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THE HETEROGENEOUS EFFECTS OF SOCIAL CUES ON DAY TIME AND NIGHT TIME ELECTRICITY USAGE, AND APPLIANCE PURCHASE: EVIDENCE FROM A FIELD EXPERIMENT IN ARMENIA

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The Heterogeneous Effects of Social Cues on Day Time and Night Time Electricity Usage, and Appliance Purchase: Evidence from a Field Experiment in Armenia

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Abstract:
This study investigates the effectiveness of "nudges" through monthly peer comparison reports on household energy consumption in Yerevan, Armenia. We collected data from 300 households for a total of 8 months. While monthly peer comparison reports show no significant effect on energy consumption, we find strong and statistically significant heterogeneous treatment effects. Specifically, we find that households utilizing electricity as their primary heating source, households where the respondent is an educated female, and households with respondents aged 56 and above experienced a decrease in electricity usage as a result of the peer comparison reports. Moreover, we discover that high electricity consumers reduce their consumption significantly after receiving the reports. However, we also observe a small "boomerang" effect, whereby households in the lower quartile of electricity consumption slightly increase their usage in response to the reports. Furthermore, we find that the bulk of the reduction in electricity consumption comes from daytime consumption when the marginal cost of electricity is higher.

Additionally, we explore the heterogeneous treatment effects of nudges on the investment in the physical stock of appliances.

JEL: Q4, Q53, Q48, Q58, C93
Keywords: demand side management, nudges, household energy consumption, peer comparison, developing country, heterogeneous treatment effects, electrical appliances

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1. Introduction

Climate change has become an existential threat to the world, necessitating an urgent and drastic reduction in greenhouse gas emissions. As household energy consumption constitutes over 30% of global energy consumption, it is imperative to reduce household energy consumption and associated carbon emissions to achieve the goal of net-zero greenhouse gas emissions by 2050 (Tsiropoulos et al.,2020). Conservation in emerging countries is of particular importance, as emerging countries exhibit the most significant increase in energy consumption. However, while numerous studies address conservation and the effect of intermediate (socio-economic) variables in Western countries, few studies have addressed conservation in emerging countries and none analyzed the joint effects of intermediate (socio-economic) variables and social peer comparisons. This is a serious lacuna, as outcomes and findings observed in the Western world usually cannot be generalized to developing nations (Henrich et al., 2010). We address this gap in the literature by conducting a social peer comparison experiment in the city of Yerevan, the capital city of Armenia.

1.1 Previous literature

For Western countries, ample evidence shows the effect of incentives and information on conservation. At the same time, there is ample evidence suggesting that residential consumers typically do not have access to the full spectrum of information related to their energy consumption due to technical or cognitive constraints (Jessoe and Rapson, 2014; Borenstein, 2009, Ito, 2014). These inherent informational limitations prevent households to make optimal energy consumption decisions (Jessoe and Rapson, 2014; Ito, 2014).

Concurrently, it has been consistently demonstrated that providing households with basic information such as their own energy consumption, various simple tips on how to save energy, and the comparison of their own energy consumption to those of similar peers can substantially decrease the energy consumption of the households (Schultz et al., 2007; Nolan et al., 2008; Allcott and Mullainathan, 2010; Allcott, 2011; Costa and Kahn, 2013; Ayres et al., 2013; Allcott and Rogers, 2014; Jessoe and Rapson, 2014; Knittel and Stolper, 2021). Among all types of information provisions, however, peer comparison (also known as nudges), has usually been shown to be a more robust and effective determinant of energy conservation. For instance, Nolan et al., (2008) found in their field experiment that although households believed that the behavior of their neighbors had the least influence on their own energy conservation behavior, it actually had the greatest impact. In other words, when participants were provided with information that their neighbors save power, it motivated them to save power as well. Moreover, it motivated them to conserve more energy compared to other common approaches used to encourage energy conservation, such as promoting environmental protection, social responsibility, or financial savings.

In addition, Ferraro et al., (2011) found that while appeals to pro-social preferences and social comparisons can have an impact on short-term water use patterns, only messages supplemented with social comparisons have a sustained effect on water demand. Specifically, one year after the treatment ended, there was no significant effect on water consumption for households that received an appeal to pro-social preferences (compared to the control group). However, up to two years after the treatment ended, there was a significant and lasting effect on water consumption for the households that received messages with social comparisons. Based on a sample of over 100,000 households, in two separate studies, Ferraro and Price (2013), and Ferraro and Miranda (2013) also conclude that messages that incorporate social comparisons were more effective in inducing behavioral change compared to messages that only appealed to prosocial motivations or provided technical information.

In contrast with the previous findings, it is puzzling to see that Murakami et al., (2022), performing a field experiment in Japan, find that the average reduction in electricity consumption due to social comparison nudges was statistically insignificant, while the effect of monetary incentives (a rebate) was 4%. However, their further investigation showed that the lack of statistical significance associated with the non-monetary nudge intervention can be attributed to the substantial heterogeneity observed in the data. The heterogeneity in their data stemmed mainly from electricity usage-related characteristics, household size, age of the respondent, age of the house, and income.

A number of other studies also found that the average response to social comparisons exhibits high levels of heterogeneity. For instance, Allcott (2011) demonstrates that households with the highest electricity consumption levels prior to the intervention tend to experience a much greater reduction in electricity usage in response to the introduction of descriptive social norms in comparison to households with the lowest levels of pre-treatment electricity consumption. Costa and Kahn (2013) document that energy conservation nudges (peer comparison) are two to four times more effective with political liberals than with conservatives. In their analysis authors show that conservatives are more likely to decline receiving the home electricity report and to express negative opinions about it.

Ayres et al., (2013) conducted two large field experiments (labelled as SMUD and PSE experiments) to study the heterogeneous treatment effects of the well-known OPOWER peer comparison experiment in the USA. Authors conclude that the impact of the Home Energy Reports (HERs) is indeed heterogeneous among the US population. The combined results of the SMUD and PSE experiments indicate that households with larger pre-experiment energy usage per square foot generally had larger energy-reducing treatment effects. However, the findings also suggest that the effectiveness of energy-saving interventions may vary depending on other household characteristics, such as the size and age of the house, and the presence of a swimming pool or spa. The frequency of energy reports did not have a significant impact on energy savings. Additionally, there was no evidence of a "boomerang" effect among households with lower initial energy usage, meaning that their energy consumption did not increase as a result of the treatment. The SMUD experiment revealed that larger houses experienced more noticeable treatment effects, and households in higher pricing tiers and those facing higher cooling degree days achieved greater reductions in energy consumption due to the treatment. However, when households with a swimming pool received energy reports, their energy usage increased. The study determined that the treatment's effectiveness varied based on the households' initial energy consumption levels, with those consuming higher amounts experiencing larger percentage reductions in energy consumption. Interestingly, the study also revealed that the five lowest deciles of energy consumers had smaller reductions compared to the average, while three out of the five highest deciles had greater reductions. In the PSE experiment, it was observed that larger, more valuable, and older households had smaller reductions in energy usage as a result of the treatment. On the other hand, households with higher initial energy usage per square foot achieved greater reductions in energy consumption. Additionally, the data suggests that the impact of the treatment on gas consumption may be less significant when home heating becomes less important.

In contrast, Knittel and Stolper (2021) find some suggestive evidence in support of the “boomerang” effect–households with lower consumption than similar neighbors (peers) tend to increase their energy consumption, on average, due to the home energy reports (HERs). They also document that the effect of HERs is heterogeneous. They also conclude that the main drivers of heterogeneity are the baseline level of energy consumption, house value, size of the dwelling, dwelling’s age, income, and the age of the respondent.

As can be seen from the literature the impact of social (peer) comparison in the realm of energy savings tends to exhibit high levels of heterogeneity with respect to various dwelling and household characteristics. It is important that in their presence the heterogeneous treatment effects are controlled and accounted for in order to achieve the most effective, and cost-efficient policy outcomes (Costa and Kahn, 2013; Harold et al, 2018; Allcott and Kessler, 2019; Knittel and Stolper, 2021; Murakami et al., 2022).

The literature above also demonstrates that the heterogeneous effects of the social peer comparisons in the context of residential energy conservation have been investigated to some extent. However, all of the literature above concentrates on developed countries (with the bulk of the studies conducted in the US), and the heterogeneous effects of social peer comparisons in the context of developing countries have been ignored so far. Studying the heterogeneous impact of social peer comparisons on residential energy conservation in emerging countries is of particular importance, as emerging countries exhibit the most significant increase in energy consumption, and attempts to replicate the outcomes and findings observed in the Western world have encountered challenges in the context of developing nations (Henrich et al., 2010). This creates a gap in the literature that needs to be addressed.

1.2 Our contribution

We close this gap in the literature by conducting a social peer comparison experiment in the city of Yerevan, the capital city of Armenia. In particular, we collect data on monthly electricity consumption for a total of eight months, along with socio-economic household and dwelling pre-treatment characteristics for about 300 households. We then divide the sample into three equally sized groups: the social peer energy consumption comparison; the social peer energy consumption, and associated monetary costs comparison; and the control group. We have chosen to divide the treatment into two separate groups based on our projection that presenting households with a comparison of their own energy consumption, along with the associated monetary costs, may have a distinct impact compared to providing them with solely a comparison of their peers' energy consumption without explicitly displaying the associated costs. In this sense, our hypothesis is different from other strains of the literature for instance when the households are incentivized to save energy via higher (lower) marginal energy prices (Ito, 2015; Ito, 2018), or via various cash-back transfers offered by the utilities or other third parties for consuming less energy (Dolan, and Metcalfe, 2015; Sudarshan. 2017).

In our study, we indeed document that the effect of social peer comparisons is highly heterogeneous with respect to dwelling and household characteristics, both in the case of simple consumption comparison, as well as comparisons containing associated costs. In particular, we find that households that consume more electricity (those located in the upper quartile of electricity consumption), and the households that use electricity as a main source of heating tend to be more sensitive towards both types of interventions. We also document a "boomerang" effect in both types of intervention–households in the lower quartile of distribution tend to increase their electricity consumption (albeit not by much) due to the peer comparison reports.

Interestingly, we also observe that the effect of the reports containing only consumption comparisons exhibits a differential impact with respect to the highly educated female respondents, whereas the reports containing a comparison of the associated costs along with the consumption comparison exhibit differential impacts with respect to respondents aged 56 and older.

Moreover, our study reveals a remarkable pattern: the significant decrease in electricity consumption primarily originates from reductions in daytime usage, which coincides with the period when electricity tariffs are higher. This finding suggests that consumers are particularly responsive to the price incentives associated with peak hours and make conscious efforts to curtail their electricity usage during these times. By taking advantage of lower electricity rates during the night time, households are able to optimize their energy consumption habits and contribute to overall energy conservation.

In addition, we conducted another survey by the end of our experimental period to check if the social peer comparisons also had any effect on the change in the physical stock of appliances. We find that the effect of social peer comparisons on the propensity to purchase home appliances is also heterogeneous with respect to household and dwelling characteristics.

To the best of our knowledge, this is the first paper that studies the heterogeneous effect of social peer comparisons with respect to such rich socioeconomic and dwelling characteristics in the context of a developing country such as Armenia. Moreover, it is one of the first studies in the context of a developing country that uniquely distinguishes between consumption patterns during different times of the day, considering the varying marginal prices of electricity.

These observations may underscore the importance of accounting for intermediate variables such as household and dwelling characteristics, as well as time-of-use pricing structures and their effectiveness in influencing consumer behavior to promote more sustainable energy consumption patterns in developing countries like Armenia. Our findings suggest that in the context of developing countries, policy makers may need to tailor their energy conservation programs to different demographic groups, and time-of-use. Therefore, our study has important policy implications with regard to the conservation of residential energy consumption in developing countries where energy consumption is rapidly increasing.

The remainder of the paper is structured as follows. Section 2 describes the conducted field experiment, provides a brief overview of the energy sector of Armenia, and the characteristics of our household data. Section 3 describes the empirical methodology and the results. Section 4 concludes.

2. Description of the Field Experiment and the Household Data

We conducted our field experiment in Yerevan, the capital city of Armenia. Armenia has the capability to generate a sufficient amount of electricity to satisfy its domestic demand. Additionally, the country engages in electricity trading with neighboring nations, with its electricity exports surpassing imports. The power generation mix in Armenia consists of approximately 40% nuclear energy, 28% hydropower, and 30% thermal power, which is derived from imported natural gas. In 2020, the total electricity generation in Armenia reached 6288 million kilowatt-hours (kWh). [1] Armenia has the least diversified energy portfolio in comparison with the countries in Eastern Europe and Central Asia, energy consumption in a country highly depends on electricity, gas, and wood. While in other countries in the region, it is concentrated in coal, LPG, solid, and other fuel types. (Krauss 2016).

The realization of economically viable energy efficiency potential as a way of solving the main challenges of the energy sector is a key priority for the Armenian Government. The law on Energy Saving and Renewable Energy has been passed by the National Parliament in 2004, which creates the legal basis for energy efficiency. However, due to the institution-level capacity gaps, the law is more declarative and has no provisions for mandatory energy efficiency measures or enforcement. (World Bank, 2013).

The residential tariff-setting principles in Armenia include the absence of seasonal tariffs despite the higher marginal cost of electricity in winter, differentiation between day and night tariffs, and the absence of fixed charges in monthly bills. Starting from February of 2021 Armenia moved from a flat electricity tariff to the increasing block tariffs (IBT) for

[1] Public Services Regulatory Commission (PSRC) of Armenia (www.psrc.am)

residential electricity. Currently, residential electricity in Armenia is priced according to the tariff schedule depicted in Figure 1 below:[2]

Figure 1: Tariff schedule

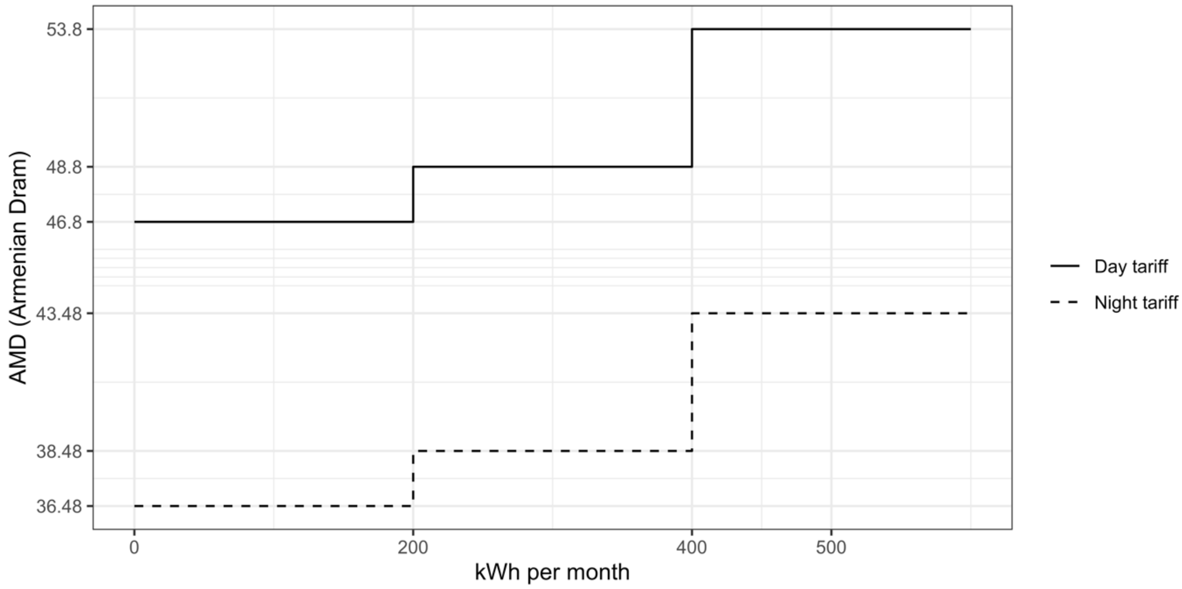


Figure 1 depicts the block rate tariffs for electricity consumption. The vertical axis represents prices in Armenian Dram (AMD), while the horizontal axis represents monthly kilowatt-hour (kWh) consumption. The data is segmented into three blocks: the first block ranges from 0 kWh to 200 kWh, the second block spans 200 kWh to 400 kWh, and the third block represents consumption exceeding 400 kWh. The graph showcases a step-wise progression, with each block connected by a horizontal line, symbolizing the corresponding price range for the given consumption range.

The solid line on the graph illustrates daytime consumption, displaying increasing tariffs for each block at rates of 46.8 AMD, 48.8 AMD, and 53.8 AMD. Information on nighttime consumption is represented by a dashed line. The nighttime tariffs mirror those of daytime consumption, but at discounted rates: 36.48 AMD, 38.48 AMD, and 43.48 AMD for the respective blocks.

[2] Residential electricity tariffs are obtained from https://psrc.am.

In contrast to typical IBT, this particular tariff structure introduces an additional feature. Customers falling within the second block of electricity usage are charged with the price per kilowatt-hour (kWh) associated with the second block for their total consumption during the billing month, not only for the part that surpasses 200 kWh. Similarly, customers falling within the third block pay the price per kWh of the third block for their total consumption, not only for the kilowatt-hours exceeding 400. This deviation from conventional IBT ensures that the price per kWh remains consistent within each block, encompassing the entirety of the customers' usage within that block, rather than solely applying to the excess consumption beyond the block threshold.

We have partnered with a major marketing agency "International Marketing Research" (IMR) headquartered in Yerevan for the data collection services.[3] The collection of the data related to the household and dwelling characteristics was administered via telephone interviews. Initially, the company contacted 4102 individuals. To assure the representativeness of the population in the sampling design procedure, IMR applies RDD (random digit dialing) methodology–dialing to pre-generated telephone numbers with a certain rule, using an Excel toolkit. That is, generating 9-digit numbers, starting with specific mobile network codes (MNC) belonging to country-eligible mobile network operators – Viva-MTS, Team Telecom, and Ucom. The contacted individuals were offered 500 AMD (the equivalent of about 1 USD) of top-up on their phone numbers after the interview, plus a 500 AMD top-up for each sent photograph of their monthly electricity bill during the experimental period. In addition, the participating households were offered to take part in the raffle by the end of the study where six participants were randomly selected and rewarded 100,000 AMD (equivalent to about 250 USD). Out of all initially contacted 604 individuals were retained. Other contacts were dropped due to refusal of being interviewed (for various

[3] https://imr.am

reasons), living outside Yerevan, or not being a major decision-maker within the household. We also dropped all the renters, as in Armenia utilities are usually paid by the owners of the dwellings rather than the individuals renting the apartment.

Out of 604 remaining respondents, 291 agreed to share their monthly electricity bills.

Thus, a total of 291 households were randomly and evenly distributed across three groups. Randomization was conducted on the household level. The first treatment group received social comparison treatment (DI), which provided feedback in the form of the average electricity consumption of similar households compared to their own electricity consumption.[4] The second treatment group received social comparison along with associated monetary costs as well (DC), which provided the same feedback as treatment DI, but also included the peer comparison of the associated monetary costs of the electricity consumption. The control group (C) only had relevant energy consumption and socio-economic data recorded. The sample messages received by each of the treatment groups are depicted in Figure 2 below.

[4] The social comparison reports were distributed via messaging software applications Viber and WhatsApp.

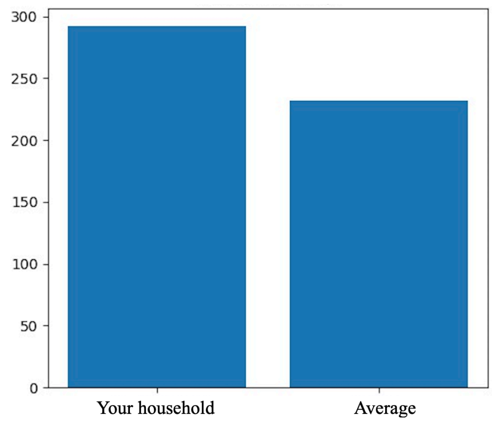
Figure 2: Monthly reports

Group DI

Dear [Name of the recipient], every month you will receive a report on your electricity consumption. This report will also reflect the average electricity consumption of other similar [by number of rooms and type of heating] households in Yerevan. The report is intended to help you see if there is an opportunity to reduce your consumption. Do not use more than necessary, study your electrical appliances and try to review your consumption habits.

	Consumption for [name of the Month]
Your household	292 kWh
Average	231 kWh

Consumption for [name of the Month]



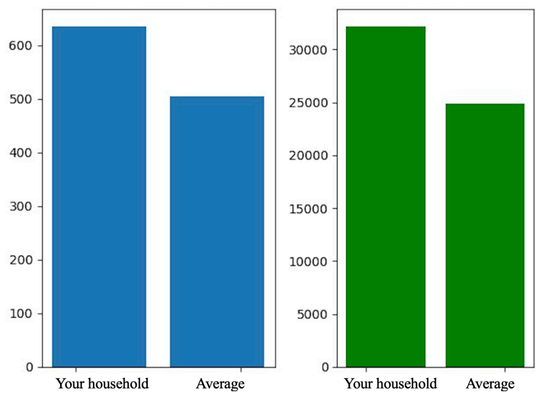
Group DC

Dear [Name of the recipient], every month you will receive a report on your electricity consumption, and the associated payment. This report will also reflect the average electricity consumption and associated payment of other similar [by number of rooms and type of heating] households in Yerevan. The report is intended to help you see if there is an opportunity to reduce your consumption. Do not use more than necessary, study your electrical appliances and try to review your consumption habits.

	Consumption for [name of the Month]	Payment made [AMD]
Your household	635 kWh	32162 AMD
Average	231 kWh	24869 AMD

Consumption for [name of the Month]

Payment made [AMD]



Note: Translated from Armenian

During the experiment 19 households were further removed from the analysis due to consistently abnormally high (>700 kWh, or >95th percentile), or near zero consumption. Thus, our final analytical sample consists of 272 monthly household observations. We present the descriptive statistics of the selected sample below:

Table 1: Descriptive statistics (proportions)

	(1)	(2)	(3)	(4)	(5)
Respondent's characteristics:	C	DI	DC	C- DI	C- DC
Female	0.500	0.549	0.506	-0.05	-0.005
Respondent pays bills	0.652	0.616	0.731	0.037	-0.078
Age:					
<36 years	0.315	0.307	0.292	0.007	0.023
36–45 years	0.468	0.462	0.472	0.006	-0.005
46–55 years	0.098	0.187	0.101	-0.089*	-0.004
56+	0.120	0.044	0.135	0.075*	-0.015
Education:					

Secondary	0.315	0.307	0.337	0.007	-0.022
Secondary-technical	0.131	0.209	0.18	-0.079	-0.05
Higher	0.554	0.483	0.472	0.071	0.083
Employment status:					
Employed	0.554	0.56	0.64	-0.006	-0.086
Part-time employed	0.076	0.088	0.034	-0.012	0.043
Self-employed	0.185	0.143	0.135	0.042	0.05
Unemployed	0.054	0.044	0.034	0.011	0.021
Pensioner	0.054	0.022	0.045	0.022	0.009
Student	0.000	0.022	0.000	-0.022	0.000
Household's characteristics:					
Pre-treatment electricity consumption:					
0-25th quantile	0.392	0.296	0.359	0.095	0.032
25th -50th quantile	0.207	0.307	0.236	-0.101	-0.03
50th -75th quantile	0.174	0.275	0.202	-0.101	-0.029
75th -100th quantile	0.229	0.121	0.202	0.107*	0.026
Number of household members:					
1 person	0.065	0.044	0.034	0.022	0.032
2–3 people	0.272	0.253	0.292	0.019	-0.021
4+ people	0.348	0.483	0.416	-0.136*	-0.068
Income:					
0-25th quantile	0.163	0.165	0.202	-0.002	-0.039
25th -50th quantile	0.142	0.22	0.202	-0.079	-0.061
50th -75th quantile	0.011	0.011	0	0	0.011
75th -100th quantile	0.261	0.132	0.113	0.129**	0.148**
Income missing	0.304	0.307	0.303	-0.004	0.001
Dwelling's characteristics:					
Dwelling type:					
Apartment	0.793	0.802	0.753	-0.009	0.041
Detached	0.207	0.198	0.247	0.009	-0.041
Number of bedrooms:					
1–2 bedrooms	0.369	0.362	0.359	0.007	0.01
3 bedrooms	0.424	0.417	0.45	0.007	-0.026
4+ bedrooms	0.207	0.22	0.191	-0.013	0.015
Source of heating:					
Electricity	0.196	0.154	0.169	0.042	0.027
Gas	0.739	0.715	0.663	0.025	0.076
Gas Stove	0.142	0.143	0.191	-0.002	-0.05
Solid fuels	0.011	0.011	0.034	0.000	-0.023

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1 presents the descriptive statistics of the selected pre-treatment household and dwelling characteristics for the control group, and two treatment groups (columns 1-3). We test for randomization of all selected household and dwelling characteristics (columns 4-5) via the difference in means across the groups as well as testing for the difference in the empirical quantiles for pre-treatment electricity consumption, and per-capita household income across the groups for the 0^{th}(min), 25^{th}, 50^{th}, and 100^{th} (max) percentiles. In our specification C stands for the households belonging to the control group, DI stands for the households receiving peer comparison reports containing the electricity consumption, and DC stands for the households receiving both peer comparison reports containing the electricity consumption along with the associated monetary costs of this consumption.

It can be seen that the randomization was quite successful and generally the differences in means for the selected variables across the groups are statistically insignificant. The only noticeable differences that are significant at the 5% level can be observed for the share of the households located in the highest quantile of the per-capita income distribution. The share of the households in the highest quartile of the per-capita income distribution is larger in the control group (26.1%) compared to both of the treatment groups (13.2% and 11.3%). This difference can be attributed to the fact that the randomization was made with respect to the mean values of the income, rather than the full quantile distribution. Moreover, more than 30% of the respondents across all groups refused to report their monthly incomes, and therefore the information on household income was simply missing for almost a third of the households.[5] Other variables, including other quantiles of per-capita income, are balanced, however.

Half of the respondents in our sample are females, have higher education, and are aged between 36 and 45 years. Also, more than half of the respondents are employed, 5% are

[5] In our regression specifications we try to control for the non-reporting of the income, and differences in the highest quantiles of the income distribution across the groups by interacting the dummy variable indicating whether the income information is missing, along with dummy variables indicating whether the household belongs to the lowest or highest quantiles of the per-capita income distribution with the treatment indicator. We also proxy for the per-capita income with the per-capita household expenditure to control for potential income misreporting. See Methods and Results section for more details.

partly employed, and about 15% report being self-employed. The remaining of the respondents report being unemployed (about 4%), or pensioners (about 4%).

The majority of the households reside in multiapartment buildings (about 80%), have three living rooms (more than 40%), and have four and more individuals (about 40%) residing within the dwelling.

About 70% of the households report using gas, about 17% report using electricity, and about 16% report using gas stoves as a main source of heating. Less than 2% also report using various solid fuels as well (such as wood, coal, or bio-fuels).

3. Methods and Results

To estimate the impact of the social-peer comparisons on electricity consumption we employ a standard difference-in-differences (DD) empirical framework estimated via ordinary least squares (OLS). To account for the heterogeneous treatment effects, we interact the DD variables (*DI* and *DC*) with various household and dwelling-specific characteristics. We also include household and month-fixed effects to take full advantage of the panel nature of our data. Our empirical specification can be expressed by Equation 1 below.

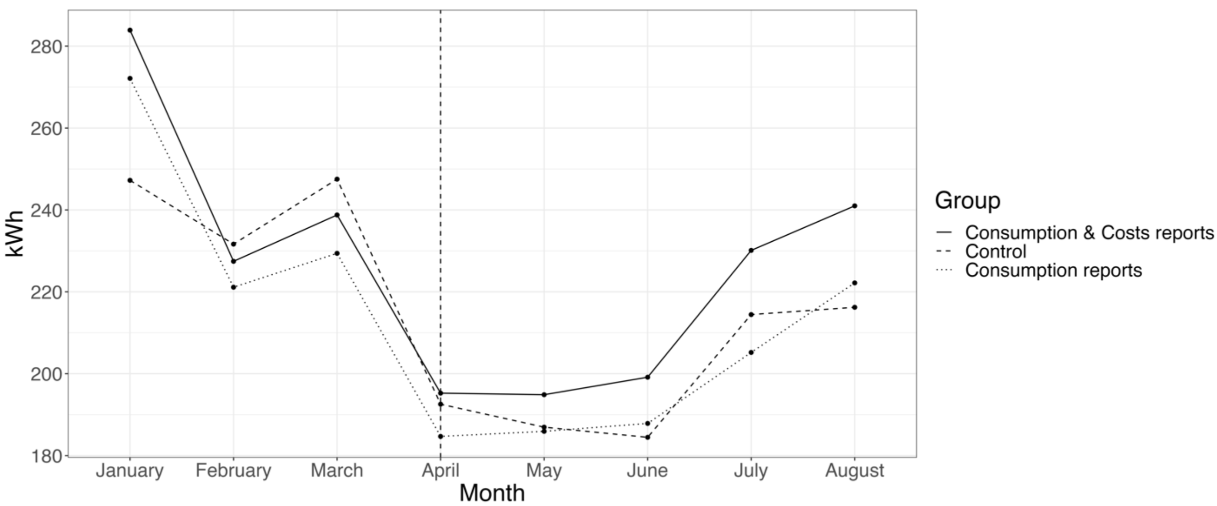
$$E_{it} = a_i + \tau_t + b_1 DI_{it} + b_2 DC + \boldsymbol{H}_{it} DI_{it} \delta_1 + \boldsymbol{S}_{it} DI_{it} \varphi_1 + \boldsymbol{D}_{it} DI_{it} \eta_1 + \boldsymbol{H}_{it} DC_{it} \delta_2 + \boldsymbol{S}_{it} DC_{it} \varphi_2 + \boldsymbol{D}_{it} DC_{it} \eta_2 + \varepsilon_{it} \quad (1)$$

Where *E* is the electricity consumption of household *i* in month *t.* The *DI* stands for the interaction term indicating observations from the treatment group receiving monthly electricity consumption peer comparison reports in the treatment period, while *DC* stands for the interaction term that indicates observations from the treatment group that in addition to electricity consumption reports, also receives the peer comparison of the associated costs of this consumption in the treatment period.

In the context of standard (DD) empirical specification the coefficients on *DI* and *DC* are of the main interest. However, in our context besides b_1 *and* b_2 we also concentrate on δ, φ, and η the coefficients on the characteristics of the household head, the household's socio-economics, and the dwelling characteristics respectively interacted with *DI* and *DC*. Terms a_i and τ_t stand for the household and month-fixed effects respectively. The ε_{it} indicates the idiosyncratic error term.

In our particular case, we can observe households' electricity consumption from January 2022 to August 2022. We started sending the reports at the beginning of April 2022. Thus, we can observe three months (January to March) of pre-treatment electricity consumption, and 5 months (April to August) of post-treatment electricity consumption periods. Figure 3 below depicts the average monthly electricity consumption during our study period by groups.

Figure 3: Monthly average electricity consumption



The estimation results of Equation 1 are presented in Table 2 below. We can see that both types of intervention prove to be statistically insignificant. However, we do see the presence of heterogeneous effects which are revealed when we interact the variables *DI* and *DC* with household and dwelling characteristics.

Table 2: Fixed effects regression results (coefficients indicate kWh)

Variables	**Total Consumption**	**Day Consumption**	**Night Consumption**

	(1)	(2)	(3)
Main Treatment Effect:			
(DI)	4.525 (31.628)	0.025 (21.148)	4.500 (12.522)
(DC)	23.601(23.280)	15.703 (16.338)	7.898 (8.627)
Respondent's characteristics:			
Female × *(DI)*	14.959 (18.803)	13.012 (12.572)	1.948 (7.165)
Female × *(DC)*	-12.542(18.737)	-11.048(12.873)	-1.493(8.311)
High Educ. Female × *(DI)*	-36.070** (17.589)	-28.264** (12.756)	-7.807 (7.575)
High Educ. Female × *(DC)*	-5.690(20.027)	1.653(13.749)	-7.343(9.041)
Age<36 × *(DI)*	-9.802 (16.477)	-7.324 (11.964)	-2.478 (5.721)
Age<36 × *(DC)*	6.602(23.733)	4.031(16.258)	2.571(8.859)
Age56+ × *(DI)*	-41.155 (33.642)	-27.741 (22.448)	-13.414 (11.841)
Age56+ × *(DC)*	-37.199*(20.259)	-23.560(14.905)	-13.638*(7.655)
Respondent pays bills × *(DI)*	3.999 (16.937)	3.468 (10.825)	0.531 (7.595)
Respondent pays bills × *(DC)*	-14.659(20.139)	-10.086(13.489)	-4.573(7.639)
Household's characteristics:			
Income 25th perc. × *(DI)*	30.072 (23.268)	13.323 (16.202)	16.749* (9.446)
Income 25th perc. × *(DC)*	45.637**(21.892)	32.927**(16.210)	12.710*(7.218)
Income 100th perc. × *(DI)*	38.129* (22.881)	27.917 (17.187)	10.212 (6.639)
Income 100th perc. × *(DC)*	-12.130(29.300)	-4.531(19.351)	-7.599(11.898)
IncomeMissing × *(DI)*	8.991(14.702)	4.883(10.761)	4.108(5.638)
IncomeMissing × *(DC)*	35.261*(18.049)	27.335**(12.823)	7.926(7.239)
HHsize4+ × *(DI)*	-8.420 (15.596)	-10.386 (11.424)	1.966 (5.770)
HHsize4+ × *(DC)*	16.284(15.896)	9.614(11.300)	6.670(5.975)
E.Cons.25th perc. × *(DI)*	26.538*(13.801)	23.645**(10.210)	2.893(4.547)
E.Cons.25th perc. × *(DC)*	28.468**(11.668)	23.408***(8.214)	5.060(4.736)
E.Cons.100th perc. × *(DI)*	-110.793***(26.369)	-89.294***(19.308)	-21.499*(11.924)
E.Cons.100th perc. × *(DC)*	-96.309***(25.910)	-71.645***(18.063)	-24.664**(10.700)
Dwelling's characteristics:			
Detached house × *(DI)*	6.325 (17.967)	1.558 (11.985)	4.767 (7.375)
Detached house × *(DC)*	5.839(18.363)	4.482(13.277)	1.358(7.066)
Rooms<3 × *(DI)*	-4.467 (16.435)	-1.107 (12.197)	-3.360 (5.009)
Rooms<3 × *(DC)*	-6.038(20.275)	-6.892(14.377)	0.854(7.121)
Rooms4+ × *(DI)*	9.163 (19.501)	19.365 (14.459)	-10.202 (7.274)
Rooms4+ × *(DC)*	-17.369(21.057)	-10.678(12.530)	-6.691(10.572)
Heating with elect. × *(DI)*	-74.609*** (25.824)	-54.351*** (19.243)	-20.258* (10.653)
Heating with elect. × *(DC)*	-57.667*(32.125)	-54.958**(23.798)	-2.710(10.989)
Household fixed effects	*yes*	*yes*	*yes*
Month fixed effects	*yes*	*yes*	*yes*
N	2083	2083	2083
adj. R^2	0.300	0.348	0.140
F-statistics	17.772	20.480	7.217
p-value	0.000	0.000	0.000

Note: Clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Column 1 of Table 2 shows the estimation results for total monthly electricity consumption, while Column 2 and Column 3 run the same estimations for consumption during the day time (when the tariff is higher), and during the night time (when the tariff is lower) respectively. We can immediately see that the bulk of the observed effect of both of the treatment types (DI and DC) is coming from the reduction in daytime consumption when the marginal cost of electricity is higher. This result is in accord with Ito et al., (2018) who conclude that people react to the experimental information provision and reduce the peak-time electricity consumption due to economic incentives.

Overall, we can observe that households that consume higher amounts of electricity – households located in the upper quartile of consumption, and households using electricity as a primary source of heating tend to decrease their consumption substantially due to receiving peer comparison reports. Households in the upper quartile of consumption reduce their monthly electricity consumption by about 110 kWh (or 0.96 standard deviations (σ)) when receiving peer comparison reports containing electricity consumption (DI group), and by about 96 kWh (0.84σ) when receiving peer reports containing both information on consumption and associated costs (DC group). Households that use electricity as a main source of heating reduced their monthly consumption by 75 kWh (0.66σ) as a result of consumption peer reports, and by about 58 kWh (0.51σ) when receiving the comparison of associated costs as well.

These results are completely in line with the literature that concludes that consumers that are in the higher decile of consumption tend to be more sensitive toward various types of information provision (see, for instance, Allcott, 2011; Ayres et al., 2013; Ferraro and Price, 2013; Ferraro and Miranda, 2013), and tariff reforms (Turdaliev and Janda, 2023; Turdaliev, 2023a).

There are several potential reasons for this observation. Firstly, high-consuming households likely had a higher baseline consumption, providing more room for substantial reductions compared to low-consuming households. Secondly, higher awareness and responsiveness among high-consuming households, driven by their greater energy usage, may have prompted more significant behavioral changes. Thirdly, high-consuming households may have had more energy efficiency opportunities (various appliances or systems), allowing for more effective energy-saving measures.

Some studies suggest that the inclusion of the "descriptive norm" aspect in the social peer comparison interventions, could lead to a decrease in usage for households that previously exceeded the norm. However, it may also increase usage for households that consumed less than the norm. These unintended outcomes, known as the "boomerang" effect in social psychology (Clee and Wicklund, 1980), are undesirable when the objective is to promote energy conservation. In our study, we document a small "boomerang" effect – consumers in the lower quartile of consumption tend to increase their energy consumption due to peer reports. The households in the DI treatment group increased their consumption by about 26 kWh (0.23σ), while those households in the DC treatment group increased consumption by 28 kWh (0.245σ).

There is conflicting evidence in the literature on the presence of the "boomerang" effect. Some studies document its presence (Schultz et al., 2007; Knittel and Stolper, 2021), while others do not find evidence in support of it (Allcott, 2011; Ayres et al, 2013; Ferraro and Miranda, 2013).

Some studies also recommend using "injunctive norms" conveying energy conservation and pro-social behavior along the peer comparison reports (see, for instance, Schultz et al, 2007). In this study, we document that in the context of Armenia, a small "boomerang" effect is still present even when the injunctive norms conveying energy conservation are included in the peer comparison reports.

Interestingly, we find some conflicting evidence with regard to the per capita income quartiles. Households receiving peer consumption comparison reports (with no associated costs) that are in the upper quartile of income distribution tend to increase their total electricity consumption by 38 kWh (0.33σ), although only at 10% of statistical significance. We also find, however, that households in the same treatment group, but are located in the lower quartile of income distribution are also increasing their nighttime electricity consumption by about 17 kWh (0.15σ).

This may suggest a possible shift in electricity consumption patterns among low-income households, as they appear to be redirecting a portion of their energy usage from daytime hours to nighttime when tariffs are lower. Generally, the results found for the DI treatment group are in accord with the findings of Harold et al., (2018), and Turdaliev (2023b) that also conclude that household income plays an important role in determining energy consumption in the case of Ireland, and Russia respectively.

On the other hand, when we look at the income quartiles for the households located in the DC treatment group, we can see that according to the results, the households in the lower quartile of income distribution tend to increase their total electricity consumption (by about 45 kWh (0.4σ)) due to peer reports, while the coefficient on the households in the upper quartile of income distribution is statistically insignificant. This result is counter-intuitive at first, however, as we look at the coefficient on the dummy variable indicating households that did not report their income in the DC group, we can see that it is positive and statistically significant. This may indicate that the proportion of the households miss-reporting their incomes (Bound et al., 2001) is larger in the DC group, and thus the income coefficients obtained for the DC group may be potentially biased.[6]

Moving to the characteristics of the household head there are two notable results. Firstly, in line with Metcalfe and Dolan (2015), we do not find any statistically significant heterogeneous effects of peer reports with respect to the households headed by females. We can see, however, that in the DI group, the households headed by educated females reduced their total monthly electricity consumption, on average, by about 36 kWh (0.316σ).[7] These results align with the findings of Mills and Schleich (2012) who conclude that higher levels of households education are associated positively and strongly with energy conservation practices, and Fischer (2008), and Harold et al., (2018) who find that complex feedback tools may not be as effective for households with lower education.

Additionally, our study aligns with Harold et al. (2018) by revealing that households headed by older individuals exhibit greater sensitivity to a treatment that includes information on associated consumption costs (referred to as the DC group). Specifically, within the DC group, these households reduce their monthly electricity usage by an average of 37 kWh (0.324σ). In contrast, the impact of peer reports on households with older household heads in the DI group is not statistically significant. This finding supports Fischer's (2008) conclusion that older households face challenges in comprehending complex energy reports. Consequently, the inclusion of monetary cost information alongside electricity consumption data likely facilitated their interpretation of the reports.

There is no evidence of statistically significant variations in the impact of peer reports based

[6] We conducted the same regression analysis (see, Appendix) employing expenditure quartiles as proxies for income quartiles, and all of the coefficients maintained similar signs and most maintained statistical significance.

[7] Simultaneously testing the overall impact of education and the impact of education by gender is not feasible. When both interaction terms are included, it results in multicollinearity issues, with the variance inflation factor (VIF) exceeding 10. However, we do examine the general effect of education by incorporating the interaction terms for the binary indicator of higher education and the DD indicators. In this scenario, the effect of education is statistically insignificant at all conventional levels of significance.

on other household and dwelling characteristics. For example, factors such as the number of rooms or whether the dwelling is a detached house or a multi-apartment do not affect how households respond to peer comparison reports. Additionally, we did not observe any significant differences in the reactions of households based on whether the household head is responsible for paying the bills.

By the end of the experiment, we also conducted one more telephone interview and asked the respondents if they have purchased any new home appliances in the last 6 months period in order to differentiate between consumption changes stemming from usage habits and those attributed to changes in the physical capital of the appliance stock. We received responses from 233 households in total with 74 households in the control group, 82 households in the DI group, and 77 households in the DC group. To evaluate this, we employed a cross-sectional regression model, as outlined in Equation 2.

$$A_i = \lambda_0 + \lambda_1 DI_i + \lambda_2 DC + \lambda_3 \boldsymbol{X} + \boldsymbol{H}_i DI_i \delta_3 + \boldsymbol{S}_i DI_i \varphi_3 + \boldsymbol{D}_i DI_i \eta_3 + \boldsymbol{H}_i DC_i \delta_4 + \boldsymbol{S}_i DC_i \varphi_4 + \boldsymbol{D}_i DC_i \eta_4 + \epsilon_i \quad (2)$$

In this equation, *A* is a binary indicator for the purchase of a new electrical appliance during the last 6 months period by the household *i*. Other variables of interest are identical to the variables described in Equation 1. *DI* and *DC* stand for the treatment indicators of the households in the group DI and DC. We also have the interaction terms of the selected characteristics of the household head (***H***), household's socioeconomics (***S***), and dwelling's characteristics (***D***) with the treatment indicators *DI* and *DC* to capture heterogeneous treatment effects. The ($\boldsymbol{X}$) stands for the vector of time-invariant controls, and the ϵ_i stands for the random error term.

Since our dependent variable is binary in nature Equation 2 is estimated via a standard probit estimation procedure. We report the estimated average marginal effects in Table 3.

Table 3: Probit regression results (average marginal effects)

Variables	**Appliance purchase**
Main Treatment Effect:	
(DI)	-0.308 (0.279)
(DC)	-0.339 (0.274)
Respondent's characteristics:	
Female × *(DI)*	0.249 (0.170)
Female × *(DC)*	0.174 (0.186)
High Educ. Female × *(DI)*	-0.141(0.192)
High Educ. Female × *(DC)*	0.280 (0.223)
Age>36 × *(DI)*	-0.163 (0.140)
Age>36 × *(DC)*	-0.381** (0.190)
Age56+ × *(DI)*	(omitted)
Age56+ × *(DC)*	0.126 (0.263)
Respondent pays bills × *(DI)*	0.270* (0.158)
Respondent pays bills × *(DC)*	0.138 (0.170)
Household's characteristics:	
Income 25th perc. × *(DI)*	0.147 (0.216)
Income 25th perc. × *(DC)*	0.007 (0.264)
Income 100th perc. × *(DI)*	-0.209 (0.235)
Income 100th perc. × *(DC)*	0.035 (0.242)
IncomeMissing × *(DI)*	-0.200 (0.159)
IncomeMissing × *(DC)*	-0.287 (0.186)
HHsize4+ × *(DI)*	0.396** (0.175)
HHsize4+ × *(DC)*	0.261 (0.187)
E.Cons.25th perc. × *(DI)*	0.340** (0.149)
E.Cons.25th perc. × *(DC)*	0.101(0.176)
E.Cons.100th perc. × *(DI)*	0.117 (0.212)
E.Cons.100th perc. × *(DC)*	0.106 (0.196)
Dwelling's characteristics:	
Detached house × *(DI)*	-0.204 (0.180)
Detached house × *(DC)*	-0.057 (0.190)
Rooms<3 × *(DI)*	-0.219 (0.163)
Rooms<3 × *(DC)*	-0.042 (0.158)
Rooms4+ × *(DI)*	-0.234 (0.167)
Rooms4+ × *(DC)*	-0.051 (0.207)
Heating with elect. × *(DI)*	0.089 (0.171)
Heating with elect. × *(DC)*	0.313* (0.190)
*Time-invariant controls (**X**)*	*yes*
N	*228*
Pseudo. R^2	*0.231*

Note: Reported coefficients are average marginal effects. *Delta-method* standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The estimated marginal effects, again, suggest that the impact of DI and DC treatments have a differential impact on various subsets of the population. For instance, the DI treatment is more effective in the case of households where the head is directly involved in paying the utility bills. In these types of households, the probability of purchasing a new electrical appliance due to the consumption peer reports increases by about 0.27.

We also observe that DI treatment increases the probability of appliance purchase in large families (4 plus members) by about 0.4 and by about 0.34 among the households in the lower quartile of consumption distribution. The same types of households, however, do not seem to exhibit any statistically significant reaction in terms of appliance purchase in the case of DC treatment.

We attribute this difference in significance to the treatment mechanisms. The inclusion of associated costs may potentially create a higher perceived financial burden and reduce the likelihood of appliance purchases. Additionally, the presence of a potential crowding-out effect (Sudarshan, 2017), where the inclusion of costs in the DC treatment offsets the effectiveness of the DI treatment, could also contribute to the lack of statistical significance for the DC treatment.

The DC treatment, on the other hand, (consumption plus associated costs) increases the probability of appliance purchase (by about 0.31) among the households that use electricity as a primary source of heating. This result suggests that the inclusion of associated costs in the treatment has a motivating effect on appliance purchases for households relying on electricity as their primary heating source. It implies that the consideration of associated costs related to electricity consumption may encourage these households to invest in new electrical appliances. Interestingly, the DC treatment also decreases the probability of appliance purchases among the households headed by younger members (aged 36 or less).

We can attribute the decrease in the probability of purchasing appliances among households headed by younger members (aged 36 or less) in response to the DC treatment (receiving peer reports on electricity consumption plus associated costs) compared to the lack of statistically significant effect from the DI treatment (receiving peer reports on electricity consumption without associated costs) to several factors. Younger household heads may be more cost-sensitive or financially constrained, leading them to be more cautious about additional appliance purchases when the associated costs are considered. They may have different priorities or preferences that allocate their resources towards other needs or have a lower interest in purchasing appliances at that stage of their lives. The inclusion of associated costs in the DC treatment could further deter them from making appliance purchases, while the DI treatment, which focuses solely on consumption without considering costs, may not impose the same financial strain and therefore does not significantly affect their appliance purchasing behavior.

We also do not find any statistically significant relationship between income and the purchase of new electrical appliances. This result is in contrast to Turdaliev (2021) who finds a strong positive relationship between the purchase of appliances and income in the case of Russia.

4. Conclusion

One of the most significant and widespread initiatives in reducing energy consumption within residential areas is the implementation of Demand Side Management (DSM) programs (Aydin et al., 2018). These programs are designed to decrease the energy demand of households, thereby contributing to the reduction of carbon emissions.

Our study focuses on reducing household energy consumption as a crucial part of global decarbonization efforts. By providing information and social cues, also known as "nudges", we investigated their effects on household energy decisions in Yerevan, Armenia. We collected data on rates of energy consumption and payments from about 300 house owners, who were randomly assigned to one of three groups: control, social consumption comparison, and social consumption comparison with a focus on monetary costs. While the overall relationship between receiving monthly peer comparison reports and reduced energy consumption was statistically insignificant, we found strong and statistically significant heterogeneous treatment effects.

We also examined the effects of information provision on electricity consumption patterns, with a particular focus on consumption during the day and night time. The findings highlight that providing information for consumption peer comparison (DI), both with and without information of the associated monetary consumption costs (DC), results in reductions in daytime electricity consumption, when the marginal cost of electricity is higher.

Notably, the study reveals that households in the upper quartile of consumption and those using electricity as a primary source of heating significantly reduce their monthly electricity consumption in response to receiving peer comparison reports.

Furthermore, the analysis identifies heterogeneous effects based on demographic characteristics. The results indicate that in the DI treatment group, households headed by educated females exhibit a statistically significant reduction in total monthly electricity consumption, suggesting the positive role of female education in driving energy conservation practices. Similarly, within the DC treatment group, households headed by older individuals demonstrate a greater sensitivity to the inclusion of information on associated consumption costs, leading to a significant decrease in monthly electricity usage. These findings underscore the importance of considering demographic factors when designing energy conservation interventions, and making them more accessible and informative for elderly parts of the population.

Moreover, the study explores the impact of information provision on appliance purchases as a proxy for changes in the physical stock of capital. The results reveal that the DI treatment increases the probability of appliance purchase among households where the head is directly responsible for paying utility bills, large families, and households in the lower quartile of consumption distribution. However, the DC treatment does not yield statistically significant effects on appliance purchase behavior for the same types of households, possibly due to the perceived financial burden associated with considering costs and the potential crowding-out effect.

Our findings contribute to the growing body of literature on the effectiveness of nudges in the context of developing countries, where rapid growth in energy consumption is observed. Previous research has suggested that interventions that have been effective in developed countries may not necessarily work in developing countries due to differences in cultural, social, and economic contexts (Henrich et al., 2010).

By shedding light on the heterogeneous effects of information provision, particularly among higher-consuming households, educated females, and older individuals, this research contributes to our understanding of the underlying mechanisms that drive electricity consumption patterns.

In addition, our research demonstrates that peer comparison reports can effectively reduce energy usage in developing countries. The results emphasize the significance of customized approaches that take into account specific demographic and housing characteristics, as well as the importance of providing information to influence electricity consumption at different times of the day in the context of emerging economies.

By integrating these insights into policy design and implementation, policymakers can develop strategies that empower individuals and households to make informed decisions regarding their electricity consumption, ultimately contributing to a more sustainable energy future.

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Appendix

Table A1: Fixed effects regression results with expenditure proxy (coefficients indicate kWh)

Variables	**Total Consumption**	**Day Consumption**	**Night Consumption**
Main Treatment Effect:			
(DI)	8.662 (29.798)	-0.640 (20.193)	9.302 (11.395)
(DC)	28.479 (23.548)	21.071 (16.596)	7.408 (8.442)
Respondent's characteristics:			
Female × *(DI)*	15.965 (18.767)	12.581 (12.702)	3.385 (7.133)
Female × *(DC)*	0.145 (22.757)	-2.335 (16.325)	2.481 (8.665)
High Educ. Female × *(DI)*	-32.617^{*} (17.925)	-24.147^{*} (12.782)	-8.470 (7.458)
High Educ. Female × *(DC)*	-16.792 (24.519)	-4.286 (17.732)	-12.506 (9.449)
Age<36 × *(DI)*	-8.201 (15.908)	-5.816 (11.488)	-2.385 (5.633)
Age<36 × *(DC)*	7.334 (21.918)	4.017 (14.921)	3.317 (8.366)
Age56+ × *(DI)*	-42.819 (34.902)	-25.413 (23.124)	-17.406 (12.247)
Age56+ × *(DC)*	-14.889 (17.833)	-8.287 (13.594)	-6.603 (6.930)
Respondent pays bills × *(DI)*	2.084 (17.077)	2.598 (10.796)	-0.514 (7.810)
Respondent pays bills × *(DC)*	-19.716 (20.342)	-13.240 (13.596)	-6.475 (7.745)
Household's characteristics:			
Expend. 25^{th} perc.× *(DI)*	-0.150 (25.294)	1.220 (16.613)	-1.369 (9.909)
Expend. 25^{th} perc. × *(DC)*	19.359 (30.984)	11.406 (22.891)	7.953 (9.957)
Expend. 100^{th} perc. × *(DI)*	16.539 (21.771)	17.940 (15.497)	-1.401 (8.344)
Expend. 100^{th} perc. ×*(DC)*	-21.929 (27.180)	-13.729 (19.388)	-8.200 (8.934)
Expend.Missing × *(DI)*	21.737 (16.290)	15.960 (11.802)	5.777 (6.323)
Expend.Missing × *(DC)*	42.097^{**} (19.735)	26.359^{*} (13.835)	15.737^{**} (7.833)
HHsize4+ × *(DI)*	-3.954 (17.066)	-7.035 (12.109)	3.081 (6.319)
HHsize4+ × *(DC)*	23.537 (17.052)	14.275 (12.516)	9.261 (6.016)
E.Cons.25^{th} perc. × *(DI)*	34.884^{**} (15.476)	30.562^{***} (11.210)	4.322 (5.186)
E.Cons.25^{th} perc. × *(DC)*	23.447^{*} (13.798)	19.144^{*} (9.881)	4.303 (5.186)
E.Cons.100^{th} perc. × *(DI)*	-111.129^{***} (26.772)	-90.743^{***} (19.888)	-20.387^{*} (11.609)
E.Cons.100^{th} perc. × *(DC)*	-80.818^{***} (24.012)	-61.497^{***} (16.606)	-19.321^{*} (10.368)
Dwelling's characteristics:			
Detached house × *(DI)*	7.008 (18.288)	1.878 (12.143)	5.131 (7.535)
Detached house × *(DC)*	-1.061 (18.560)	0.208 (13.661)	-1.269 (6.865)
Rooms<3 × *(DI)*	-13.271 (15.285)	-6.920 (11.117)	-6.352 (4.896)
Rooms<3 × *(DC)*	-9.056 (17.811)	-9.031 (12.959)	-0.025 (6.360)
Rooms4+ × *(DI)*	-0.383 (19.814)	12.672 (14.374)	-13.055^{*} (7.675)
Rooms4+ × *(DC)*	-15.919 (19.335)	-8.323 (11.812)	-7.595 (9.771)
Heating with elect. × *(DI)*	-72.196^{***} (25.610)	-54.338^{***} (19.081)	-17.858^{*} (10.026)
Heating with elect. × *(DC)*	-71.019^{**} (32.335)	-63.122^{***} (23.859)	-7.897 (11.084)
Household fixed effects	*yes*	*yes*	*yes*
Month fixed effects	*yes*	*yes*	*yes*
N	2083	2083	2083
adj. R^2	0.299	0.347	0.139
F-statistics	19.102	20.141	7.347
p-value	0.000	0.000	0.000

Note: Clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Probit regression results with expenditure proxy (average marginal effects)

Variables	**Appliance purchase**
Main Treatment Effect:	
(DI)	-0.309 (0.245)
(DC)	-0.186 (0.251)
Respondent's characteristics:	
Female × *(DI)*	0.270 (0.166)
Female × *(DC)*	0.098 (0.194)
High Educ. Female × *(DI)*	-0.209 (0.185)
High Educ. Female × *(DC)*	0.312 (0.240)
Age>36 × *(DI)*	-0.152 (0.135)
Age>36 × *(DC)*	-0.334^{*} (0.184)
Age56+ × *(DI)*	(omitted)
Age56+ × *(DC)*	0.081 (0.240)
Respondent pays bills × *(DI)*	0.206 (0.144)
Respondent pays bills × *(DC)*	0.051 (0.161)
Household's characteristics:	
Expend. 25^{th} perc. × *(DI)*	0.135 (0.194)
Expend. 25^{th} perc. × *(DC)*	0.048 (0.196)
Expend. 100^{th} perc. × *(DI)*	0.051 (0.199)
Expend. 100^{th} perc. × *(DC)*	-0.061 (0.235)
Expend.Missing × *(DI)*	-0.067 (0.166)
Expend.Missing × *(DC)*	-0.496^{**} (0.218)
HHsize4+ × *(DI)*	0.352^{**} (0.166)
HHsize4+ × *(DC)*	0.094 (0.182)
E.Cons.25^{th} perc. × *(DI)*	0.309^{**}(0.140)
E.Cons.25^{th} perc. × *(DC)*	0.089 (0.178)
E.Cons.100^{th} perc. × *(DI)*	0.157 (0.207)
E.Cons.100^{th} perc. × *(DC)*	0.060 (0.191)
Dwelling's characteristics:	
Detached house × *(DI)*	-0.188 (0.170)
Detached house × *(DC)*	0.055 (0.182)
Rooms<3 × *(DI)*	-0.205 (0.154)
Rooms<3 × *(DC)*	-0.043 (0.155)
Rooms4+ × *(DI)*	-0.215 (0.166)
Rooms4+ × *(DC)*	-0.054 (0.199)
Heating with elect. × *(DI)*	0.082 (0.171)
Heating with elect. × *(DC)*	0.335^{*} (0.202)
*Time-invariant controls (**X**)*	*yes*
N	*228*
Pseudo. R^2	0.241

Note: Reported coefficients are average marginal effects. *Delta-method* standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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