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Abstract

Using a long-term randomized field experiment in Yerevan, Armenia, we study heterogeneous household responses to behavioural energy reports in a post-Soviet transition-economy setting. Households were assigned to a control group, a consumption-comparison report arm, or a consumption-plus-cost report arm that added monetary bill information to the same peer comparisons. Reports were sent monthly during two report-delivery periods separated by a prolonged pause. Average treatment effects mask substantial heterogeneity by socioeconomic status (SES), female education, baseline electricity use, and electric heating. High-SES households respond differently to the added monetary information than low-SES households, while households with a tertiary-educated female respondent exhibit more conservation-oriented responses. Both patterns are clearest during report-delivery months under the consumption-plus-cost reports. Households using electricity for heating show strong conservation-oriented responses, whereas low-baseline users can exhibit boomerang-type increases under consumption-plus-cost reporting. Responses during pause months also differ across groups, implying that intermittent reporting is not uniformly beneficial but depends on subgroup targeting and report content.

Keywords: Demand-side management; intermittent nudges; peer comparison; socioeconomic status; principal component analysis; heterogeneous treatment effects; post-Soviet economy; developing country; Armenia.
JEL codes: Q41; Q48; Q58; C93; D91.

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1. Introduction

Reducing household energy demand is a central component of climate mitigation and energy-security policy. Climate policy requires urgent and substantial reductions in greenhouse gas emissions (IPCC, 2023), and household energy use accounts for a sizeable share of global energy consumption (Tsiropoulos et al., 2020). Behavioural interventions, including social-comparison nudges, have therefore attracted attention as complements to price-based demand-side management policies. However, recent demand-side policy studies show that the effectiveness of these interventions depends not only on average treatment effects, but also on which households respond. Heterogeneity in treatment effects by baseline energy use is well documented in the literature (see, e.g., Allcott, 2011; Ayres, Raseman, and Shih, 2013; Knittel and Stolper, 2021; Murakami et al., 2022).

This question is especially important beyond high-income settings. Although electricity demand in advanced economies is rising again because of data centres, artificial intelligence, and broader electrification, most projected growth in global electricity demand remains concentrated in emerging market and developing economies (IEA, 2026). Yet much of the evidence on behavioural energy interventions comes from high-income settings, and such findings do not always generalize to other institutional, social, and cultural contexts (Henrich, Heine, and Norenzayan, 2010). Socioeconomic status (SES) and female education are likely to be particularly relevant in these settings because they can shape both the effectiveness and the distributional consequences of energy and climate policies (Dutta, Saha, and Mukta, 2025; Cheng, Walshe, and Mi, 2025; Shen, Ma, and Li, 2025; Heymann et al., 2026). However, causal evidence from randomized field experiments remains limited.

Thus, in this paper, we focus on two underexamined dimensions of heterogeneity in behavioural energy interventions: socioeconomic status and female education. Although these dimensions may matter even in high-income Western countries, they are especially relevant in developing and post-Soviet transition economies, where tighter budget constraints and gendered patterns of household decision-making can shape how households process and act on energy feedback. The limited existing evidence partly reflects data constraints: many nudge experiments do not collect sufficiently granular household-level socioeconomic characteristics or cannot credibly link survey data to administrative or billing outcomes. To the best of our knowledge, no previous randomized field experiment on household energy nudges has explicitly examined heterogeneity in responses along both socioeconomic status and female education, and this gap is especially pronounced in developing and post-Soviet transition economies. We address this gap by using detailed data from a long-run randomized field experiment in Yerevan, Armenia, which combines electricity billing records with rich baseline survey measures of household assets, dwelling characteristics, respondent demographics, and education.

Socioeconomic status and women's education are plausible moderators of household responses to behavioural energy interventions because they shape both constraints and capabilities, including the ability to adjust electricity use and the capacity to interpret and act on information provided in energy reports. For instance, in development economics, adoption of beneficial technologies is often limited not only by expected returns, but also by liquidity constraints, fixed transaction costs, learning, and attention (Duflo, Kremer, and Robinson, 2011; Dupas, 2014; Fowlie and Meeks, 2021). At the household level, resource allocation is also shaped by who controls resources and by the human capital of household decision-makers (Thomas, 1990; Lundberg, Pollak, and Wales, 1997; Duflo, 2012). Applied to energy reports, these studies imply that SES may condition whether households can act on feedback, while female education may condition how information is interpreted and translated into routine consumption choices. The Armenian setting is well suited to studying these margins because residential consumers face an increasing-block tariff and pronounced seasonal variation in electricity demand (Turdaliev, Sargsyan, and van Koten, 2026). These features make electricity costs salient and create scope for adjustment, but households may differ in whether they can respond to that scope without reducing comfort and in how they process report information. The post-Soviet setting also provides evidence outside the high-income contexts that dominate the behavioural energy literature.

In the experiment, we randomly assigned households to one of three groups: a control group, a treatment arm receiving monthly consumption-comparison reports, and a treatment arm receiving consumption-plus-cost reports that added monetary cost information to the same peer comparisons. Reports were delivered intermittently, with two report-delivery periods separated by a prolonged pause. This design allows us to examine whether treatment responses differ across socioeconomic subgroups and whether those differences persist when reports stop and reappear when report delivery resumes. The design therefore links two questions that are usually studied separately: who responds to behavioural energy reports, and whether those responses persist under intermittent reporting.

To measure socioeconomic status, we construct a household SES index using principal component analysis (PCA) (Jolliffe, 1986; Vyas and Kumaranayake, 2006). Following Filmer and Pritchett (2001), we derive the index from durable assets and dwelling characteristics, an approach widely used when reported income is missing, noisy, or incomplete (McKenzie, 2005; Vyas and Kumaranayake, 2006; Howe, Hargreaves, and Huttly, 2008). We then standardise and validate the index and estimate heterogeneous treatment effects by SES and by whether the respondent is a woman with tertiary education. We also examine heterogeneity by baseline electricity consumption and electric heating, which are standard energy-use moderators in this literature and provide a benchmark for interpreting the SES and female-education results.

The empirical results show that average treatment effects are an incomplete guide to behavioural responses in this setting. Treatment effects vary substantially by SES and female education, and the effect of adding monetary information depends on household characteristics. High-SES households do not simply respond more or less than low-SES households. Instead, their response changes with report content: during report-delivery months, the consumption-plus-cost report shifts their response upward relative to low-SES households. By contrast, households with a tertiary-educated female respondent display more conservation-oriented responses, with the strongest estimate also appearing during delivery of the consumption-plus-cost reports. In the other treatment-phase cells, the female-education interactions point toward lower electricity consumption but are less precisely estimated, and thus we interpret them as directional evidence.

Heterogeneity also appears along baseline energy-use characteristics, which we include as established moderators in the behavioural energy literature (Allcott, 2011; Ayres, Raseman, and Shih, 2013; Harold, Lyons, and Cullinan, 2018; Knittel and Stolper, 2021; Murakami et al., 2022). Households using electricity for heating exhibit the strongest and most robust conservation-oriented responses. Low-baseline-consumption households sometimes exhibit boomerang-type increases, especially under consumption-plus-cost reports. For high-baseline-electricity consumers, the evidence is more concentrated: the only statistically significant high-baseline interaction appears during report-delivery months with the consumption-comparison reports, while the corresponding estimates in other treatment-phase cells are negative but imprecisely estimated. Comparing report-delivery and pause months further shows that treatment effects are not equally persistent across groups. For electric-heating households, conservation effects persist during the pause, although they are generally weaker than during report-delivery months.

Taken together with earlier findings, these results show that intermittent report delivery can preserve some conservation-oriented responses during pause months, especially among households with electric heating (Turdaliev, Sargsyan, van Koten, 2026). They also show why average effects are a poor basis for judging whether intermittent report delivery is beneficial. Once heterogeneity by socioeconomic status and female education is accounted for, intermittent reporting is better understood as a context-dependent design whose consequences vary across household groups and depend on report content.

Overall, this paper contributes to the literature by showing that behavioural energy reports in a transition-economy setting cannot be evaluated only through average electricity reductions. The same intervention produces different effects depending on household resources, female education, technical saving potential, and report content. This matters for policy because low-cost behavioural intervention programmes are attractive in settings with limited demand-side-management budgets, but their efficiency and distributional consequences depend on who responds and in which direction.

The remainder of this paper is structured as follows. Section 2 reviews the related literature. Section 3 provides background on Armenia's electricity pricing and describes the experimental design and treatment reports. Section 4 presents the data and key variables. Section 5 explains the construction and validation of the SES index using principal component analysis. Section 6 outlines the empirical strategy. Section 7 presents the results, including heterogeneity by socioeconomic status, female education, baseline consumption, and electric heating, as well as differences between report-delivery and pause months. Section 8 concludes.

2. Related Literature

Evidence from high-income residential energy markets shows that information, incentives, and social comparison feedback can reduce household energy use (Allcott and Mullainathan, 2010; Allcott, 2011; Ayres, Raseman, and Shih, 2013; Allcott and Rogers, 2014; Jessoe and Rapson, 2014). A central reason is that households often do not observe or process the information needed to optimise electricity consumption, especially when tariffs, technologies, and attention costs make energy choices difficult to evaluate (Borenstein, 2009; Jessoe and Rapson, 2014; Ito, 2014). Demand-side management programmes therefore often combine pricing and information tools to reduce residential demand (Aydin, Brounen, and Kok, 2018).

One prominent strand of this research studies social-norm and peer-comparison messages, often referred to as behavioural nudges. In electricity settings, peer-comparison reports are among the more consistently effective informational interventions, reducing energy use by giving households feedback on their own consumption, simple conservation tips, and comparisons with similar peers (Schultz et al., 2007; Nolan et al., 2008; Allcott and Mullainathan, 2010; Allcott, 2011; Costa and Kahn, 2013; Ayres, Raseman, and Shih, 2013; Allcott and Rogers, 2014; Knittel and Stolper, 2021). Evidence from water demand points to a similar mechanism: social-comparison messages can generate more persistent reductions than purely informational or pro-social appeals (Ferraro, Miranda, and Price, 2011; Ferraro and Price, 2013; Ferraro and Miranda, 2013).

The policy relevance of these interventions depends not only on average treatment effects, but also on who responds. In energy-nudge experiments, responses often vary with baseline consumption, household characteristics, and dwelling or technology constraints (Allcott, 2011; Costa and Kahn, 2013; Ayres, Raseman, and Shih, 2013; Knittel and Stolper, 2021; Murakami et al., 2022). Compared with baseline consumption and heating technology, socioeconomic and demographic moderators remain less settled. Observational and cross-country studies suggest that education, financial literacy, and broader socioeconomic status are associated with energy-conservation practices, residential energy use, energy-efficiency investments, and environmental concern (Mills and Schleich, 2012; Brounen, Kok, and Quigley, 2012; Brent and Ward, 2018; Pampel, 2014). Feedback interventions may also require households to notice, understand, and act on information that is not always salient in routine energy decisions (Fischer, 2008). Household responses to behavioural energy interventions may therefore depend on whether the information is salient and understandable, whether households engage with it, and, in some contexts, whether they trust the institutions or actors delivering it (Jessoe and Rapson, 2014; Buchanan, Russo, and Anderson, 2015; Caferra, Colasante, and Morone, 2021). Experimental evidence also shows that demand-side responses can vary across household social characteristics (Harold, Lyons, and Cullinan, 2018), although not all studies detect robust demographic heterogeneity, including by female household headship (Dolan and Metcalfe, 2015). This makes socioeconomic status and female education important but under-examined margins for studying whether behavioural energy reports work equally across households. These margins may be especially consequential in developing and transition economies because household constraints are often more binding and are less well captured by income alone. Socioeconomic status can reflect appliance stocks, liquidity, housing quality, access to energy-efficient technologies, and the ability to adjust consumption without reducing comfort.

Moreover, in emerging-economy settings, informational frictions may be larger and households may face tighter constraints, including limited liquidity for energy-efficiency investments and institutional factors that shape trust in utilities and public messaging. Electricity use also varies systematically with household income and composition, suggesting that socioeconomic characteristics may shape how households respond to energy information (Brounen, Kok, and Quigley, 2012). These constraints may matter more where households have limited savings or credit access, where dwellings and appliances are less efficient, and where reported income is noisy or incomplete (Fowlie and Meeks, 2021; Bound et al., 2001).

For this reason, a multidimensional socioeconomic status (SES) index can be more informative than a single income variable when studying household responses to energy feedback in these settings. Female education may also matter because women often play an important role in daily household energy practices, durable-good choices, and the translation of information into routine consumption decisions, while gender gaps in education and decision-making may be more pronounced in many developing and transition-economy settings. Recent energy and climate evidence suggests that female education can shape household energy and environmental outcomes. Dutta, Saha, and Mukta (2025) link female education to lower-carbon household consumption patterns, Cheng, Walshe, and Mi (2025) show that reducing gender inequality in education is associated with climate-mitigation gains, and Shen, Ma, and Li (2025) show that gender is related to energy poverty, clean-energy access, and energy expenditure in rural China. Taken together, this evidence suggests that women's education may matter for energy behaviour through several margins, including information processing, household decision-making, and access to cleaner technologies. We therefore treat women's education as a baseline source of heterogeneity in household responses to energy information, consistent with broader development evidence linking women's empowerment to household welfare and resource allocation (Duflo, 2012).

Findings from post-Soviet household data further indicate that energy-policy responses vary with household energy characteristics and with other constraints that are not visible in average electricity consumption alone. Turdaliev, Sargsyan, and van Koten (2026) document heterogeneity in responses to behavioural energy reports by baseline consumption and electric heating. Turdaliev (2023) estimates that Russian households respond to household- and dwelling-specific increasing-block electricity tariffs, but that the implied average electricity-demand response is small. Turdaliev (2021) finds that the same type of tariff reform increased households' propensity to purchase major electrical appliances, while Turdaliev and Janda (2024) find that it also increased households' propensity to purchase dirty fuels, especially among households without district heating. Turdaliev (2025) further documents that dirty-fuel purchase responses to increasing-block tariff reform vary by energy-technology access, utility subsidies, household-head gender, and vulnerable employment status. Sargsyan and Turdaliev (2024) link unreliable electricity supply in the Kyrgyz Republic to worse child anthropometric outcomes, with stronger adverse effects for girls. Together, these studies motivate looking beyond average electricity-consumption effects and incorporating household-level constraints and adjustment margins into the evaluation of energy policies in post-Soviet settings.

A final distinction concerns the content of the reports. Our experiment separates consumption-comparison peer reports from consumption-plus-cost reports. Adding monetary cost information may strengthen conservation by increasing bill salience, but it may also weaken responses if reported costs are perceived as small relative to income or if households respond negatively to the framing. For low-income households, the bill may be a salient budget item, whereas for higher-income households the same amount may be too small to trigger behavioural adjustment. These mechanisms imply that identical nudges can generate different responses across SES, and that adding explicit cost information, as in the consumption-plus-cost report arm, may amplify or attenuate savings depending on households' perceived budget constraints and ability to process energy-related financial information (Brent and Ward, 2018). This channel differs from policies that directly change marginal prices or provide monetary incentives, such as time-varying prices, rebates, or reward programmes (Dolan and Metcalfe, 2015; Sudarshan, 2017; Ito, Ida, and Tanaka, 2018). The distinction is important because adding cost information may interact with SES and female education even when the underlying electricity tariff is unchanged.

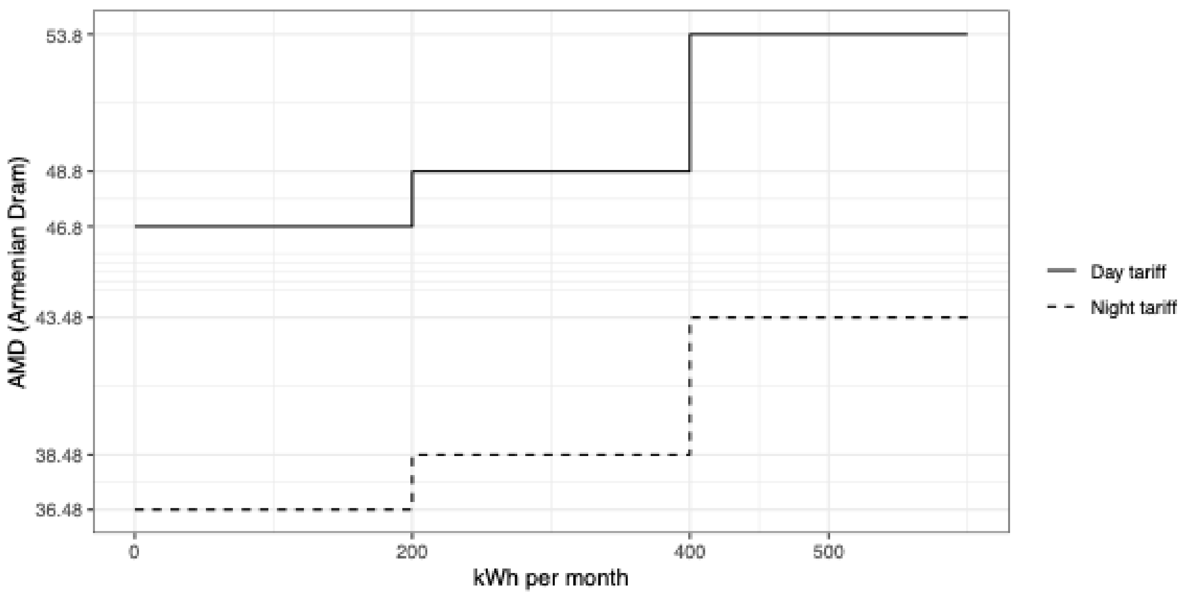
Taken together, this evidence shows that social peer comparisons can reduce energy use, but that responses are heterogeneous in ways that matter for cost-effective policy design (Costa and Kahn, 2013; Harold, Lyons, and Cullinan, 2018; Allcott and Kessler, 2019; Knittel and Stolper, 2021; Murakami et al., 2022). Most existing evidence focuses on baseline consumption, heating technology, and other dwelling characteristics, and it comes primarily from high-income settings. Much less is known about whether responses to behavioural energy nudges vary systematically by socioeconomic status and female education, especially in developing and post-Soviet transition economies, where these dimensions may be particularly relevant for both effectiveness and equity (Duflo, 2012; Fowlie and Meeks, 2021). We address this gap by using a long-run randomised field experiment in Yerevan, Armenia. We combine an intermittent report design with a transparent PCA-based measure of socioeconomic status and examine how treatment responses vary by SES and female education.

3. Armenia's Electricity Context and the Experimental Design

3.1. Electricity Pricing

Armenia has one of the least diversified energy portfolios in Eastern Europe and Central Asia. Unlike many countries in the region, where coal, LPG, liquid fuels, and other solid fuels account for meaningful shares of energy consumption, Armenia's reported energy use is concentrated mainly in natural gas, electricity, and wood. Combined with Armenia's dependence on imported natural gas, this narrow energy portfolio increases household exposure to tariff changes and external energy-price shocks (Krauss, 2016; Kochnakyan et al., 2013). Residential electricity tariffs are centrally regulated and were historically flat. Since February 2021, however, Armenia has used an increasing block tariff (IBT) system under which tariffs depend on monthly consumption and vary by time of day, with a lower night tariff (23:00–07:00) and a higher day tariff (07:00–23:00). As shown in Figure 1, the tariff schedule consists of three consumption blocks: 0–200 kWh, 200–400 kWh, and above 400 kWh. A distinctive feature of the Armenian IBT is that households pay a single tariff applied to total monthly consumption. Thus, crossing a consumption threshold causes the higher tariff to apply to all electricity consumed rather than only to the units above the threshold.
Figure 1 below depicts the electricity tariff schedule faced by households in our sample.

Figure 1: Electricity Tariff Schedule



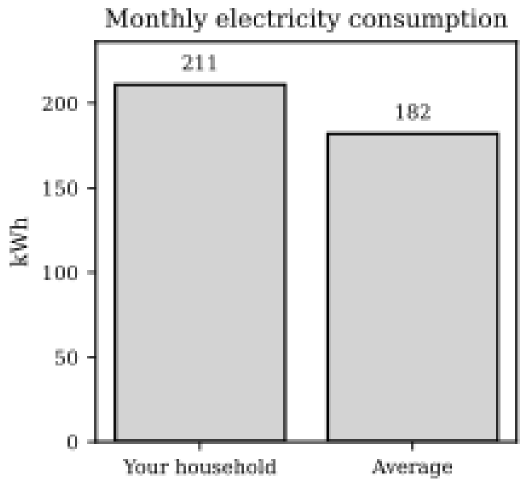
Note: The solid line shows the day tariff applied from 07:00 to 23:00, and the dashed line shows the night tariff applied from 23:00 to 07:00. Tariffs are reported in Armenian drams per kWh. Under Armenia's increasing-block tariff, the applicable rate is determined by total monthly consumption and applies to all electricity consumed during the month.

3.2. Intervention Content

After the baseline survey and collection of pre-treatment electricity bill information, we randomly assigned households to one of three arms: a control arm, a consumption-information (CI) report arm, and a consumption-plus-cost information (CCI) report arm. This three-arm design allows us to estimate the effects of the two report arms relative to the control arm and to assess how adding cost information changes the response.

Households in the CI treatment received peer-comparison electricity reports showing their monthly consumption relative to the average consumption of comparable households in the study sample, defined by the number of rooms and heating type. Households in the CCI treatment received the same peer comparisons, supplemented with monetary cost information that displayed the household's electricity payment alongside the corresponding average payment for comparable households. The control arm did not receive feedback, but its electricity consumption was tracked throughout the study in the same way as for treated households. Following the social-norm literature, the reports also included a simple injunctive cue encouraging conservation (see, e.g., Schultz et al., 2007). The report format was held constant over time so that variation in outcomes can be attributed to treatment timing and content rather than changes in design. Figures 2 and 3 illustrate example reports for the CI and CCI treatment arms, respectively.

Figure 2: Example of the CI Treatment Report

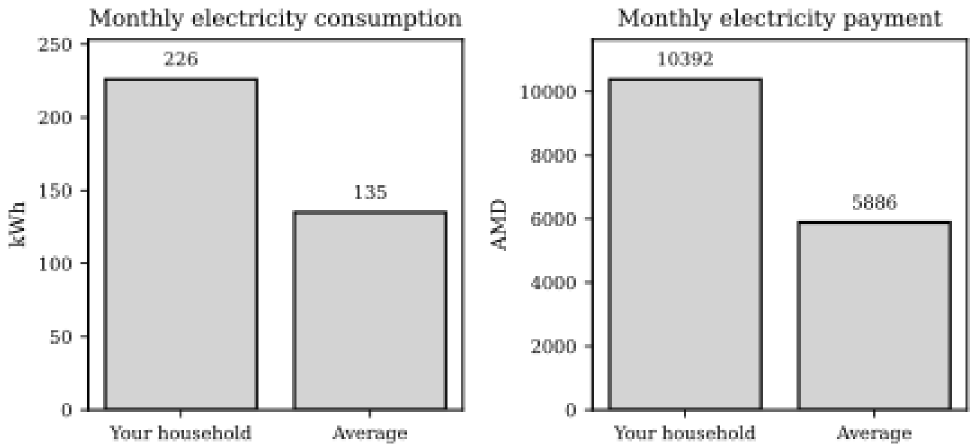


Every month you will receive a short summary of your household's electricity use. The summary also shows the average electricity use of comparable households in Yerevan, defined by the number of rooms and the main heating type. The goal is to help you spot where reductions may be possible. Please try to limit unnecessary use, check the appliances you operate most often, and reflect on everyday consumption habits.

Note: The reports were originally delivered to households in Armenian and are shown here in English translation. The layout is adapted for presentation purposes.

Figure 3: Example of the CCI Treatment Report

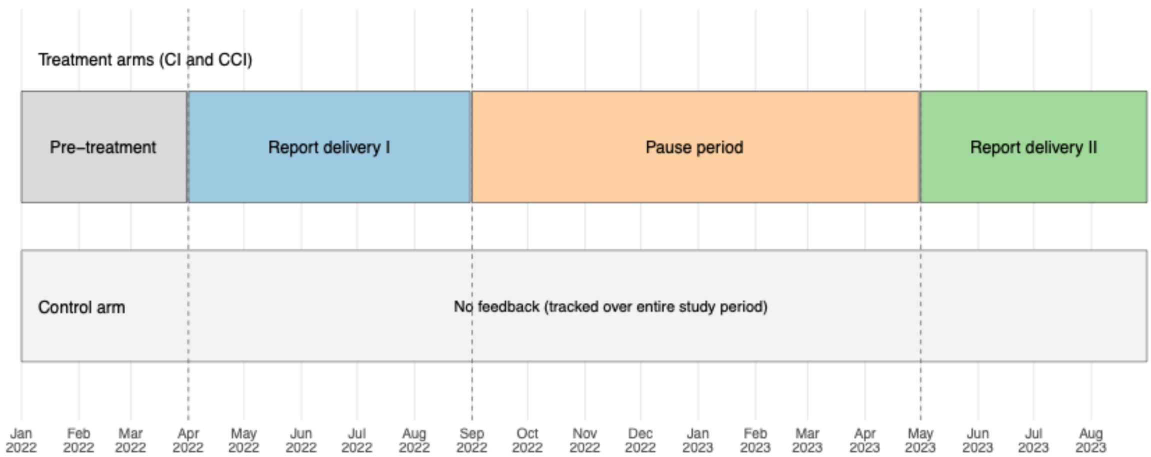
Every month you will receive a short summary of your household's electricity use together with the corresponding payment. The summary also reports the average electricity use and payment among comparable households in Yerevan, defined by the number of rooms and the main heating type. The goal is to help you identify potential savings. Please try to limit unnecessary use, check the appliances you operate most often, and reflect on everyday consumption habits.



Note: The reports were originally delivered to households in Armenian and are shown here in English translation. The layout is adapted for presentation purposes.

A defining feature of the report design is its intermittent timing. Following a three-month pre-treatment period with no feedback (January to March 2022), reports were delivered to the two treatment arms during an initial five-month report-delivery phase (April to August 2022), paused for eight months (September 2022 to April 2023), and reintroduced for a second four-month report-delivery phase (May to August 2023). In our experiment, this variation in timing allows us to examine whether treatment effects differ between report-delivery and pause months, across report contents, and across household subgroups. Figure 4 summarizes the timing of report delivery across treatment and control arms.

Figure 4: **Experimental Timeline and Treatment Phases**



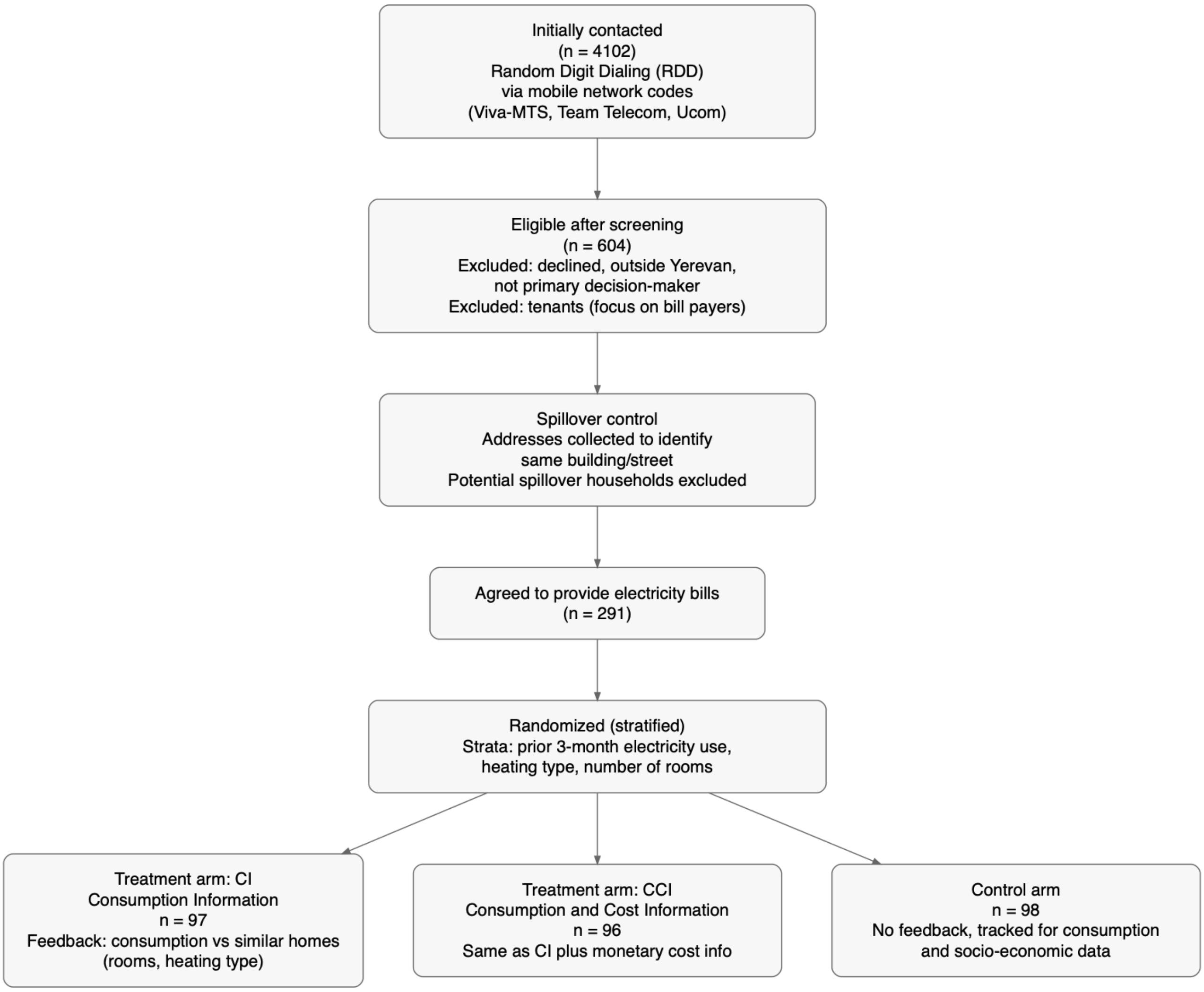
Note: The figure summarizes the experimental timeline from January 2022 to August 2023. Households assigned to the CI and CCI treatment arms received reports during the first report-delivery period, April-August 2022, and again during the second report-delivery period, May-August 2023. No reports were sent during the pause period, September 2022-April 2023. Control households received no feedback and were tracked over the full study period. Vertical dashed lines mark transitions between phases.

Data collection and recruitment were undertaken in collaboration with International Marketing Research (IMR), a Yerevan-based survey and market research firm. [1] Recruitment used

[1] International Marketing Research (IMR) is a Yerevan-based survey and market research firm with extensive experience in quantitative and qualitative fieldwork. It operates under ICC/ESOMAR professional standards and has collaborated with a range of major international organisations and private-sector clients, including the World

telephone-based random-digit dialing of Armenian mobile numbers. The initial recruitment reached 4,102 residents. After screening, 604 respondents completed a baseline survey on dwelling characteristics, durable assets, and socio-demographics. Of these, 291 households agreed to provide monthly electricity billing data and were enrolled in the experiment. Households were randomly assigned at the household level to a control group (n = 98), a CI group (n = 97), or a CCI group (n = 96). To improve comparability across arms, assignment was stratified using pre-treatment electricity consumption and key demand-related household characteristics, in particular heating type and number of rooms. Figure 5 summarizes the recruitment, screening, and assignment process.

Figure 5: **Recruitment, Screening, and Random Assignment**



Note: The figure summarizes the recruitment, screening, spillover-control, and random assignment process. Random digit dialing was used to contact households through mobile network codes. Eligible households were screened to exclude households outside Yerevan, tenants, households that declined participation, and respondents who were not the primary household decision-maker. The final experimental sample includes 291 households randomly assigned to the consumption information arm (CI), the consumption-plus-cost information arm (CCI),

Bank, UNICEF, Yandex, HSBC, Philip Morris International, and Coca-Cola (https://www.imr.am). In this study, recruitment relied on random-digit dialing across Armenian mobile numbers associated with the country's main mobile network operators, namely Viva-MTS, Team Telecom, and Ucom.

or the control arm. Randomization was stratified by prior three-month electricity use, heating type, and number of rooms.

4. Data and Variables

The baseline experimental sample comprises 291 households. The panel follows households over 20 consecutive months. The balanced panel would contain 5,820 household-month observations. We removed 251 observations with unusually high monthly electricity use above 700 kWh, corresponding to more than the 95th percentile: 76 from CI households, 95 from CCI households, and 80 from control households. We also excluded 35 household-month observations because electricity-use data were missing for specific months, typically when households did not report their consumption on time: 16 from CI households, 13 from CCI households, and 6 from control households. These exclusions leave 5,534 household-month observations. After these exclusions, 16 households have no usable electricity-consumption observations remaining in the three-month pre-treatment period and therefore cannot be assigned to a baseline-consumption group. Excluding these households yields a heterogeneity-regression sample of 5,334 observations from 275 households.

The panel covers the pre-treatment period, the first report-delivery period, the pause period, and the second report-delivery period. This structure provides repeated observations on the same households and allows the analysis to study treatment responses across the different report-delivery and pause phases and across different seasons of the year, including both hot and cold months. Moreover, the study is conducted within a single urban context whose population is relatively homogeneous, with 98.94% of Yerevan's population reported as Armenian[2]. This reduces cross-regional and cross-group variation in the sampling frame relative to large multi-region post-Soviet panels and supports the internal comparability of households in the experimental sample.[3]

The primary outcome variable is monthly household electricity consumption, measured in kilowatt-hours (kWh). The baseline survey collected information on dwelling characteristics, durable assets, and socio-demographics, including variables used to construct the SES index and the female education indicator. We also observe whether households use electricity for heating and their pre-treatment electricity consumption. Because these baseline characteristics are time invariant, household fixed effects absorb their main effects; the empirical analysis uses them primarily through interactions with treatment and phase indicators.

Table 1. Summary Statistics (baseline household cross-section)

Variable	N	Mean	SD
Female respondent	291	0.512	0.501
Respondent pays utility bills	291	0.670	0.471
Employed	291	0.588	0.493

[2] https://worldpopulationreview.com/cities/armenia/yerevan

[3] Our sample also closely resembles the population of Yerevan on key household energy characteristics; a detailed comparison is reported in Turdaliev, Sargsyan, and van Koten (2026). Moreover, although the empirical sample comprises 5,334 household-month observations, its sample-to-population ratio exceeds that of one of the largest household panels in the post-Soviet space—the RLMS-HSE—by an order of magnitude, once the smaller population size of Yerevan is taken into account.

Age	291	40.619	9.647
Higher education	291	0.509	0.501
Technical secondary education	291	0.165	0.372
Secondary education	291	0.323	0.468
Reported monthly household income (AMD)	203	354,000	234,000
Reported monthly household expenditure (AMD)	209	240,000	204,000
Household size	291	4.364	1.729
Baseline electricity consumption (kWh)	275	213.443	98.255
Private house	291	0.247	0.432
Multi-apartment building	291	0.753	0.432
Number of rooms	291	2.900	1.130
Electricity as primary heating source	291	0.210	0.408
Gas as primary heating source	291	0.667	0.472
Stove as primary heating source	291	0.155	0.362
Solid fuels as primary heating source	291	0.027	0.164

Note: The table reports baseline household-level summary statistics for the experimental sample. Binary variables are coded as 0/1 so their means can be interpreted as sample proportions. Income and expenditure are reported in Armenian dram (AMD). The number of observations differs for income and expenditure because these variables are missing for some households. Baseline electricity consumption is reported for 275 households because 16 households have no usable electricity-consumption observations in the three-month pre-treatment period after the outcome-data exclusions.

Table 1 reports summary statistics for the baseline household cross-section. In addition to demographic, housing, and heating variables, the table reports self-reported household income and expenditure, which are available for fewer households because of item non-response.
The baseline statistics show substantial variation across households along dimensions central to the analysis. Slightly over half of respondents are female, and approximately two thirds report being responsible for paying utility bills. Respondents are, on average, 40.6 years old, employment is common, and educational attainment is relatively high, with about half reporting higher education. Among households that report monetary measures, mean monthly income and expenditure are AMD 354,000 and AMD 240,000, respectively, with substantial dispersion in both variables.

Households contain, on average, 4.36 members and predominantly live in multi-apartment buildings. Heating technologies also vary: gas is the most common primary heating fuel, while electricity heating and stove-based heating are used by sizeable minorities, and solid-fuel heating is rare. Baseline electricity consumption is dispersed, with a mean of about 213.5 kWh and a standard deviation of about 98.3 kWh. Overall, the baseline data provide meaningful variation in socioeconomic conditions, housing characteristics, heating technologies, and pre-treatment electricity demand. Table 2 examines whether these characteristics were balanced across experimental arms at baseline. [4]

Table 2: Randomisation Balance Across Three Arms (baseline)

Variable	N	CI p-value	CCI p-value	Joint p-value
Female respondent	291	0.617	0.667	0.863

[4] Descriptive statistics by experimental arm are reported in Turdaliev, Sargsyan, and van Koten (2026).

Respondent pays utility bills	291	0.619	0.191	0.171
Employed	291	0.713	0.233	0.473
Age	291	0.699	0.559	0.597
Higher education	291	0.226	0.153	0.304
Technical secondary education	291	0.162	0.289	0.327
Secondary education	291	0.840	0.578	0.854
Reported monthly household income	203	0.183	0.070	0.172
Reported monthly household expenditure	209	0.663	0.387	0.684
Household size	291	0.061	0.362	0.173
Baseline electricity consumption (kWh)	275	0.670	0.841	0.913
Private house	291	0.969	0.287	0.493
Multi-apartment building	291	0.969	0.287	0.493
Number of rooms	291	0.794	0.943	0.963
Electricity as primary heating source	291	0.626	0.786	0.887
Gas as primary heating source	291	0.611	0.245	0.508
Stove as primary heating source	291	0.859	0.405	0.572
Solid fuels as primary heating source	291	0.992	0.396	0.653

Note: *p*-values are from regressions of each baseline covariate on indicators for the CI and CCI treatment arms, with the control arm as the reference category. The joint p-value tests whether the CI and CCI coefficients are both equal to zero.

Table 2 reports regression-based randomisation balance tests. For each baseline covariate, we regress the covariate on indicators for the consumption information (CI) and consumption-plus-cost information (CCI) report arms, with the control arm as the reference category. The table reports *p*-values for the individual treatment indicators and a joint *p*-value testing whether both treatment coefficients are equal to zero.

Overall, the balance tests are consistent with successful randomisation and show no evidence of systematic baseline imbalance across experimental arms. Core demographic characteristics, education variables, dwelling characteristics, heating technologies, and baseline electricity consumption are balanced across groups. Baseline electricity use is a key moderator in the heterogeneity analysis, and it is also well balanced across treatment arms (joint *p*-value = 0.913). Self-reported household income displays a lower *p*-value for the CCI arm, but the corresponding joint test is insignificant and no similar pattern appears for household expenditure. Given the number of balance tests, the smaller sample for self-reported income measure, and the absence of systematic patterns across related variables, we do not interpret this as evidence of meaningful imbalance.

Taken together, Tables 1 and 2 provide the descriptive foundation for the empirical strategy. Table 1 documents substantial baseline variation in socioeconomic conditions, housing characteristics, heating technologies, and electricity demand, while Table 2 indicates that these characteristics are balanced across experimental arms. This supports interpreting subsequent heterogeneous treatment effects as differences by baseline household characteristics rather than artefacts of pre-treatment imbalance.

5. Empiricial Strategy

To study whether responses to behavioural energy reports differ by socioeconomic status (SES), we require a baseline measure that reflects persistent household resources rather than short-run income fluctuations. We construct a household-level SES index using standard principal component analysis (PCA) on nine baseline inputs: eight durable-asset indicators and dwelling size, measured by the number of rooms. The asset indicators are ownership of air conditioning, a blender, an automatic dishwasher, a food processor, an LCD TV, a microwave oven, a separate refrigerator, and an automatic washing machine. Asset-index PCA is widely used when reported income is missing, noisy, or an incomplete measure of longer-run economic position (Filmer and Pritchett, 2001; McKenzie, 2005; Vyas and Kumaranayake, 2006; Howe, Hargreaves, and Huttly, 2008). Because most inputs are binary, we treat the index as a transparent within-sample ranking measure rather than as a structural model of welfare.

5.1. PCA Construction

Let $X_i \in \mathbb{R}^K$ denote the vector of SES input variables for household *i*, where K = 9. In our application, X_i includes indicators for durable assets (dishwasher, washing machine, microwave, food processor, blender, LCD TV, separate refrigerator, an air-conditioning) indicator, and the number of rooms in the apartment.
Because the variables are measured on different scales, all inputs are standardised before applying PCA.

$$Z_{ki} = \frac{X_{ki} - \mu_k}{\sigma_k}, k = 1, \ldots, K$$

Here μ_k and σ_k are the household-level sample mean and standard deviation of input k. Let

$$Z_i = \left(Z_{1i}, \ldots, Z_{Ki}\right)'$$

denote the vector of standardised SES inputs. PCA is applied to the correlation matrix of the original SES inputs, equivalently to the covariance matrix of the standardised variables. Let

$$w = \left(w_1, \ldots, w_K\right)'$$

be the unit-length eigenvector associated with the largest eigenvalue. The raw SES score is

$$SES_{Score_i} = \Sigma_{k=1}^{K} w_k Z_{ki}$$

We then standardise this score to obtain the SES index used in the heterogeneity analysis:

$$SES_{z_i} = \frac{SESscore_i - \mu_{SESscore}}{\sigma_{SESscore}}$$

where $\mu_{SESscore}$ and $\sigma_{SESscore}$ denote the mean and standard deviation of the raw PCA score in the household-level estimation sample. The resulting index has mean zero and standard deviation one in the household-level estimation sample. For the main heterogeneity specifications, we define a binary high-SES indicator using the median of the standardised index:

$$HighSES_i = \mathbf{1}\{SES_{Z_i} > median(SES_Z)\}$$

The low-SES group is the omitted category. In the regression specification, $HighSES_i$ enters through interactions with the phase-treatment indicators:

$$T_{it} \times HighSES_i$$

where

$$T_{it} = \left(Info_{Active_{it}}, Info_{Passive_{it}}, Cost_{Active_{it}}, Cost_{Passive_{it}}\right)'$$

5.2. Diagnostic Checks and Validation

In PCA-based SES measurement, the first principal component is the natural candidate index because it is the weighted linear combination of the input variables that explains the largest share of common variation. Following this convention, we treat PC1 as the candidate SES ranking measure and then assess whether it is suitable for the empirical analysis. Table 3 reports the inputs used to construct the PCA-based SES index. The ownership rates provide useful variation for ranking households: LCD TVs and automatic washing machines are common, dishwashers, food processors, and air conditioning are relatively uncommon, and microwave ovens, blenders, and separate refrigerators occupy the middle of the distribution. We orient the first principal component so that higher values correspond to greater asset ownership and larger dwellings; with this orientation, all nine inputs have positive weights.

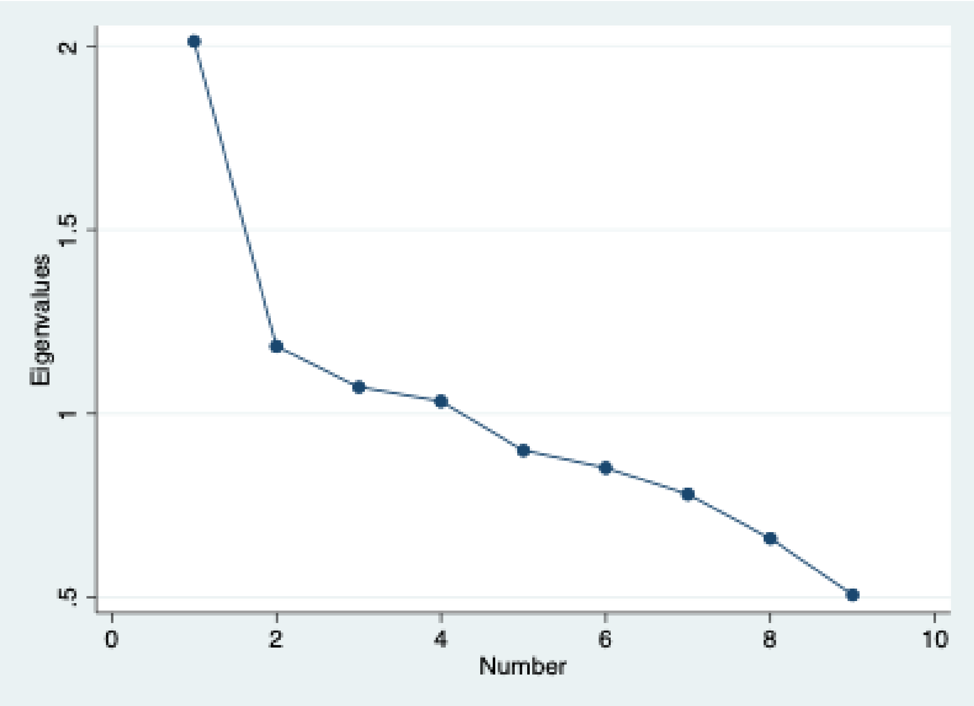
Table 3: Variables Used to Construct the PCA-Based SES Index

Variable	Description	Mean	SD	PC1 weight
Blender	Ownership of blender	0.230	0.422	0.528
Dishwasher (automatic)	Ownership of automatic dishwasher	0.089	0.286	0.160
Food processor	Ownership of food processor	0.103	0.305	0.443
LCD TV	Ownership of LCD television	0.808	0.395	0.278
Microwave	Ownership of microwave oven	0.271	0.445	0.461
Refrigerator (separate)	Ownership of separate refrigerator	0.186	0.389	0.209
Washing machine (automatic)	Ownership of automatic washing machine	0.766	0.424	0.231
Air conditioning	Ownership of air conditioning unit	0.110	0.313	0.268
Dwelling size	Number of rooms in the apartment	2.900	1.130	0.204

Note: The table reports the variables used to construct the socioeconomic-status index. Asset variables are binary indicators equal to one if the household owns the item and zero otherwise. Dwelling size is measured as the number of rooms in the apartment. The final column reports the loading of each variable on the first principal component (PC1), which is used to construct the SES index.

We use four diagnostic checks. First, the scree plot in Figure 6 shows that PC1 has the largest eigenvalue and that there is no clear secondary break in the eigenvalue profile.

Figure 6: Scree Plot of Eigenvalues from the PCA



Notes: The figure displays the scree plot of eigenvalues from the principal component analysis of household asset ownership and dwelling characteristics. The first principal component has an eigenvalue larger than the subsequent components, and the remaining eigenvalues decline without a clear secondary break.

Second, the loading matrix in Table 4 confirms that PC1 has a monotone asset-wealth interpretation after orienting the component so that higher values represent higher SES. All PC1 weights are positive. Higher-order components have mixed signs and are therefore less suitable for the simple rank-based heterogeneity analysis used in the paper.

Table 4:

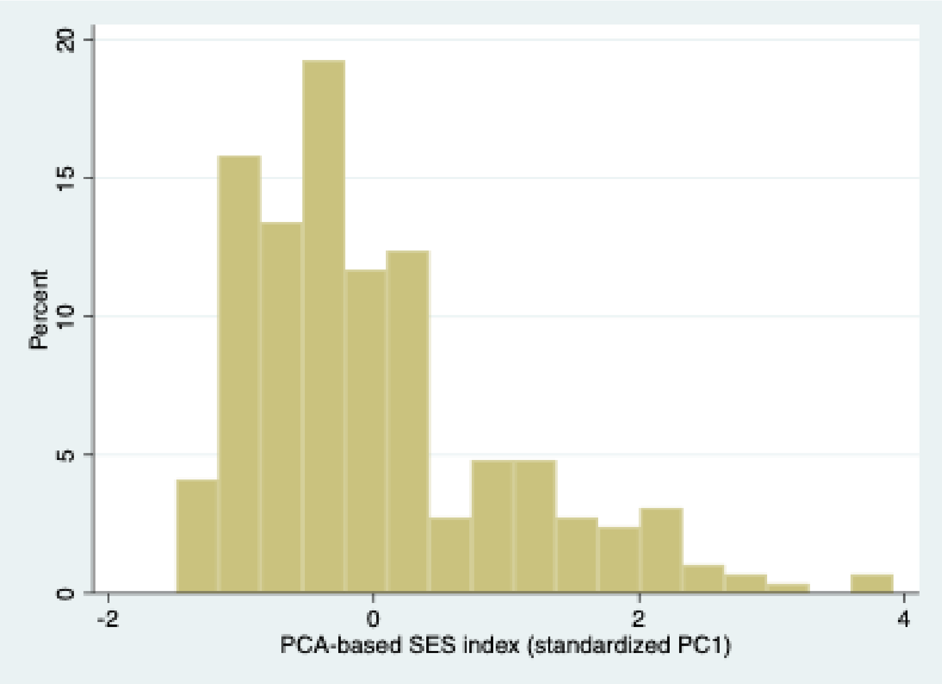
Variable	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**	**PC9**
Dishwasher (automatic)	0.160	0.592	0.150	−0.404	0.141	0.064	0.627	−0.127	−0.074
Washing machine (automatic)	0.231	0.197	0.628	0.093	0.185	−0.596	−0.272	0.122	0.161
Microwave	0.461	−0.067	−0.227	−0.039	−0.241	−0.269	−0.096	−0.768	0.029
Food processor	0.443	−0.335	0.004	−0.314	−0.300	0.059	0.204	0.379	0.560
Blender	0.528	−0.239	0.067	−0.162	0.099	0.097	−0.099	0.245	−0.738
LCD TV	0.278	−0.113	−0.365	0.292	0.781	−0.038	0.170	0.025	0.223
Refrigerator (separate)	0.209	0.318	−0.250	0.624	−0.420	−0.207	0.270	0.305	−0.131
Air conditioning	0.268	0.054	0.458	0.431	−0.024	0.677	−0.044	−0.221	0.139
Number of rooms	0.204	0.566	−0.347	−0.203	0.017	0.228	−0.607	0.182	0.149

Notes: Loadings are from the PCA loading matrix with components in columns and SES variables in rows. The SES index used in the empirical analysis is based on PC1 and is standardised to have mean zero and standard deviation one.

Third, Figures 7 and 8 show that the index has meaningful dispersion across households. The distribution is right-skewed, with most households concentrated at lower and middle SES values and a thinner upper tail. This shape is consistent with the asset-ownership pattern in

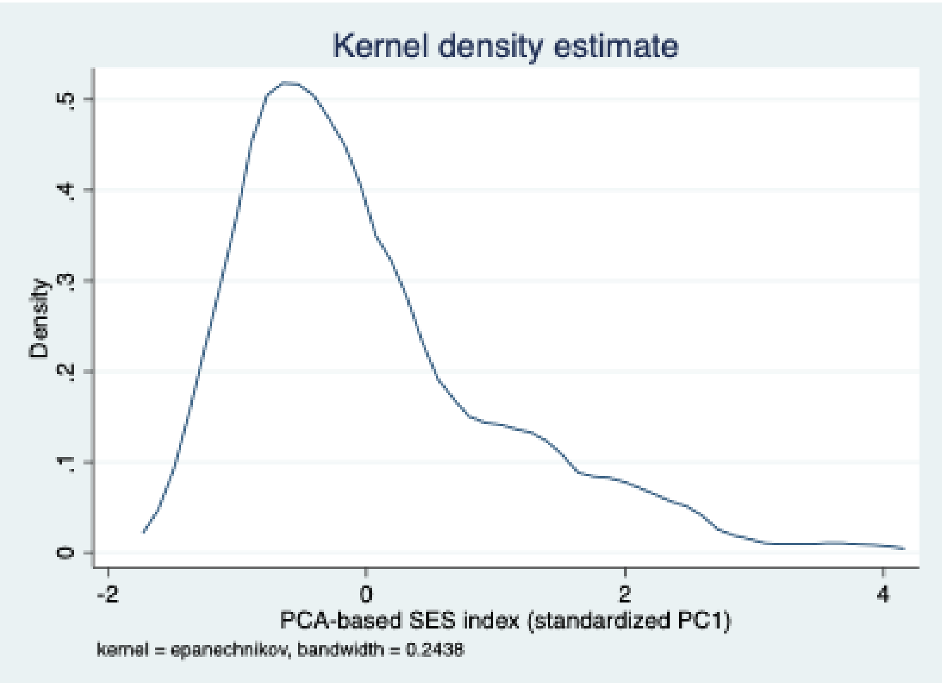
Table 3 and supports the use of a median split as a transparent, within-sample classification of lower- and higher-SES households.

Figure 7: Distribution of the Standardized SES Index



Notes: The figure shows the distribution of the socioeconomic status (SES) index constructed from the first principal component of household asset ownership and dwelling characteristics. The index is standardised to have mean zero and unit variance.

Figure 8: Kernel Density of the Standardized SES Index



Notes: The figure presents a kernel density estimate of the standardised SES index based on the first principal component. The density confirms the right-skewed distribution observed in the histogram.

Fourth, we compare the PCA-based SES measure with reported household income via a descriptive validation exercise. If the asset-based index is a plausible proxy for longer-run household economic position, higher SES scores should be positively associated with reported income. Table 5 shows that this is the case in both the continuous-index and median-split specifications.

Table 5: Association Between the PCA-Based SES Measures and Reported Household Income

VARIABLES	(1) HHincome on SES_{Z_i}	(2) HHincome on $HighSES_i$
SES index (PC1), standardized (mean 0, sd 1)	48,772.841***	
	(16,757.356)	
High SES (median split of SES_{Z_i}) = 1		96,807.227***
		(32,906.843)
Constant	360,043.065***	311,376.106***
	(16,514.426)	(20,223.943)
Observations	203	203
R-squared	0.039	0.043

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The table reports cross-sectional associations using the household baseline sample with non-missing reported income. The regressions are used as face-validity checks for the PCA-based SES measure.

A one-standard-deviation increase in SES_{Z_i} is associated with AMD 48,772.841 higher monthly household income, and households above the median SES threshold report AMD 96,807.227 higher monthly income on average than households below the median. Both associations are statistically significant at the 1% level. Because income is observed for only part of the sample and may be measured with error, these regressions should be interpreted only as face-validity checks. They support using SES_{Z_i} as a proxy for longer-run household economic position in the heterogeneity analysis.

Taken together, the diagnostic checks above support using PC1 as the primary SES ranking measure in our heterogeneity analysis.

5.4. Estimation Strategy

We estimate household fixed-effects regressions with calendar-month fixed effects to study how assignment to the two report arms affects monthly electricity consumption across report-delivery and pause months. The dependent variable is monthly electricity consumption in kWh for household i in month t. The source of identifying variation is randomized assignment interacted with the timing of report delivery and pause phases. Because treatment assignment is time invariant, it is absorbed by household fixed effects; the identified treatment variables are therefore treatment-arm-by-phase indicators rather than treatment assignment alone.

Equation (1) presents our econometric specification:

$$tot_{it} = \alpha_i + \lambda_t + D_{it}^{'}\beta + D_{it}^{'}\Gamma X_i + P_t^{'}\Delta X_i + \varepsilon_{it} \quad (1)$$

In Equation (1), D_{it} is the vector of treatment-arm-by-phase indicators, defined as:

$$D_{it} = (CI_i \times Intervention_t, CI_i \times Pause_t, CCI_i \times Intervention_t, CCI_i \times Pause_t)'$$

where CI_i indicates assignment to the consumption information report arm and CCI_i indicates assignment to the consumption-plus-cost information report arm. $Intervention_t$ equals one during active report-delivery months and $Pause_t$ equals one during pause months; both indicators are zero in the pre-treatment period.

The phase vector is:

$$P_t = (Intervention_t, Pause_t)'$$

and the heterogeneity vector is:

$$X_i = (HighSES_i, HeatElec_i, LowBase_i, HighBase_i, EducFem_i)'$$

where $HighSES_i$ is the indicator for households above the median of the PCA-based socioeconomic-status index, $HeatElec_i$ identifies households using electricity as a primary source for heating, $LowBase_i$ and $HighBase_i$ identify low- and high-baseline electricity consumers, and $EducFem_i$ identifies households with a tertiary-educated female respondent.[5]

The matrices Γ and Δ collect the interaction coefficients: rows correspond to treatment-phase or phase indicators, respectively, and columns correspond to the household characteristics in X_i. The products $D_{it}'\Gamma X_i$ and $P_t'\Delta X_i$ therefore provide compact notation for the treatment-heterogeneity terms and the phase-by-characteristic controls.

The household fixed effect α_i absorbs all time-invariant household characteristics, including treatment assignment, the main effects of X_i, and time-invariant assignment-by-characteristic terms. The calendar-month fixed effect λ_t absorbs aggregate month-specific variation, including seasonality, common demand shocks, and the main effects of the phase indicators. The interaction terms remain identified because they vary across households and over the report-delivery calendar.

The coefficient vector β estimates treatment-arm-by-phase differences for the omitted household-characteristic group: lower-SES households without electric heating, in the middle-baseline-consumption group, and without a tertiary-educated female respondent.

The matrix Γ contains the treatment-effect heterogeneity estimates. Each element is interpreted as the difference in a treatment-arm-by-phase effect associated with the corresponding household characteristic. For a subgroup defined by one characteristic, the full subgroup effect is obtained by adding the corresponding coefficient in β to the relevant element of Γ.

[5] Since tertiary-educated female respondents may be more likely to live in higher-SES households, we examined the relationship between the SES measures and the female-education indicator. Households with a tertiary-educated female respondent have, on average, a higher SES score ($p = 0.013$), but the correlation between the above-median SES indicator and the female-education indicator is very small and statistically insignificant ($r = 0.053$, $p = 0.394$). These diagnostics indicate that the SES and female-education indicators capture distinct household dimensions.

The matrix Δ contains the phase-by-characteristic controls. These terms allow households with different baseline characteristics to have different consumption patterns during report-delivery and pause months in the absence of treatment. Including them helps ensure that the heterogeneity estimates in Γ do not capture subgroup-specific seasonal demand patterns or other phase-related changes common to treated and control households.

Standard errors are clustered at the household level to allow for serial correlation in the error term ε_{it} within households. Because the specification includes several interaction terms, multiple-testing concerns are relevant. We therefore interpret the heterogeneity estimates using statistical significance together with magnitude, sign consistency, and coherence across treatment arms and phases, rather than relying on individual p-values alone or treating the analysis as an unrestricted search across possible moderators. SES and female education are the main theory-motivated margins of interest and were defined before outcome estimation, while electric heating and baseline consumption provide benchmark comparisons from the energy-nudge literature. This approach is consistent with Viviano, Wüthrich, and Niehaus (2026), who emphasize that the appropriate degree of multiple-hypothesis adjustment depends on the structure and cost of the research problem rather than on a universal rule.

6. Results

Table 6 reports the household fixed-effects estimates from Equation (1). The dependent variable is monthly electricity consumption in kWh. The central result is that average treatment-arm estimates are modest, while the economically meaningful variation appears across pre-specified household characteristics, report content, and treatment timing. This emphasis on heterogeneity is consistent with prior evidence that behavioural energy interventions often generate uneven responses across households rather than a single uniform effect (Costa and Kahn, 2013; Ayres, Raseman, and Shih, 2013; Harold, Lyons, and Cullinan, 2018; Knittel and Stolper, 2021; Murakami et al., 2022).

The phase-specific treatment estimates are small and statistically insignificant for the omitted subgroup, defined as lower-SES households that do not use electricity for heating, have middle-range baseline consumption, and do not have a tertiary-educated female respondent. The consumption information (CI) report estimates are positive in both report-delivery and pause months (8.8 and 11.6 kWh), while the consumption-plus-cost information (CCI) report estimates are slightly negative in both phases (about -5.0 kWh). None is statistically significant. This pattern indicates that the pooled treatment indicators alone do not capture the main empirical structure in the data.

The SES results show that report content matters for the distribution of responses. Under the CI reports, the high-SES interactions are negative during both report-delivery months (-15.6 kWh) and pause months (-10.3 kWh), but neither estimate is statistically distinguishable from zero. Under the CCI reports, the signs reverse: the high-SES interactions are positive during both report-delivery and pause months. The CCI interaction in report-delivery months is economically meaningful and statistically significant (20.8 kWh, $p = 0.045$; about 9.8 percent of mean pre-treatment monthly consumption), while the pause-month estimate is positive but less precisely estimated (12.4 kWh, $p = 0.159$). This pattern is informative because the high-SES differential response changes sign across report content. The estimates therefore do not support a simple conclusion that high-SES households are uniformly more or less responsive. Instead, they suggest that adding monetary cost information shifts the response of high-SES households upward relative to lower-SES households, especially during report-delivery months.

Table 6: Heterogeneous Effects of Report Assignment Across Report-Delivery and Pause Months

	(1)	(2)	(3)
VARIABLES		**se**	**pval**
CI_Report delivery	8.785	(11.371)	0.440
CI_Pause	11.630	(11.098)	0.296
CCI_ Report delivery	-4.990	(11.073)	0.653
CCI_ Pause	-5.004	(9.835)	0.611
CI_ Report delivery × High SES	-15.633	(11.412)	0.172
CI_ Pause × High SES	-10.309	(11.935)	0.388
CCI_ Report delivery × High SES	20.842**	(10.338)	0.045
CCI_ Pause × High SES	12.372	(8.762)	0.159
CI_ Report delivery × heatel	-47.079**	(20.204)	0.021
CI_ Pause × heatel	-36.411*	(20.768)	0.081
CCI_ Report delivery × heatel	-89.981***	(20.942)	0.000
CCI_ Pause × heatel	-47.397***	(14.001)	0.001
CI_ Report delivery × pre25	16.292	(12.685)	0.200
CI_ Pause × pre25	11.569	(11.926)	0.333
CCI_ Report delivery × pre25	30.857***	(10.307)	0.003
CCI_ Pause × pre25	17.669*	(10.126)	0.082
CI_ Report delivery × pre100	-70.379***	(25.269)	0.006
CI_ Pause × pre100	-34.952	(26.584)	0.190
CCI_ Report delivery × pre100	-21.932	(14.800)	0.140
CCI_ Pause × pre100	-11.441	(12.348)	0.355
CI_ Report delivery × FemEdu	-18.322	(13.227)	0.167
CI_ Pause × FemEdu	-16.754	(11.926)	0.161
CCI_ Report delivery × FemEdu	-31.794***	(11.626)	0.007
CCI_ Pause × FemEdu	-15.644	(9.494)	0.101
Constant	246.132***	(4.281)	0.000
Observations		5,334	
R-squared		0.233	
Number of id		275	
Month FE		Yes	
Household FE		Yes	
Phase × heterogeneity interactions		Yes	

Standard errors are clustered at the household level.

*** p<0.01, ** p<0.05, * p<0.1.

Note: Standard errors clustered at the household level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is monthly electricity consumption in kWh. CI denotes the consumption information report arm, and CCI denotes the consumption-plus-cost information report arm. *Report delivery* refers to months when reports were delivered, and *Pause* refers to months when reports were not delivered. *High SES* is an indicator for households above the median of the standardized PCA-based SES index. *heatel* indicates households using electricity as the primary heating source. *pre25* indicates households in the bottom quartile of pre-treatment electricity consumption, and *pre100* indicates households in the top quartile. *FemEdu* indicates households with a tertiary-educated female respondent. All specifications include household fixed effects, calendar-month fixed effects, and phase-by-heterogeneity controls. Coefficients are reported in monthly kWh.

One interpretation is that the monetary component of the report changes the salience of electricity costs differently across households. Prior evidence links residential energy use and conservation behaviour to income, household composition, and financial literacy, which makes it plausible that the same cost information is processed differently across socioeconomic groups (Brounen, Kok, and Quigley, 2012; Brent and Ward, 2018). The present results therefore complement evidence that moral suasion, price incentives, rebates, and rewards need not operate as equivalent demand-side instruments (Ito, Ida, and Tanaka, 2018; Sudarshan, 2017).

The female-education estimates point in the opposite direction. All four interactions for households with a tertiary-educated female respondent are negative: -18.3 kWh during CI report-delivery months, -16.8 kWh during CI pause months, -31.8 kWh during CCI report-delivery months, and -15.6 kWh during CCI pause months. The strongest and most precisely estimated difference appears during CCI report-delivery months (corresponding to about 14.9 percent of mean pre-treatment monthly consumption, p = 0.007). The consistency of the signs suggests that female education is associated with more conservation-oriented responses to the reports, especially when the reports make electricity costs explicit.

This result is consistent with related evidence that education, knowledge, and household characteristics are associated with energy-conservation practices and energy-efficient technology adoption (Mills and Schleich, 2012), and that feedback design and demand-side stimuli can generate heterogeneous household energy responses (Fischer, 2008; Harold, Lyons, and Cullinan, 2018). It also aligns with broader household-energy evidence linking female education to lower-carbon consumption (Dutta, Saha, and Mukta, 2025) and gender-related household characteristics to energy poverty, clean-energy access, and energy expenditure (Shen, Ma, and Li, 2025).

The benchmark energy-use characteristics remain important. Households using electricity for heating have large and statistically significant negative interactions in all four treatment-phase cells. The estimates are larger during report-delivery months than during pause months in both report arms: -47.1 versus -36.4 kWh for the CI report, and -90.0 versus -47.4 kWh for the CCI report. This is equivalent to about 22.1 versus 17.1 percent of mean pre-treatment monthly consumption for CI and about 42.3 versus 22.3 percent for CCI. These estimates indicate that households that may have a greater technical scope for electricity savings account for a large conservation-oriented response (see, e.g., Ayres, Raseman, and Shih, 2013).

Baseline electricity consumption also shapes treatment heterogeneity, but the pattern is asymmetric. Low-baseline households have positive interactions in all four cells, with the clearest evidence under the CCI report: the interaction is positive and statistically significant both during report-delivery months (30.9 kWh, p = 0.003; about 14.5 percent of mean pre-treatment monthly consumption) and during pause months (17.7 kWh, p = 0.082; about 8.3 percent). The contrast with the CI report is informative: the corresponding low-baseline interactions under CI are positive but smaller and statistically imprecise, suggesting that the boomerang-type response is most pronounced when peer comparison is combined with monetary cost information. This interpretation is consistent with Sudarshan (2017), who shows that adding monetary incentives to peer-comparison feedback can eliminate the conservation effect of the nudge. High-baseline households have negative interactions in all four cells, but the only statistically significant estimate is for the CI report-delivery months (-70.4 kWh, p = 0.006; about 33.1 percent of mean pre-treatment monthly consumption). These benchmark results align our study with evidence from transition economies and the broader behavioural energy literature showing that baseline demand, household energy technologies, and other household constraints shape responses to energy policies (Allcott, 2011; Ayres, Raseman, and Shih, 2013; Murakami et al., 2022; Turdaliev and Janda, 2024; Turdaliev, 2025; Turdaliev, Sargsyan, and van Koten, 2026).

Taken together, the CCI results show that monetary cost information is not a neutral add-on to peer comparison. In some groups, adding cost information appears to strengthen conservation-oriented responses: this is most visible among households using electricity for heating and among households with a tertiary-educated female respondent. In other groups, however, the same monetary framing is associated with higher consumption relative to the omitted subgroup, especially among low-baseline households and high-SES households during report-delivery months. The contrast with the CI report suggests that monetary information changes the interpretation of the peer-comparison message rather than simply increasing its salience. This pattern is consistent with evidence that monetary incentives or monetary framing can interact with behavioural feedback in non-linear ways, including by weakening conservation effects in some settings (Sudarshan, 2017; Ito, Ida, and Tanaka, 2018).

The comparison between report-delivery and pause months shows that persistence is not uniform across groups. Conservation-oriented interactions generally attenuate during pause months for electric-heating households, high-baseline households, and households with a tertiary-educated female respondent. At the same time, the positive high-SES interaction under the consumption-plus-cost report is larger during report-delivery months than during pause months. Report delivery therefore strengthens responses, but the direction of that strengthening depends on the household group and the report content.

Overall, Table 6 shows that behavioural energy reports do not generate a single uniform treatment response. The same randomized report assignment is associated with conservation-oriented responses among households with electric heating, high baseline use, and a tertiary-educated female respondent, but with positive differential responses among low-baseline households and high-SES households under CCI reporting. Average treatment effects are therefore an incomplete guide to both the effectiveness and the distributional consequences of the intervention.

7. Conclusion

We study how households respond to behavioural energy reports in a post-Soviet transition-economy setting. Using a randomized field experiment in Yerevan, Armenia, we combine monthly household electricity-consumption with detailed baseline survey measures and a PCA-based index of socioeconomic status. The analysis compares consumption-information (CI) with consumption-plus-cost infromation (CCI) comparison reports across report-delivery and pause months, with particular attention to heterogeneity by SES, female education, baseline electricity use, and electric heating.

The central finding is that average treatment effects conceal economically important differences across households. Standard energy-use characteristics remain important: households using electricity for heating show the strongest conservation-oriented responses, while high-baseline users reduce consumption most clearly during report-delivery months in the CI report group. Low-baseline households, by contrast, show relative increases, especially under CCI reporting. These findings reinforce prior evidence that behavioural energy responses depend on baseline demand, household technologies, and other adjustment margins (Costa and Kahn, 2013; Ayres, Raseman, and Shih, 2013; Knittel and Stolper, 2021; Murakami et al., 2022).

The study's main contribution is to show that SES and female education matter beyond these standard energy-use moderators. High-SES households do not respond uniformly more or less than lower-SES households; their differential response depends on report content and is positive during report-delivery months in the CCI group. Households with a tertiary-educated female respondent display more conservation-oriented responses across report types and phases, with the strongest evidence during CCI report-delivery months. These results suggest that household resources and gender-related human capital shape how households process and act on energy information, even after accounting for baseline consumption and heating technology.

A second implication is that monetary cost information is not a neutral addition to peer comparison. In some groups, especially households using electricity for heating and households with a tertiary-educated female respondent, CCI reports are associated with stronger conservation-oriented responses. In other groups, especially low-baseline and high-SES households during report-delivery months, the same monetary framing is associated with less conservation-oriented responses. This contrast suggests that adding cost information can change how households interpret peer-comparison messages rather than simply making the message more salient.

The pause-month results also qualify the interpretation of intermittent report delivery. Effects generally weaken when reports are no longer sent, but this attenuation has different implications across household groups. For groups with conservation-oriented responses, weaker pause-month effects imply some loss of savings. For groups with upward responses, weaker pause-month effects imply that potentially counterproductive responses also fade. Intermittent delivery therefore affects not only persistence, but also the distribution and direction of responses across households.

With regard to policy, the results argue against one-size-fits-all behavioural messaging. Baseline electricity use and electric heating help identify households with greater technical saving potential, while SES and female education help identify how households may process and act on the same information. In developing and transition-economy settings, where demand-side-management budgets are limited and distributional concerns are salient, programme design should test whether monetary cost information improves conservation for the intended groups rather than assuming that it is a harmless enhancement to peer comparison.

The evidence should be interpreted as reduced-form effects of randomized report assignment. The design identifies how responses differ across household groups and report types, but it does not separately isolate the roles of attention, liquidity constraints, intra-household decision-making, or technology constraints. Future work can build on these findings by testing alternative message designs and by measuring engagement, household decision-making, and technology constraints more directly.

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Abstrakt

Pomocí dlouhodobého randomizovaného terénního experimentu v Jerevanu v Arménii zkoumáme heterogenní reakce domácností na behaviorální zprávy o spotřebě energie v prostředí postsovětské transformující se ekonomiky. Domácnosti byly náhodně zařazeny do kontrolní skupiny, skupiny dostávající zprávy porovnávající jejich spotřebu se spotřebou srovnatelných domácností nebo skupiny dostávající zprávy kombinující porovnání spotřeby s informací o peněžních nákladech na spotřebu. Zprávy byly zasílány měsíčně během dvou období jejich distribuce, která byla oddělena delší přestávkou. Průměrné efekty intervence zakrývají značnou heterogenitu v závislosti na socioekonomickém statusu (SES), vzdělání ženy v domácnosti, výchozí úrovni spotřeby elektřiny a využívání elektřiny k vytápění. Domácnosti s vysokým SES reagují na doplnění peněžní informace odlišně od domácností s nízkým SES, zatímco domácnosti, v nichž má žena terciární vzdělání, vykazují výraznější reakce směřující ke snižování spotřeby. Oba tyto vzorce jsou nejzřetelnější v měsících, kdy byly zprávy zasílány, a to zejména u zpráv kombinujících informace o spotřebě a nákladech. Domácnosti využívající elektřinu k vytápění vykazují výrazné reakce vedoucí ke snížení spotřeby, zatímco domácnosti s nízkou výchozí spotřebou mohou při zasílání zpráv obsahujících informace o spotřebě a nákladech vykazovat nárůst spotřeby typu „boomerang“. Reakce v měsících bez zasílání zpráv se rovněž mezi jednotlivými skupinami liší, což naznačuje, že přerušované poskytování těchto informací není přínosné pro všechny domácnosti stejným způsobem, ale jeho účinnost závisí na cílení na konkrétní skupiny a na obsahu poskytovaných zpráv.

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