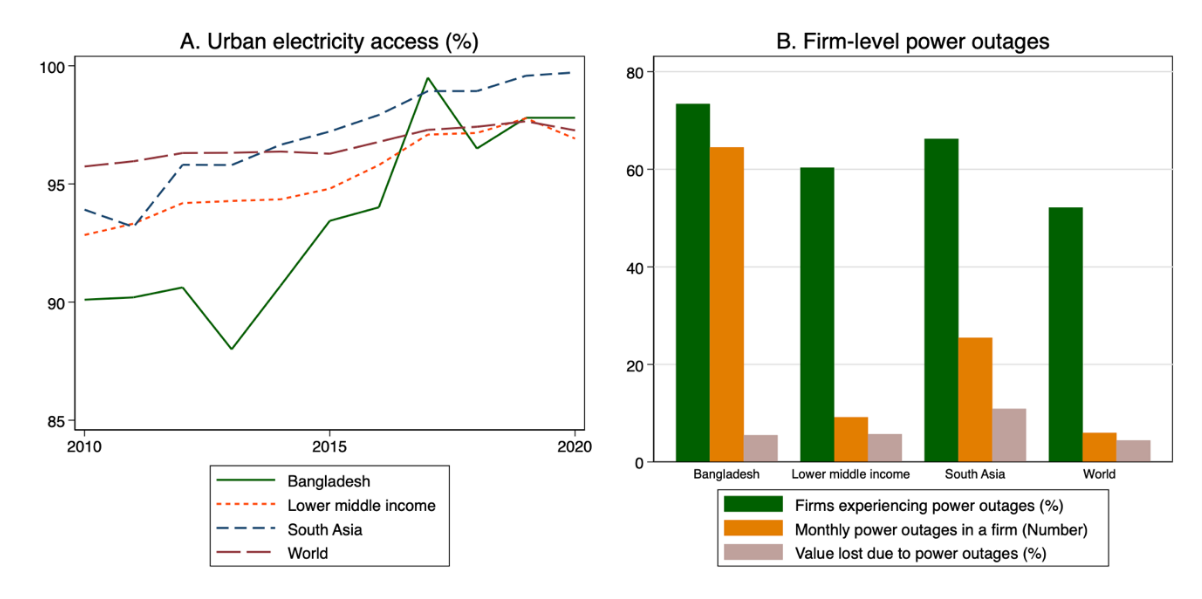


Fig. 1. Access to and scarcity of electricity.

Notes. Fig. 1A plots the percentage of urban households with access to electricity for years 2010-20. Fig. 1B plots firm-level power outages. All data comes from the World Development Indicators of the World Bank (World Bank, 2022).

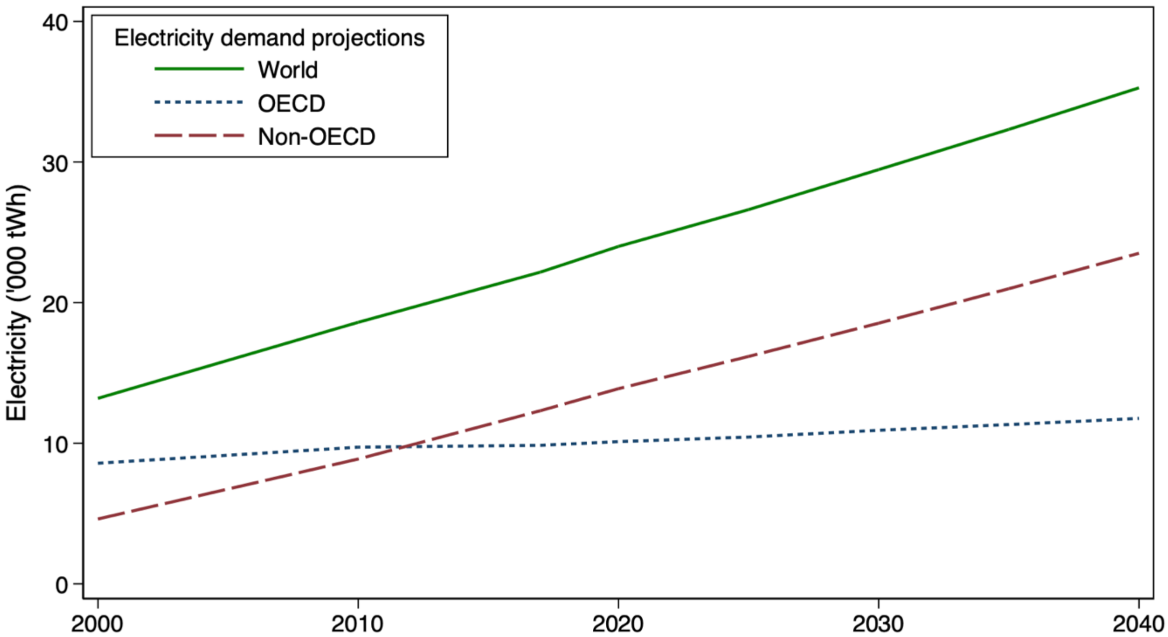
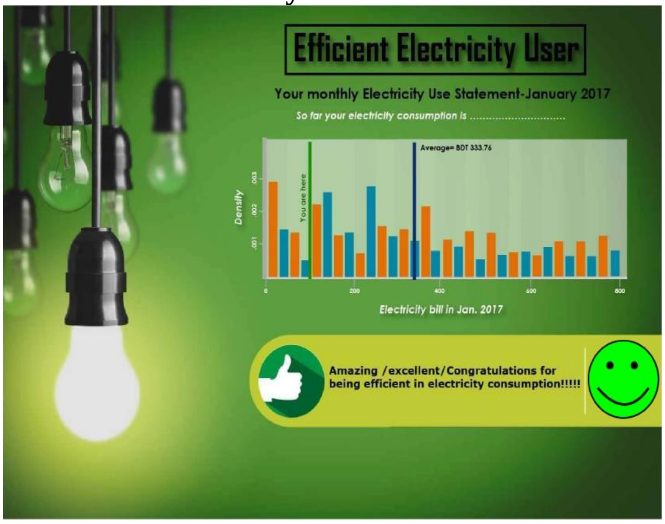


Fig. 2. Electricity demand projections.

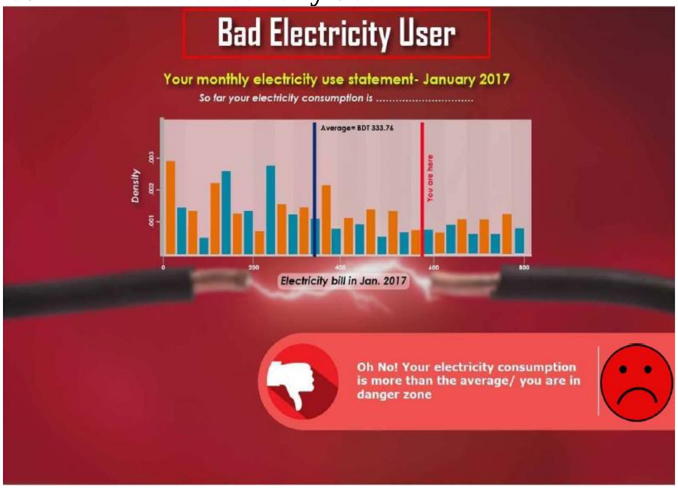
Notes. Fig. 2 plots electricity demand projections for world, OECD and non-OECD countries for the years 2010-20. All data comes from ExxonMobil (2019).

A. Energy saving tips

B. Efficient electricity user



C. Inefficient electricity user



D. Average electricity user

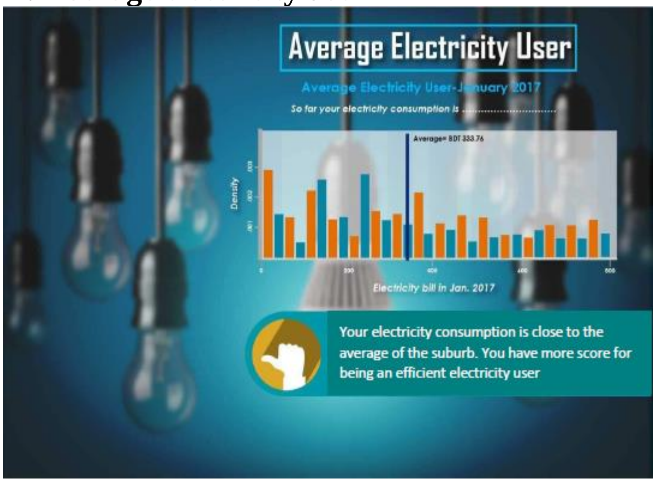


Fig. 3. Information flyers.

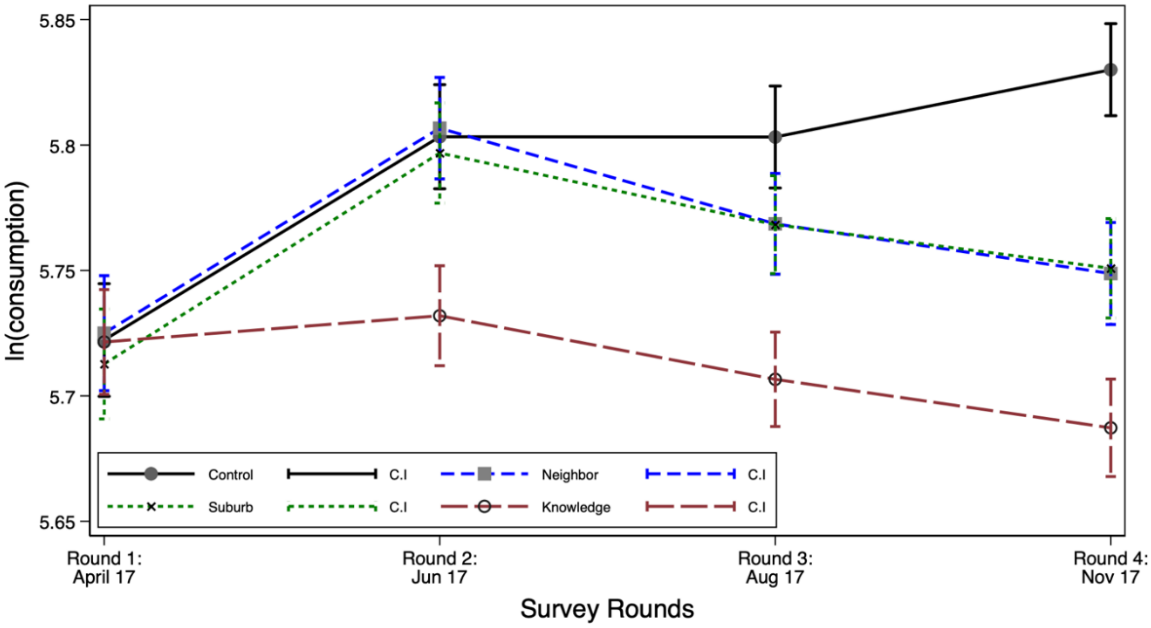


Fig. 4. Mean log energy consumption (kWh) over survey rounds.

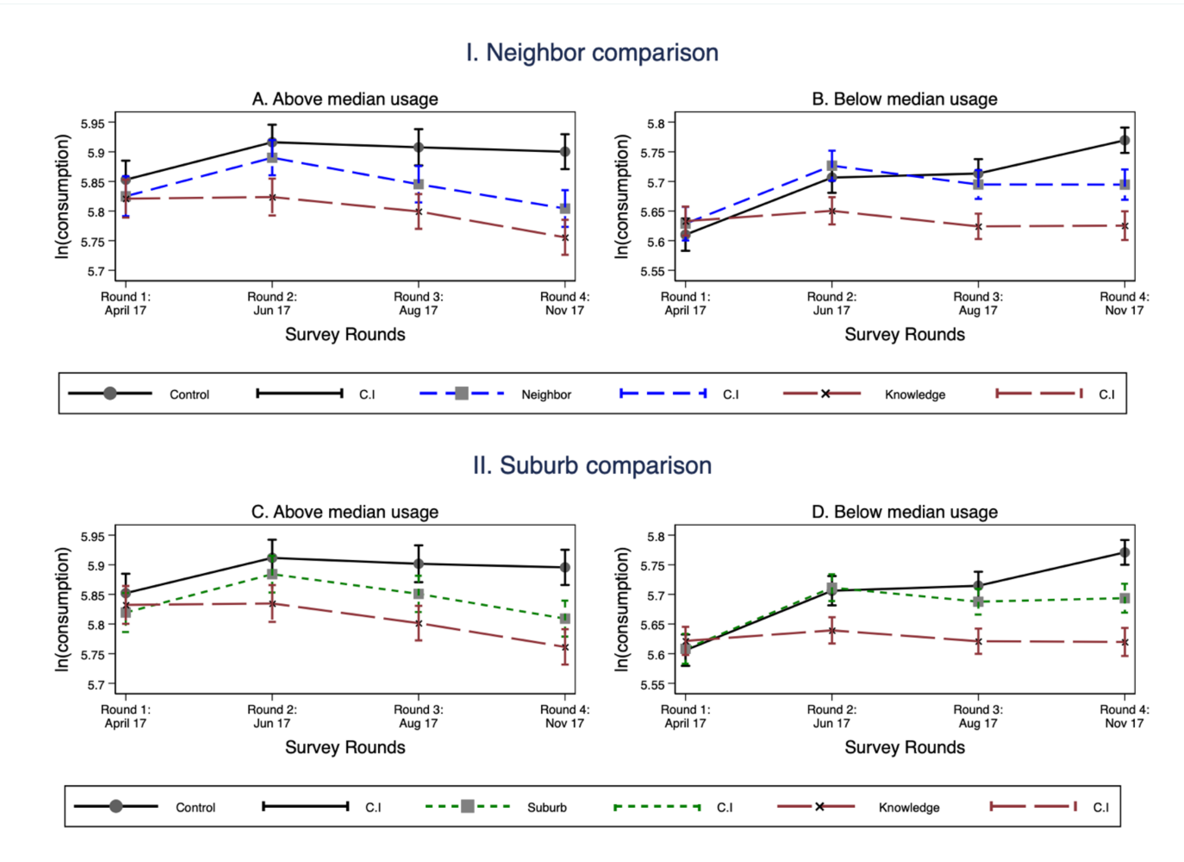


Fig. 5. Neighbor and knowledge treatment effects for above and below pre-baseline median electricity users.

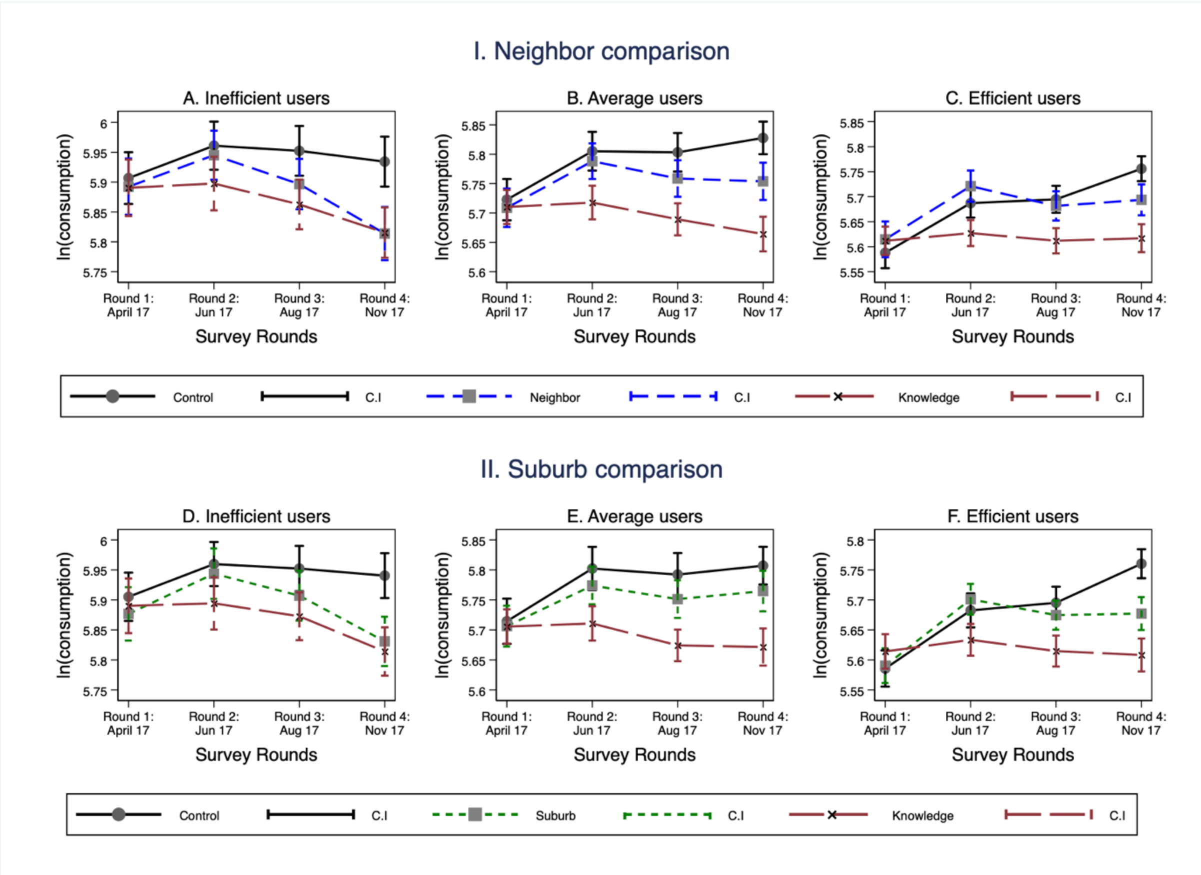


Fig. 6. Treatment effects by baseline efficiency level.

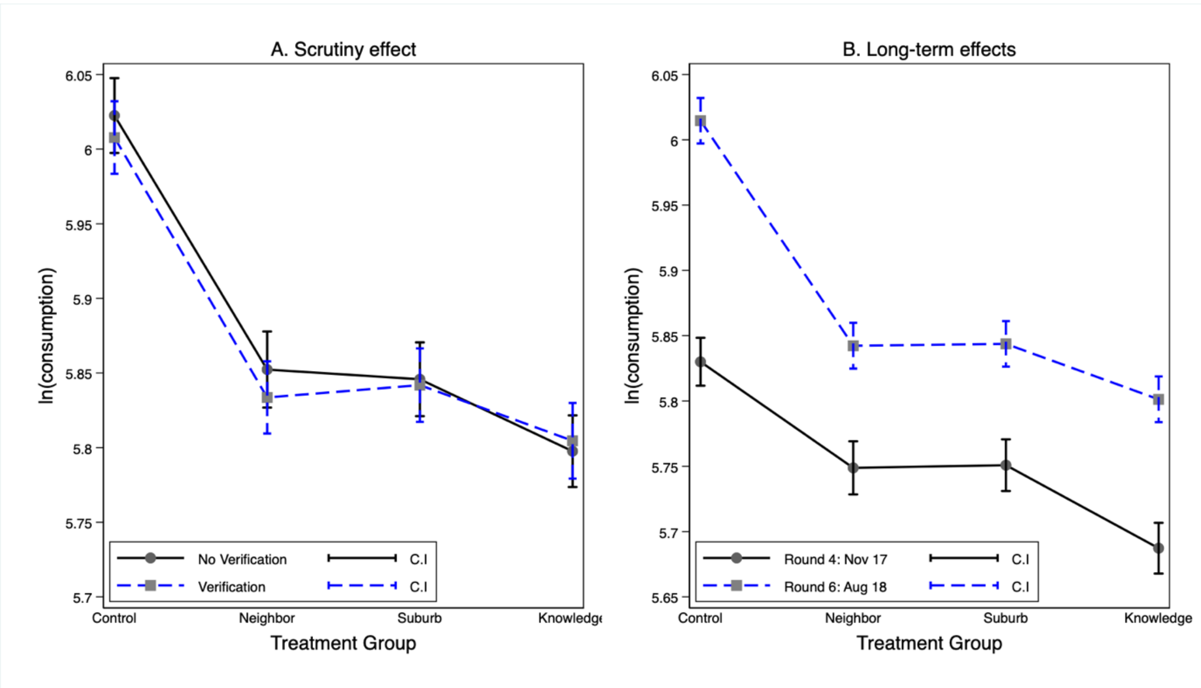


Fig. 7. Scrutiny and long-term treatment effects.

Tables

Table 1. Timeline of survey

Round	Timeline	Treatment delivered?	Expected treatment effects?	Full sample?
1	April 2017	Yes	No	Yes
2	June 2017	Yes	Yes (short term)	Yes
3	August 2017	Yes	Yes (short term)	Yes
4	November 2017	No	Yes (short term)	Yes
5	April 2018	No	Yes (longer term)	No
6	August 2018	No	Yes (longer term)	Yes

Notes. We recruited 2,394 households, of which 2,248 remained throughout the intervention periods and therefore forming the estimating sample. We surveyed 1,250 households in round 5.

Table 2. Baseline electricity consumption and household characteristics by treatment

	Control (T0)	Neighbor (T1)	Suburb (T2)	Knowledge (T3)	T1 - T0	T2 - T0	T3 - T0
Electricity consumption (kwh)	322.820	325.339	319.405	320.602	2.519	-3.415	-2.218
	[117.48]	[125.55]	[114.82]	[110.41]	(7.273)	(6.950)	(6.837)
Expenditures (Taka)	1726.325	1727.076	1715.954	1692.806	0.751	-10.371	-33.519
	[671.28]	[690.08]	[733.49]	[668.06]	(40.733)	(42.030)	(40.150)
Log(consumption)	5.722	5.725	5.713	5.721	0.003	-0.010	-0.001
	[0.320]	[0.331]	[0.317]	[0.301]	(0.019)	(0.019)	(0.019)
Log(expenditures)	7.393	7.390	7.383	7.375	-0.004	-0.010	-0.018
	[0.333]	[0.345]	[0.339]	[0.326]	(0.020)	(0.020)	(0.020)
Daily AC use	0.829	0.822	0.838	0.835	-0.007	0.009	0.006
	[0.377]	[0.383]	[0.369]	[0.372]	(0.023)	(0.022)	(0.022)
No. power outage (last 3 days)	1.156	1.155	1.146	1.124	-0.001	-0.010	-0.032
	[0.990]	[0.975]	[0.987]	[1.003]	(0.059)	(0.059)	(0.060)
No. rooms	3.497	3.459	3.520	3.554	-0.038	0.022	0.057
	[0.956]	[0.928]	[0.924]	[0.967]	(0.057)	(0.057)	(0.058)
No. of obs.	550	567	568	563			

Notes. Baseline (Round 1) data were collected in April 2017. Standard deviations in brackets "[]". Standard errors in parentheses "()". Reported results are for 2,248 households that remained throughout the intervention period.

Table 3. Average treatment effects

	(1) Round 1 (April 2017)	(2) Round 2 (June 2017)	(3) Round 3 (August 2017)	(4) Round 4 (November 2017)
Neighbor treatment	0.003	0.003	-0.035**	-0.081***
	(0.019)	(0.018)	(0.017)	(0.017)
Suburb treatment	-0.010	-0.007	-0.035**	-0.079***
	(0.019)	(0.017)	(0.017)	(0.016)
Knowledge treatment	-0.001	-0.071***	-0.097***	-0.143***
	(0.019)	(0.017)	(0.017)	(0.016)
Constant (control)	5.722***	5.803***	5.803***	5.830***
	(0.014)	(0.013)	(0.012)	(0.011)
No. of obs.	2,248	2,248	2,246	2,226
R-squared	0.000	0.011	0.015	0.032

Notes. Estimated coefficients of treatment groups are the respective average treatment effects in comparison to the control group (i.e., constant). Estimations follow equation (1). Robust standard errors in parentheses. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Table 4. Treatment effects by pre-baseline consumption type

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel I. Neighbor comparison							
	A. Above median usage				B. Below median usage			
Variables	Round 1 (April 17)	Round 2 (June 17)	Round 3 (Aug 17)	Round 4 (Nov 17)	Round 1 (April 17)	Round 2 (June 17)	Round 3 (Aug 17)	Round 4 (Nov 17)
Neighbor	-0.028	-0.026	-0.062**	-0.096***	0.019	0.020	-0.019	-0.075***
	(0.028)	(0.025)	(0.026)	(0.026)	(0.024)	(0.022)	(0.021)	(0.020)
Knowledge	-0.032	-0.092***	-0.108***	-0.144***	0.023	-0.056***	-0.089***	-0.144***
	(0.027)	(0.026)	(0.026)	(0.025)	(0.022)	(0.021)	(0.020)	(0.020)
Constant	5.853***	5.916***	5.908***	5.900***	5.610***	5.707***	5.713***	5.769***
	(0.019)	(0.018)	(0.019)	(0.018)	(0.016)	(0.016)	(0.015)	(0.013)
No. of obs.	797	797	797	794	883	883	882	869
R-squared	0.002	0.017	0.021	0.039	0.001	0.016	0.025	0.055

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel II. Suburb comparison							
	C. Above median usage				D. Below median usage			
Variables	Round 1 (April 17)	Round 2 (June 17)	Round 3 (Aug 17)	Round 4 (Nov 17)	Round 1 (April 17)	Round 2 (June 17)	Round 3 (Aug 17)	Round 4 (Nov 17)
Suburb	-0.033	-0.028	-0.051*	-0.086***	0.002	0.005	-0.027	-0.077***
	(0.028)	(0.026)	(0.026)	(0.026)	(0.022)	(0.020)	(0.019)	(0.019)
Knowledge	-0.020	-0.077***	-0.100***	-0.134***	0.016	-0.067***	-0.094***	-0.151***
	(0.028)	(0.026)	(0.026)	(0.025)	(0.022)	(0.020)	(0.019)	(0.019)
Constant	5.852***	5.912***	5.902***	5.896***	5.606***	5.706***	5.715***	5.771***
	(0.020)	(0.019)	(0.019)	(0.018)	(0.016)	(0.015)	(0.014)	(0.013)
No. of obs.	808	808	807	803	873	873	872	862
R-squared	0.002	0.010	0.018	0.033	0.001	0.019	0.029	0.064

Notes. Estimated coefficients of treatment groups are the respective average treatment effects in comparison to the control group (i.e., constant) for different pre-baseline consumption status. Estimations follow equations (2) and (3). Robust standard errors in parentheses. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Table 5. Treatment effects by baseline efficiency level

Panel I. Neighbor comparison

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	A. Inefficient users				B. Average users				C. Efficient users			
Variables	Round 1 (April 17)	Round 2 (June 17)	Round 3 (Aug 17)	Round 4 (Nov 17)	Round 1 (April 17)	Round 2 (June 17)	Round 3 (Aug 17)	Round 4 (Nov 17)	Round 1 (April 17)	Round 2 (June 17)	Round 3 (Aug 17)	Round 4 (Nov 17)
Neighbor	-0.014	-0.016	-0.056	-0.120***	-0.014	-0.017	-0.045	-0.074***	0.027	0.034	-0.013	-0.062***
	(0.039)	(0.035)	(0.036)	(0.037)	(0.029)	(0.027)	(0.027)	(0.025)	(0.029)	(0.026)	(0.024)	(0.024)
Knowledge	-0.016	-0.063*	-0.090**	-0.119***	-0.012	-0.087***	-0.114***	-0.164***	0.024	-0.060**	-0.083***	-0.139***
	(0.039)	(0.036)	(0.036)	(0.036)	(0.028)	(0.026)	(0.026)	(0.024)	(0.025)	(0.024)	(0.022)	(0.023)
Constant	5.907***	5.961***	5.952***	5.934***	5.723***	5.805***	5.803***	5.828***	5.588***	5.687***	5.695***	5.756***
	(0.026)	(0.024)	(0.025)	(0.025)	(0.021)	(0.020)	(0.020)	(0.017)	(0.019)	(0.018)	(0.016)	(0.015)
No. of obs.	458	458	458	456	597	597	596	587	625	625	625	620
R-squared	0.000	0.007	0.014	0.031	0.000	0.020	0.031	0.064	0.002	0.023	0.023	0.053

Panel II. Suburb comparison

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	D. Inefficient users				E. Average users				F. Efficient users			
Variables	Round 1 (April 17)	Round 2 (June 17)	Round 3 (Aug 17)	Round 4 (Nov 17)	Round 1 (April 17)	Round 2 (June 17)	Round 3 (Aug 17)	Round 4 (Nov 17)	Round 1 (April 17)	Round 2 (June 17)	Round 3 (Aug 17)	Round 4 (Nov 17)
Suburb	-0.029	-0.016	-0.045	-0.110***	-0.008	-0.028	-0.041	-0.042	0.005	0.018	-0.021	-0.083***
	(0.036)	(0.034)	(0.034)	(0.034)	(0.031)	(0.029)	(0.029)	(0.028)	(0.025)	(0.023)	(0.022)	(0.022)
Knowledge	-0.015	-0.065*	-0.080**	-0.126***	-0.009	-0.091***	-0.118***	-0.135***	0.028	-0.049**	-0.080***	-0.152***
	(0.037)	(0.034)	(0.033)	(0.033)	(0.029)	(0.028)	(0.027)	(0.027)	(0.025)	(0.024)	(0.023)	(0.022)
Constant	5.905***	5.960***	5.952***	5.940***	5.714***	5.802***	5.792***	5.807***	5.586***	5.683***	5.695***	5.760***
	(0.024)	(0.022)	(0.023)	(0.023)	(0.023)	(0.022)	(0.022)	(0.019)	(0.018)	(0.017)	(0.016)	(0.015)
No. of obs.	500	500	499	497	520	520	519	517	661	661	661	651
R-squared	0.001	0.007	0.011	0.033	0.000	0.022	0.038	0.047	0.002	0.014	0.022	0.066

Notes. Estimated coefficients of treatment groups are the respective average treatment effects in comparison to the control group (i.e., constant) for baseline efficiency levels. Estimations follow equations (4) and (5). Robust standard errors in parentheses. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Supplementary materials

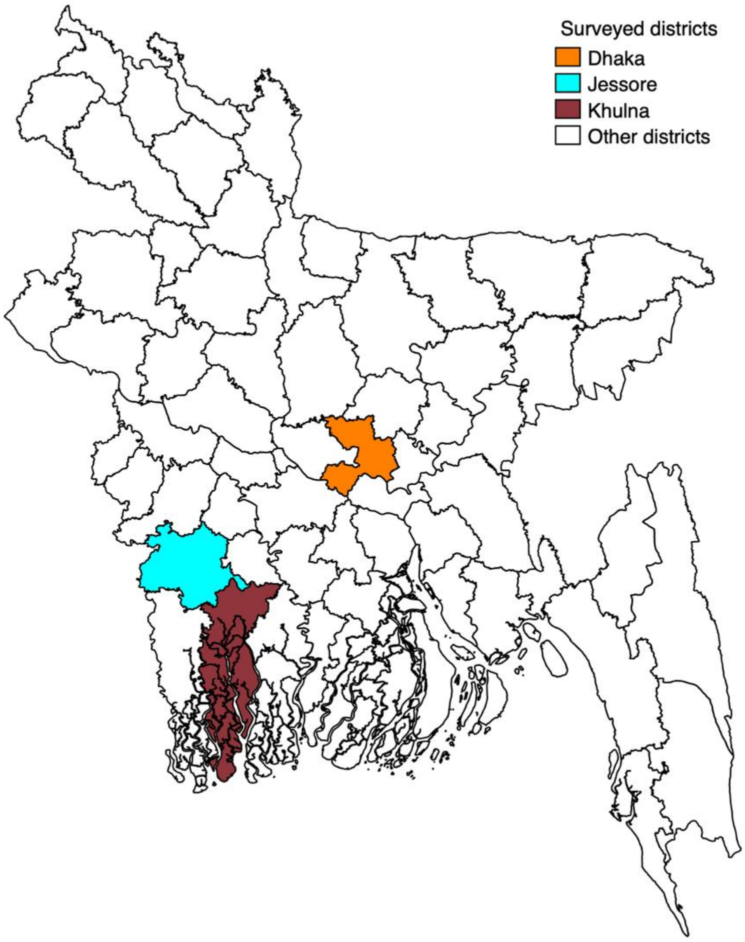


Figure S1. Survey districts

Table S1. Survey areas

Area name	All treatments	Control	Suburb	Knowledge	Neighbor
Badda	291	65	73	70	83
Dhanmondi	163	42	42	39	40
Jessore	209	58	54	49	48
Khilgaon	238	64	57	62	55
Khulna	286	57	74	81	74
Mirpur	310	79	73	73	85
Mohammadpur	286	69	71	79	67
Puran Dhaka	109	27	35	25	22
Rayerbazar	123	36	28	25	34
Uttara	233	53	61	60	59
No. of Obs.	2,248	550	568	563	567

Notes. Reported information are for 2,248 households that remained throughout the intervention period.

Table S2. Total potential benefits of treatments

	Neighbor treatment	Suburb treatment	Knowledge treatment
Population (total)	166,303,494	166,303,494	166,303,494
Target urban population (% of total population)	20.76	20.76	20.76
Household size	4.4	4.4	4.4
Target urban households (total)	7,845,371	7,845,371	7,845,371
Average electricity bill (BDTk)	1,727.076	1,715.954	1,692.806
Average electricity use (kWh)	325.339	319.405	320.602
Reduction due to treatment	8.1%	7.9%	14.3%
Average reduction in electricity bill per household (BDTk)	139.893	135.560	242.071
Total potential reduction in electricity bill (Billion BDTk)	1.10	1.06	1.90
Average reduction in energy consumption per household (kWh)	26.35	25.23	45.85
Total potential reduction in energy consumption (gWh)	206.74	197.96	359.68

Notes. Data comes from the Bangladesh Household Income and Expenditure Survey (HIES) 2016 (BBS 2016) and the World Development Indicators (World Bank 2022).