A Comparison of Contests and Contracts to Deliver Cost-Effective Energy Conservation

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Abstract

Incentivizing agents to exert costly, unobservable effort is a long-standing problem in economics. We conduct a field experiment in Hanoi, Vietnam where we randomize households into tiered contracts and contests to induce energy conservation. We find that both contests and contracts achieve similar energy savings relative to a pure control group but contests are twice as cost-effective. We build a model of energy consumption and estimate it using our experimental variation. Counterfactual simulations reveal that under most conditions where effort (abatement) is only partially correlated with observed measures of performance (energy use), contests dominate as incentives for energy conservation. We discuss potential implications for wide-spread policies on demand-side management in the residential electricity sector.

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1 Introduction

Global well-being is under threat from climate change, and decarbonization of the electricity sector is necessary to reduce carbon emissions to levels that would prevent widespread and catastrophic damage. The energy sector in low- and middle-income countries presents particular challenges, marked by two key characteristics: (a) higher rates of particulate and carbon emissions per unit electricity generated and (b) low aggregate energy production and transmission losses resulting in lack of access and reliability of electricity. In response to these concerns and because electricity markets traditionally clear almost entirely on the supply side, policymakers are actively promoting demand-side management initiatives, including energy conservation programs in urban households, such as tiered pricing, behavioral nudges, and direct "bonus" payments to keep energy use below a target maximum. Urban energy conservation could help address the problem of grid balancing, that is reducing peak demand, especially as low- and middle-income countries (LMICs) – including Vietnam where we are conducting our study – transition to a larger share of their electricity being generated from renewable resources. This is crucial to achieving the emissions reduction promise of renewable energy.

However, the issue of incentivizing agents (households) to exert costly, unobservable effort (energy abatement) is a long-standing and open question in economics. In many settings, including ours, the principal (utility) observes a performance measure (energy use) correlated with agent's effort but not the effort directly because the principal is unable to observe shocks beyond the control of the agent (e.g. weather, household demand shock). Different incentive schemes have been proposed and studied, including behavioral nudges and individual contracts (Brandon et al., 2019). Behavioral nudges attempt to change household decisions by providing information. Individual contracts reward households that reduce their energy consumption, relative to their own past consumption, by a certain percentage. Another possible solution is to use rank-ordered tournaments that incentivize relative performance, thereby obviating the need for the principal to observe common shocks.

We draw on a rich theoretical and nascent empirical literature on contracts and rank-ordered tournaments to test aggregate conservation across contracts and contests and recover parameters that allow us to understand their effects at scale. We address three key questions. First, what is the cost effectiveness of contests relative to contracts in reducing energy conservation when contracts are incomplete because household's abatement effort and costs are unobservable to the utility. Second, do these effects persist over time and after the end of the contest/contract period? Third, how can these programs be scaled in a cost-effective and

fiscally feasible manner in LMICs?

To answer our research questions, we first conduct a randomized field experiment during the summer of 2023. We design contests and contracts. Specifically, we partner with a state-owned electric utility in Hanoi, Vietnam, and utilize their mobile app as a platform for our energy savings contests and contracts. This collaboration has made it possible for us to recruit thousands of households to participate in our study. Then, we randomize the participants into a control and three treatment groups. The first two treatment groups receive contracts of different terms and conditions, while the third treatment group engages in contests. Our treatment period spans 30 days, commencing from July 15, 2023, and concluding on August 13, 2023.

We utilize the experimental data along with a reduced-form empirical analysis to estimate the impacts of our experimental contests and contracts. Our preliminary findings indicate that both contests and contracts effectively promote energy conservation. To be more specific, on average, households in the treatment groups reduce their energy consumption by approximately 7% to 9% in comparison to the control group. Furthermore, our empirical results provide robust evidence of a "deadline effect". The treatment groups only exhibit noticeable differences in energy usage compared to the control group during the final two weeks of the treatment, with the most significant impact observed during the last week of the treatment period. Additionally, we will explore the heterogeneous treatment effects with the aim of pinpointing the households in which the treatment most effectively encourages energy savings.

Next, we leverage our experimental data to estimate a structural model for the purpose of uncovering key parameters. These parameters enable us to deduce an optimal contract and make a comparison between our contest and the ideal contract. Additionally, our structural model provides a means to assess the welfare implications associated with various energy savings programs. Our initial findings indicate that, in terms of cost-effectiveness, contests outperform the optimal contract. This performance gap widens as the average payout increases.

We make important contributions to the empirical literature on tournaments. Specifically, we provide new evidence on a classic question in the tournaments literature: whether tournaments dominate contracts (Lazear and Rosen, 1981; Green and Stokey, 1983). A strength of our analysis is that the tournament and contract designs faced by participants are randomly assigned and we observe a high-frequency performance measure (i.e., energy use) before, during, and after the competitions. Importantly, relative to prior work, we provide a large-

scale field experiment in a typical major urban metropolitian city in an LMIC generating externally valid results.

Importantly, the paper not only informs the design of energy conservation policies and the efficiency in incentivizing behavior to manage demand in the context of LMICs, but also provide us with the cost-effectiveness of various energy conservation programs and consequently a menu of costs per metric ton of CO2 abated. Thus, this paper makes a significant contribution to the body of research on energy conservation in LIMCs. While numerous researchers have investigated policies aimed at reducing energy consumption and promoting investments in energy efficiency within developed countries (Ito, 2015; Levinson, 2016; Houde and Aldy, 2017; Fowlie et al., 2018), there remains a need for further research on energy conservation policies within the context of LMICs (Davis et al., 2014; Costa and Gerard, 2021; Berkouwer and Dean, 2022).

The paper is organized as follows: Section 2 describe our randomized field experiment. Section 3 provides details on the data and descriptive statistics. Section 4 examines the empirical specifications and findings regarding the impacts of our experimental contracts and contests on electricity consumption, including their heterogeneous effects. Section 5 describes our structural model and the estimation process. Section 6 discusses our structural model's results. Section 7 assesses the cost-effectiveness and welfare implications of our different energy conservation programs. Finally, Section 8 concludes.

2 The Experiment

2.1 Sampling

Our target population is households in Hanoi, the capital and the second largest city of Vietnam. With rapid economic growth since the Vietnamese economic reform started in 1986, the city has seen many Hanoians moving out of poverty and into the middle class. Many households can now afford new televisions, refrigerators, or air-conditioners for the first time. The city's hot and humid weather also spurs demand for new and heavy use of air conditioners. Those trends in energy consumption put the city at the top of the nation in terms of electricity consumption per person. At the same time, Hanoi (and the rest of Vietnam) also faces energy constraints that manifest into rolling blackouts and intermittent electricity access. In these respects, Hanoi is well representative of urban populations where

energy use is expected to dramatically increase over the next three decades.

The electric utility in Hanoi, EVN HANOI, has over 2.8 million customers, and 90% of them have smart meters. About 25% of all households in Hanoi have installed the utility's app. Through our partnership with the utility and the utility app's developer, we advertise our program and recruit participants through different channels, including the utility's official website, and fan pages, banners and ads in the utility's app, and offline marketing. Since we primarily advertise the program via banners and ads in the utility's app, the majority of our sample for this initial study will include households that already have downloaded the utility's app for tracking energy use and making bill payments.

2.2 Treatment Assignment

We have 16,365 households that register for the study. Subsequently, we narrow down the pool of households using the criteria specified in our pre-analysis plan, resulting in a final cohort of 11,094 participants. These criteria primarily serve the purpose of eliminating outliers and households with extensive missing or zero daily energy consumption data.

The research team randomize each household in one of four groups, three treatment groups and one control group. Two treatment groups are assigned to contracts, with each group differing in the thresholds of energy savings they must reach to win a price. The third treatment group is assigned to contests. The duration of treatments is 30 days from mid-July to mid-August. The control group is not assigned contest or contract participation. Participants can use their smart meters to monitor their progress by default, so all households, including the control group, receive information about their past and current daily electricity use on the electric utility company's app.

The groups are as follows:

- Treatment 1, Contract with low thresholds. This group receives $4.35 USD if they conserve 5% of electricity compared to their average daily energy use during the same treatment period in the previous year, $6.52 if they conserve 10% and $10.87 if they conserve 15%. This group also receives weekly text message reminders, saying "There are [insert number] days left in the contract which ends on [insert end date]. Check the app to see your energy savings."
- Treatment 2, Contract with high thresholds. This group receives $6.52 USD if they

conserve 10% of electricity compared to their average daily energy use during the same treatment period in the previous year, $10.87 if they conserve 15% and $15.22 if they conserve 20%. This group also receives weekly text message reminders, saying "There are [insert number] days left in the contract which ends on [insert end date]. Check the app to see your energy savings."

- Treatment 3, Contest. This group will compete in groups of about 50 households in energy conservation. Of every 50 households, only the household that conserves the most energy, compared to their average daily energy use during the same treatment period in the previous year, will receive a prize of $87. This group will also receive weekly text message reminders, saying "There are [insert number] days left in the contest which ends on [insert end date]. Check the app to see your energy savings."

- Control group, No contest or contract participation. This group does not participat in either contract or the contest. This group receives weekly text message reminders, saying: "Please check the app to see your energy savings."[1]

Households assigned to the contest treatment are sorted into groups based on their average consumption in the period between July 15, 2022 and August 13, 2022 (i.e., the comparison period for the experimental period) to ensure that contest participants are competing with households that are similar in energy consumption.

Our recruitment and registration phase initiates on June 15, 2023, and wraps up on July 06, 2023. Subsequently, on July 15, 2023, households are individually informed of their specific treatment or energy savings program. Importantly, households remain uninformed about the presence of other treatments within our study. Both contests and contracts also commence on July 15, 2023, and conclude on August 13, 2023. On August 17, 2023, the utility sends text messages to households in the treated group to inform them about the culmination of the program and express gratitude for their participation. The utility also conveys that the outcomes of contracts and contests will be disclosed through notifications on the app and via text messages within a span of 10 days.

[1]To avoid dissatisfaction and exclusion, we agreed to pay out a small amount of about $0.40 USD to participants selected in the control group and thank them for enrolling in the program after the program ends.

3 Data

3.1 Variables

The main variable of interest is daily electricity consumption at the household level. This variable is obtained from the utility company, which measures electricity consumption with smart meters installed in every home. We obtain daily electricity consumption at the household level during the length of the competitions and contracts. We continue to collect this information until at least twelve months after the end of the experiment [2]

Weather plays a significant role in influencing a household's electricity consumption and their likelihood of winning contracts or contests. As a result, we will gather daily street-level air temperature data from Visual Crossings. This dataset encompasses the air temperature variable, along with a "feels like" temperature variable, which takes into account temperature and humidity to provide a more accurate representation of the perceived outdoor temperature. Utilizing these air temperature variables, we also compute the Cooling Degree Days (CDD) and Heating Degree Days (HDD) by summing the number of cooling and heating degree days for each month.

We do not have demographic or income information for participants. However, we intend to leverage their street addresses and street-level housing data as a proxy for assessing their wealth or income level. To assess the cost-effectiveness and welfare impacts, we also obtain administrative data from the utility, allowing us to quantify the benefits of energy savings in terms of reduced energy production, carbon emissions, and the prevention of blackouts and system failures.

3.2 Balance Checks

We assess the balance between the treatment and control groups by examining household historical electricity consumption data. More precisely, we analyze the average daily electricity consumption for each month leading up to the intervention, spanning from July 2022 to May 2023, as part of our balance checks. For each of these variables, we will run the following

[2]Our attrition rate is notably low, with only 8 out of 11,094 participants discontinuing their involvement. Attrition occurs since those 8 participants move out of Hanoi during the experiment and stop services with the utility. Also, due to measurement issues, the daily consumption of some households may not be recorded. We drop the household-day combinations in which this occurs.

Table 1: Balance analysis: Past electricity consumption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Control	Treatment 1		Treatment 2		Treatment 3		F-test
Month	Mean (kWh)	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	p-value
July 2022	12.388	0.233	0.164	0.111	0.500	0.130	0.430	0.581
August 2022	11.488	0.211	0.170	0.160	0.295	0.154	0.312	0.543
September 2022	10.621	0.140	0.329	0.134	0.350	0.116	0.413	0.733
October 2022	8.441	0.077	0.482	0.123	0.260	0.099	0.366	0.697
November 2022	8.324	0.079	0.462	0.131	0.222	0.133	0.215	0.562
December 2022	8.601	0.097	0.423	0.164	0.174	0.072	0.549	0.594
January 2023	8.814	0.114	0.377	0.223	0.081	0.027	0.827	0.294
February 2023	8.762	0.086	0.480	0.134	0.265	0.079	0.512	0.733
March 2023	8.423	0.116	0.309	0.119	0.286	0.055	0.619	0.677
April 2023	9.053	0.026	0.832	0.168	0.173	0.070	0.566	0.541
May 2023	11.447	0.120	0.439	0.235	0.130	0.214	0.166	0.410

Notes: An observation in each row is a household. Columns 2-7 report the coefficients and p-values from OLS regressions of average daily consumption on three indicators: treatment 1, treatment 2, and treatment 3. Column 8 reports the p-value from a joint test of statistical significance of all three indicators.

specification:

$$y_i = \alpha + \sum_k 1\{\text{treatment}_i = k\}\beta_k + \varepsilon_i,$$

where treatment_i is a variable indicating the treatment assignment of household i. The regression includes indicators for all treatment groups except for the control group (the omitted category). In our balance analysis, we report estimates for the coefficients $\{\beta_k\}$, their standard errors, and the p-value from a joint test of statistical significance of all coefficients on the treatments indicators (i.e., a test where $H_0 : \beta_1 = \beta_2 = \cdots = \beta_K = 0$) for every variable listed above.

We complement these mean comparison tests with Kolmogorov-Smirnov equality-of-distribution tests for each covariate that is a continuous variable (e.g., electricity consumption). In these tests, we compare the distribution of a variable in a given treatment group with that of the control group. The null hypothesis is that the distributions are equal.

Table 1 presents the outcomes of our balance checks, indicating that there are no noticeable disparities in historical electricity consumption patterns between the control and treatment groups. Kolmogorov-Smirnov tests support this finding by failing to reject the null hypothesis of equal distributions, further indicating the comparability of the control and treatment groups.

Table 2: Treatment effects: Cross-sectional variation

	(1)	(2)	(3)	(4)
	Consumption (kWh)		Consumption (kWh) (in logs)	
Treatment 1	-0.763	-0.914	-0.071	-0.085
	(0.180)	(0.087)	(0.015)	(0.009)
Treatment 2	-0.538	-0.794	-0.054	-0.074
	(0.182)	(0.089)	(0.015)	(0.009)
Treatment 3	-0.629	-0.835	-0.055	-0.072
	(0.182)	(0.093)	(0.015)	(0.009)
Controls	No	Yes	No	Yes
Observations	329752	329192	326283	325724
Mean	12.998	12.999	2.368	2.368
Test	0.454	0.346	0.441	0.272

Notes: Standard errors clustered at the household level in parentheses. All specifications include day fixed effects. Columns 2 and 4 include controls for the average daily consumption of the household in each of the months before the experiment (July 2022 to May 2023). Row 'Mean' reports the mean of the dependent variable in the estimation sample. Row 'Test' reports the two-sided p-value of an F-test where the null is that treatments 1, 2, and 3 have equal coefficients.

4 Empirical Analysis

4.1 Treatment Effects

In our study, households are required to provide consent to participate in a summer energy conservation program. Among the participants who join the study, we randomize treatment assignments. It is important to emphasize that participants remain uninformed about the specifics of contracts and contests until after they have been assigned a treatment. They are exclusively informed about their own treatment and are not privy to information regarding other treatment options. Thus, our initial focus centers on estimating average treatment effects on the households who are interested in participating in our study.

To measure these treatment effects, we will run the following regression:

$$y_i = \alpha + \sum_k 1\{\text{treatment}_i = k\}\beta_k + X_i'\delta + \varepsilon_i, \tag{1}$$

where y_i is the overall electricity consumption or average daily consumption during the study

period, X_i is a set of covariates (one specification includes no covariates, another specification includes the covariates used in the balance analysis), and ε_i is an error term.

Equation (1) makes use of energy consumption during the length of the experiment. Table 2 shows the results from regression (1). In columns (1) and (2), the dependent variable represents daily energy consumption in its original levels. In columns (3) and (4), the dependent variable represents the natural logarithm of daily energy consumption. All specifications include day fixed effects. Columns 2 and 4 include controls for the average daily consumption of the household in each of the months before the experiment (July 2022 to May 2023). Row 'Mean' reports the mean of the dependent variable in the estimation sample. Row 'Test' reports the two-sided p-value of an F-test where the null is that treatments 1, 2, and 3 have equal coefficients. Results suggest that households participating in contracts and contests reduce energy use by approximately 5% to 9% compared to households in the control group. All coefficients demonstrate statistical significance at the 1% significance level. The results do not offer sufficient evidence to reject the null hypothesis that the effects of contracts and contests are identical.

Next, we repeat this analysis using data that extends beyond the end of the study period. We use data on the electricity use of households during the month-long study period as well as during the months after the study period concluded to measure whether the treatments caused energy savings that extend beyond the treatment period. Specifically, we will run the following regressions:

$$y_{i,t} = \alpha + \sum_k \sum_t 1\{\text{treatment}_i = k\} 1\{t = \tau\} \beta_{k,\tau} + X_i' \delta + \varepsilon_{it}, \tag{2}$$

where $y_{i,t}$ is energy use $t \in \{0, 1, 2, \cdots, \bar{T}\}$ months after the beginning of the study, and $\beta_{k,\tau}$ measures the average impact of treatment k on electricity consumption τ months after the beginning of the study (where the control group is the excluded category), and ε_{it} is an error term clustered at the household level.

Table 3 shows the results from regression (2). Columns 1 and 4 restrict the sample from June 1, 2023 to August 13, 2023. Columns 2 and 5 restrict the sample from May 1, 2023 to August 13, 2023. Columns 3 and 6 use the full sample (July 1, 2022 to August 13, 2023). The dependent variable represents daily energy consumption in its original levels in Columns (1) to (3) and represents the natural logarithm of daily energy consumption in columns (4) to (6). All specifications include day fixed effects and household fixed effects. Row 'Mean' reports the mean of the dependent variable in the estimation sample. Row 'Test'

Table 3: Treatment effects: Within-household variation

	(1)	(2)	(3)	(4)	(5)	(6)
	Consumption (kWh)			Consumption (kWh) (in logs)		
	June 1, 2023 –	May 1, 2023 –	Full sample	June 1, 2023 –	May 1, 2023 –	Full sample
Post * Treatment 1	-0.969	-0.932	-0.892	-0.085	-0.080	-0.080
	(0.073)	(0.070)	(0.100)	(0.006)	(0.006)	(0.008)
Post * Treatment 2	-0.944	-0.876	-0.740	-0.078	-0.077	-0.077
	(0.074)	(0.070)	(0.101)	(0.006)	(0.006)	(0.008)
Post * Treatment 3	-0.938	-0.905	-0.756	-0.081	-0.079	-0.072
	(0.075)	(0.075)	(0.104)	(0.006)	(0.006)	(0.008)
Observations	718792	1062185	4430382	711137	1051916	4397592
Mean	13.084	12.599	10.313	2.373	2.329	2.131
Test	0.910	0.713	0.236	0.523	0.820	0.606

Notes: Standard errors clustered at the household level in parentheses. All specifications include day fixed effects and household fixed effects. Row 'Mean' reports the mean of the dependent variable in the estimation sample. Row 'Test' reports the two-sided p-value of an F-test where the null is that treatments 1, 2, and 3 have equal coefficients. Columns 1 and 4 restrict the sample from June 1, 2023 to August 13, 2023. Columns 2 and 5 restrict the sample from May 1, 2023 to August 13, 2023. Columns 3 and 6 use the full sample (July 1, 2022 to August 13, 2023).

reports the two-sided p-value of an F-test where the null is that treatments 1, 2, and 3 have equal coefficents. The findings remain consistent across various specifications, indicating that households engaging in contracts and contests reduce their energy consumption by around 7% to 9% when compared to households in the control group. All coefficients exhibit statistical significance at the 1% level. Similarly to the results presented in Table 2, we do not find sufficient evidence to reject the null hypothesis that the effects of contracts and contests are equal[3]

As well, we exploit the within-household variation in incentives to conserve energy and run an analysis that resembles equation (2), but that uses data that precedes the start of the experiment.

$$y_{i,t} \quad = \quad \alpha + \sum_{k} \sum_{t} 1\{\text{treatment}_i = k\} 1\{t = \tau\} \beta_{k,\tau} + X_i' \delta + \varepsilon_{it}, \tag{3}$$

where $y_{i,t}$ is energy use $t \in \{-\bar{T}, -\bar{T}-1, \ldots, 0, 1, \ldots, \bar{T}\}$ months relative to the beginning of the study, and $\beta_{k,\tau}$ measures the average impact of treatment k on electricity consumption τ months relative to the beginning of the study (where the control group is the excluded category), and ε_{it} is an error term clustered at the household level. Given the within-

[3]According to our power calculation provided our pre-analysis plan, it is highly probable that our sample size is inadequate for detecting any difference of 3% or less in magnitude.

household variation in incentives to conserve energy, equation (3) includes household effects.

Figure 1 plots coefficients $\beta_{k,\tau}$ across different time intervals, providing a visual representation of the treatment effects over a temporal horizon. Figure 1A illustrates the difference in energy usage (in kWh) between treatment group 1 and the control group over time, as measured by week-level indicators. Likewise, Figure 1B and 1C display the energy usage difference (in kWh) for treatment group 2 and 3, respectively, relative to the control group across time. All model specifications incorporate day fixed effects and household fixed effects. The dataset covers the period from June 1, 2023, to August 13, 2023. Week 0 represents the week before the experiment commencement, and week 1 corresponds to the initial week of the experiment. Weeks -6 and -5 are combined, as are weeks 4 and 5, due to a sample restriction, with weeks -6 and 5 each containing only two days.

The coefficients observed before the treatment period affirm the balance between the control and treatment groups, indicating no statistically significant difference in daily energy consumption across these groups. Similarly, the coefficients two weeks after the treatment are not statistically significant, implying that the treatments do not exhibit any immediate effect within the initial two weeks. However, the treatment effects begin to emerge and become more pronounced in week 3, with the most substantial effects occurring during the final week of treatment. These results clearly suggest the presence of a "deadline effect". As households approach the conclusion of their contracts or contests, they intensify their efforts to enhance their chances of winning or securing prizes.

4.2 Heterogeneous Effects

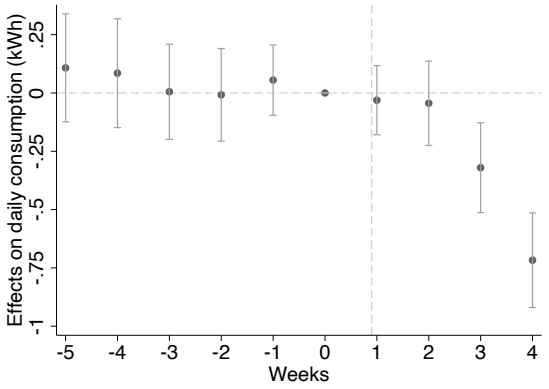
We will investigate heterogeneous effects based on historical electricity consumption, temperature, and location. The objective is to identify the households where the program most effectively induces energy savings.

Consider a covariate Z_i (e.g., past monthly electricity consumption) that has been demeaned (i.e., the mean value of Z_i is zero). To measure heterogeneous treatment effects, we will run the following regression:

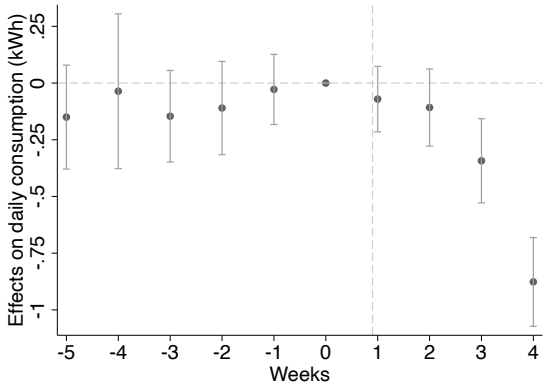
$$y_i = \alpha + \sum_k 1\{\text{treatment}_i = k\}\beta_{1,k} + \sum_k 1\{\text{treatment}_i = k\}Z_i\beta_{2,k} + X_i'\delta + \varepsilon_i,$$

where y_i is electricity consumption during the study period (i.e., overall electricity consumption or average daily consumption), X_i is a set of covariates that includes Z_i, and ε_i is an

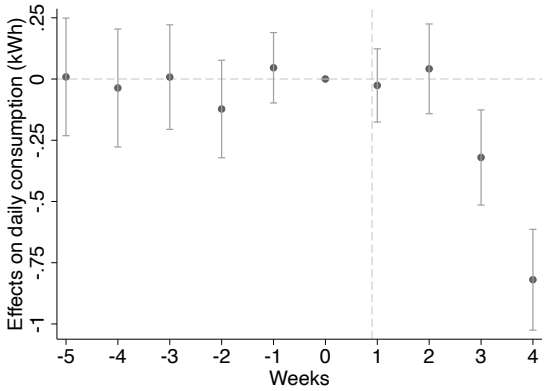
Figure 1: Time effects: Within-household variation



A) Treatment 1 vs Control



B) Treatment 2 vs Control



C) Treatment 3 vs Control

Notes: Standard errors clustered at the household level in parentheses. An observation is a household–day combination. Each figure plots the differential energy use (in kWh) of the treatment group X relative to the control group over time, measured by indicators at the week level. All specifications include day fixed effects and household fixed effects. The sample includes data from June 1, 2023 until August 13, 2023. Week 0 is the week before the experiment started, week 1 is the first week of the experiment. Weeks -6 and -5 are grouped together, just as weeks 4 and 5, as weeks -6 and 5 only have two days given the sample restriction.

error term.

In this model, the effect of treatment k on the treated, given Z, is $\beta_{1,k} + \beta_{2,k}Z$. Since Z is demeaned, the average effect of treatment k on the treated is simply β_k^1.

5 Structural Model and Estimation

5.1 Model: Household's Energy Consumption

In this section, we introduce a model to rationalize households' optimal choice of energy consumption when they face no incentives (control group) or some form of incentive (individual contract or participant in a contest).

A household has an *ideal consumption* level, $S \geq 0$, and chooses its *energy consumption*, e, which is subject to an unanticipated random shock $\varepsilon \sim N(0, \sigma^2)$, which realizes after the choice of e. The realized energy consumption is $\hat{e} = e + \varepsilon$. The household's preferences over energy consumption are represented by

$$E_\varepsilon[\gamma(\hat{e} - S)^2 - c\hat{e}].$$

That is, the household values matching its ideal consumption, with the parameter γ representing the importance of this matching, and it dislikes paying for energy consumption, where c is the price of a kWh.

Consider a set of N households with the same preferences, i.e., the same parameters S, γ, and σ. These households make simultaneous energy-consumption choices. Let $\hat{\mathbf{e}} = (\hat{e}_1, ..., \hat{e}_N)$ be the vector of households' realized consumption, where $\hat{e}_i = e_i + \varepsilon_i$. Under an incentive program that rewards energy reduction, household i receives a reward of $I_i(\hat{\mathbf{e}})$. Taking the energy-consumption choices by other household as given, household i choose its energy consumption to maximize

$$U_i(e_i, e_{-i}) = E_{\varepsilon_i}\Big[E_{\varepsilon_{-i}}[I_i(e_i + \varepsilon_i, \hat{\mathbf{e}}_{-i})] - \gamma(e_i + \varepsilon_i - S)^2 - c(e_i + \varepsilon_i)\Big].$$

We study equilibrium energy consumption under different incentive programs.

Proposition 1 (No Incentives; Control Group)**.** *Without an incentive for energy reduction,*

each household's energy consumption is

$$e^* = \max\left\{S - \frac{c}{2\gamma}, 0\right\}. \tag{4}$$

Without an incentive for energy reduction, $I(\hat{\mathbf{e}}) = 0$. If energy was free, the household would target its ideal point. The larger the marginal cost of energy, the further away the household's energy consumption from its ideal consumption. The parameter γ determines the relative importance of the energy cost on deviations from the ideal point. The larger γ, the more moderate the deviations from the household's ideal point.

Next, we consider the role of an incentive for energy reduction. We consider individual contracts and also contests. In our analysis, the goal of the principal is to *minimize* the household energy consumption (equivalently, the household's expected realized consumption since $E[\varepsilon] = 0$), subject to a budget constraint.

We start the analysis with individual contracts. For household i, the principal considers an individual contract that rewards it based on its realized consumption, regardless of the consumption of other households, i.e., $I_i(\hat{\mathbf{e}}) = W(\hat{e}_i)$. Moreover, the reward is subject to the constraint $0 \leq W(\hat{e}_i) \leq B$, where B is the principal's per-household budget. Thus, the principal solves

$$\min_{e_i, W(\cdot)} \hat{e}_i \tag{5}$$

subject to

1. $e_i \in \arg\max_{\widetilde{e}_i \geq 0} \; -\gamma(\widetilde{e}_i - S)^2 - c\widetilde{e}_i + \sigma^2 + E_{\hat{e}_i}[W(\hat{e}_i)|\widetilde{e}_i]$
2. $0 \leq W(\hat{e}_i) \leq B$ for all $\hat{e}_i \geq 0$.

Proposition 2 (Optimal Individual Contract)**.** *An optimal individual contract is a* threshold contract

$$W(\hat{e}) = \begin{cases} B & \hat{e} \leq \ell, \\ 0 & \hat{e} > \ell. \end{cases}$$

In other words, the principal's optimal contract rewards the household whenever the energy consumption is sufficiently low. The optimal threshold ℓ depends on the parameters of the model.

Under an optimal individual contract with threshold r, household i's problem is to choose energy consumption to solve

$$\max_{e_i \geq 0} \; BF(\ell - e_i) - \gamma(e_i - S)^2 - ce_i. \tag{6}$$

Next, we consider the use of contests to incentivize energy reduction. The principal organizes a contest where N households simultaneously make energy consumption choices, e_i. The household with the lowest realized consumption, $\hat{e}_i$, receives a prize of V.

Proposition 3 (Contests)**.** *Consider a contest between N households. In a symmetric equilibrium, each household chooses an energy consumption of*

$$e^* = S - \frac{(c+I)}{2\gamma}, \tag{7}$$

where $I = V \int (N-1)(1-F(\varepsilon_i))^{N-2} f^2(\varepsilon_i) d\varepsilon_i$.

Consider contracts that award a prize $V = v \times N$, where v is the per-household budget, so larger contests award larger prizes. In that case, how does the contract's incentive changes with N? To answer this question, we find the optimal size of the contest, N^*, which is the solution to

$$\max_{N \geq 2} \; vN \int (N-1)(1-F(\varepsilon_i))^{N-2} f^2(\varepsilon_i) d\varepsilon_i.$$

The optimal size of the contest depends on σ. Table 4 shows the optimal size of the contest for different values of sigma. With a low variance of the common shock, $\sigma \leq 1$, the optimal size is "as large as possible." As the variance increases, the optimal size is finite, and when $\sigma \geq 5$, three competitors is optimal.

σ	N^*
1	$+\infty$
2	22
3	7
4	4
5+	3

Table 4: Optimal size of the contest for different values of σ.

5.2 Individual Contracts versus Contests

How does a household's energy consumption in an optimal contract compare to its energy consumption in a contest? To answer this question, let us focus on an interior solution. Let $g(e) = 2\gamma(e - S) + c$. Under a contract, the household solves problem (6), which yields the first-order condition

$$g(e^*_{contract}) = -Bf(\ell - e^*_{contract}).$$

Under a contest, the household's energy consumption is

$$g(e^*_{contest}) = -I$$

where $I = V \int (N-1)(1 - F(\varepsilon))^{N-2} f^2(\varepsilon) d\varepsilon$.

Thus, the comparison of $e^*_{contract}$ and $e^*_{contest}$ hinges on the comparison between I and $Bf(\ell - e^*_{contract})$. To make the comparison fair, we set the contest prize equal to the contract's expected payout to the N households, i.e.,

$$V = NBF(\ell - e^*_{contract}).$$

A contest dominates a contract whenever $e^*_{contest} < e^*_{contract}$, which is equivalent to

$$Bf(\ell - e^*_{contract}) < NBF(\ell - e^*_{contract}) \int (N-1)(1 - F(\varepsilon))^{N-2} f^2(\varepsilon) d\varepsilon$$

which is the same as

$$\frac{f(\ell - e^*_{contract})}{F(\ell - e^*_{contract})} < \int N(N-1)(1 - F(\varepsilon))^{N-2} f^2(\varepsilon) d\varepsilon$$

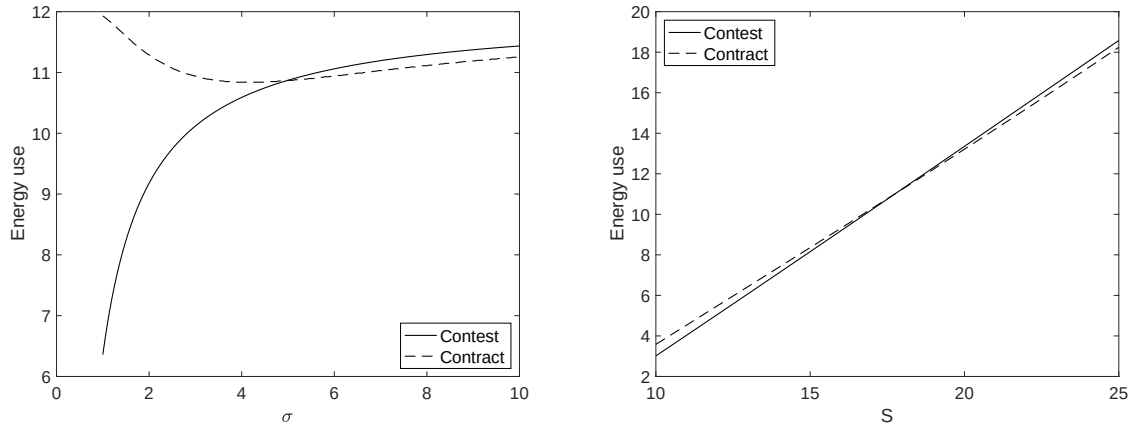
Denote ϕ be the density of the standard normal and Φ be the cdf. Then, the left-hand side of the inequality above is:

$$\frac{1}{\sigma} \underbrace{\frac{\phi\left(\frac{\ell - e^*_{contract}}{\sigma}\right)}{\Phi\left(\frac{\ell - e^*_{contract}}{\sigma}\right)}}_{IMR(z)}, \tag{8}$$

where IMR is the inverse mills ratio and $z = \frac{\ell - e^*_{contract}}{\sigma}$. The IMR is decreasing.

Depending on the model's parameters, a contest can dominate individual contracts or vice-versa. Figure 2 provides examples.

Figure 2: Comparing contests and contracts



A) Varying σ B) Varying S

Notes: Panel A fixes $N = 2$, $\ell = 15$, $B = 1$, $\gamma = 0.025$, $c = 0.3$, and $S = 18$, and shows the optimal energy use under a contract and a contest for different values of σ. Panel B fixes $N = 2$, $\ell = 15$, $B = 1$, $\gamma = 0.025$, $c = 0.3$, and $\sigma = 10$, and shows the optimal energy use under a contract and a contest for different values of S.

5.3 Estimation

In the empirical analysis, each household is of one of $K = 56$ types, each type denoted by $\kappa = 1, ..., K$. We chose types based on past energy consumption between July 15 and August 13, 2022—i.e., one year earlier than the experimental period. Let N_κ be the number of households of type κ.

A household's type determines its preferences through the parameters γ_κ and S_κ. We assume that idiosyncratic shocks are i.i.d. drawn from $N(0, \sigma_\kappa^2)$.

In our experiment, we will have households of type κ assigned to four treatment conditions: control, contract I, contract II, and contest. For estimation, we leverage this variation and the assumption that households behave optimally given the incentive they were randomly assigned.

We estimate the parameters of the model, Θ, in several steps:

1. The observed energy consumption of household i assigned to treatment t will be given by

$$e_{i,\kappa,t} = e^*_{t,\kappa}(\Theta_\kappa) + \varepsilon_{i,\kappa,t},$$

where $e^*_{t,\kappa}$ denotes the solution the household's problem. We can recover σ_κ by

computing the standard deviation of $\{e_{i,\kappa,t} - \frac{1}{N_\kappa}\sum_j e_{j,\kappa,t}\}_t$ for every κ, since $\varepsilon_{i,\kappa,t} \equiv e_{i,\kappa,t} - \frac{1}{N_\kappa}\sum_j e_{j,\kappa,t}$.

2. Given σ_k, and noting that c (price of a kWh) and N (households in each contest) are known, we can compare the energy consumption of households of a given type κ across the contest treatment and the control group to recover γ_κ. To see how, we know from Equation 4 and Equation 9 that

$$e^*_{\kappa,\text{control}} - e^*_{\kappa,\text{contest}} = \frac{I_\kappa}{2\gamma_\kappa},$$

where $I_\kappa = V\int(N-1)(1-F(\varepsilon_i))^{N-2}f^2(\varepsilon_i)d\varepsilon_i$ can be computed given σ_k and N. Given I_κ, we can estimate γ_κ by comparing the mean consumptions of type-κ households assigned to the control and contest groups.

3. Given an estimate of γ_κ, S_κ can be estimated by subtracting $c/2\gamma_\kappa$ and $(c+I_\kappa)/2\gamma_\kappa$ to the mean consumptions of type-κ households assigned to the control and contest groups, respectively (see Equation 4 and Equation 9).

4. In practice, we group types to gain power in estimating these parameters. We group types into four groups to estimate γ_κ and σ_κ. We estimate S_κ separately for each type. That is, we estimate a total of $K + 8 = 64$ parameters.

5.4 Estimation Results

Using our experimental data we estimate $(S_\kappa, \gamma_\kappa, \sigma_\kappa)$ for $\kappa = 1, ..., 56$. For each type, we estimate its ideal consumption S_κ. The summary statistics of these 56 parameters are: mean 435.56, minimum 150.744, maximum 838.29, and standard deviation 169.50. To gain power, we constrain the parameters γ_κ and σ_κ to be the same for groups of 14 types. Our estimates are given by:

Type	γ	σ
1-14	0.00085	61.312
15-28	0.00130	65.074
29-42	0.00143	82.479
42-56	0.00267	124.411

Table 5: Optimal size of the contest for different values of σ.

Using these parameters, we compute the price elasticity of demand at current prices is. Our model predicts that without an incentive to reduce energy consumption, a household of type κ will choose to consume

$$e^*_\kappa = S_\kappa - \frac{c}{2\gamma_\kappa}.$$

where c the price of electricity. Thus, the expected demand for energy is the weighted sum of energy consumption across households

$$E = \sum_{\kappa=1}^{K} \alpha_\kappa \left(S_\kappa - \frac{c}{2\gamma_\kappa} \right),$$

where α_κ is the fraction of household of type κ, which we compute from our experimental data according to

$$\alpha_\kappa = \frac{\text{Number of Households of type } \kappa}{\text{Number of Households}}.$$

Then, the price-elasticity of energy consumption is

$$\frac{dE}{dc}\frac{c}{E} = \frac{-c}{\sum_{\kappa=1}^{K} \alpha_\kappa \left(S_\kappa - \frac{c}{2\gamma_\kappa} \right)} \sum_{\kappa=1}^{K} \frac{\alpha_\kappa}{2\gamma_\kappa}.$$

Using our estimates for α_κ, S_κ, and γ_κ, and the price of electricity in Vietnam of $c = 0.11$ dollars per kWh, we obtain a price-elasticity of energy consumption at current prices of

$$\frac{dE}{dc}\frac{c}{E} = \frac{-0.11}{392.4816} \times 377.0053 = -0.1057.$$

Counterfactual Contracts. We our empirical model to simulate the average consumption across households, computed as

$$\sum_{\kappa=1}^{K} \alpha_\kappa e^*_\kappa,$$

and the average expected payout, computed as

$$\sum_{\kappa=1}^{K} \alpha_\kappa \sum_{p=1}^{P} V_p F_\kappa(\ell_p - e^*_\kappa),$$

where V_p is the prize for a household with an energy reduction below ℓ_p. To gain empirical variation, our experiment implemented multi-threshold contracts with different prizes for different levels of energy reduction. The first contract offered \$4.35 for a 5 percent reduction, \$6.52 for a 10 percent reduction, and \$10.87 for a 15 percent reduction. The second contract offered \$6.52 for a 5 percent reduction, \$10.87 for a 10 percent reduction, and \$15.22 for a

20 percent reduction.

The table shows the model prediction regarding average consumption and expected payoff for the two experimental contracts.

Experimental Contracts (Model Prediction)

L_1 (%)	L_2 (%)	L_3 (%)	V_1 ($)	V_2 ($)	V_3 ($)	Av. kWh daily	Av. kWh monthly	Av. Payout ($)
5.00	10.00	15.00	4.35	6.52	10.87	12.57	377.20	3.05
10.00	15.00	20.00	6.52	10.87	15.22	12.42	372.56	3.67

Table 6: Simulated average consumption and expected payouts for the two experimental contracts.

One practical difficulty in implementing contracts is the *uncertainty* regarding the expected payout. A priori, it is unclear what the principals' cost of implement a contract will be. If every household achieves the maximum reduction in the first contract, the principal would expect to pay $10.87 per household. Thus, the principal needs a budget of (at most) $10.87 per household.

In our model, an optimal contract features a single threshold. We compute the energy reduction from implementing a contract that rewards a household with a prize of v if the realized energy consumption is below L. Table 7 shows average consumption and expected payout for different contracts, where the threshold L is optimally computed for a give per-household budget v.

Prize (v)	Optimal Threshold ($L^*(v)$)	Av. kWh	Av. kWh	Av. Payout
1	0.20	13.03	390.92	0.36
2	0.18	12.98	389.36	0.74
3	0.04	12.92	387.73	1.14
4	0.12	12.87	386.14	1.54
5	0.39	12.82	384.52	1.94
6	0.03	12.76	382.80	2.41
7	0.01	12.70	381.13	2.86
8	0.01	12.65	379.39	3.34
9	0.15	12.59	377.68	3.81
10	0.29	12.53	375.98	4.29
15	0.24	12.24	367.22	7.08
20	2.34	11.95	358.46	9.62
25	5.29	11.65	349.64	11.9
30	7.28	11.36	340.80	14.62
35	9.77	11.07	331.99	17.15
40	11.76	10.78	323.33	20.01
45	14.15	10.49	314.80	22.64
50	16.48	10.21	306.43	25.31
55	18.39	9.94	298.27	28.34
60	20.53	9.68	290.27	31.20
65	22.41	9.41	282.43	34.31
70	24.21	9.16	274.76	37.52
75	25.48	8.91	267.25	41.36
80	26.87	8.66	259.88	45.13
85	28.42	8.42	252.69	48.73
90	29.54	8.19	245.71	52.89
95	30.66	7.97	239.01	57.06
100	31.75	7.75	232.53	61.28

Table 7: Expected consumption and payout for an optimal contract (determined by the optimal threshold $L^*(v)$) for different per-househol budgets (prizes, v).

The last two columns of Table 7 give us a relationship between average consumption and expected payout. Figure 3 plots this relationship, showing that decreasing and convex.

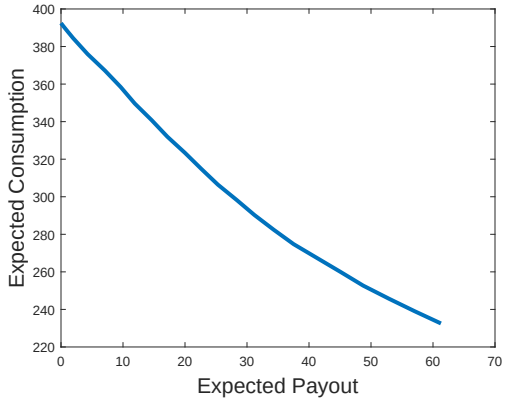


Figure 3: Expected consumption as a function of the expected payout under optimal individual contracts.

In fact, we can fit a quadratic function to model this relationship obtaining

$$\text{Av. kWh} = 392.6403 - 3.920542(\text{Av. Payout}) + .0214189(\text{Av. Payout})^2$$

The R^2 of this model is 0.9998. Using this formula, we can find the average energy reduction in percentage terms

$$E[\text{Reduction}] = \frac{3.920542(\text{Av. Payout}) - .0214189(\text{Av. Payout})^2}{392.6403}.$$

Figure 4 plots the expected reduction as a function of the expected payout. To achieve a 4 percent energy reduction, the average payout per household is \$4.1. Note that the relationship is almost linear for reductions of 10 percent or less, meaning that it costs about \$1 per household to achieve a 1 percent reduction in energy consumption.

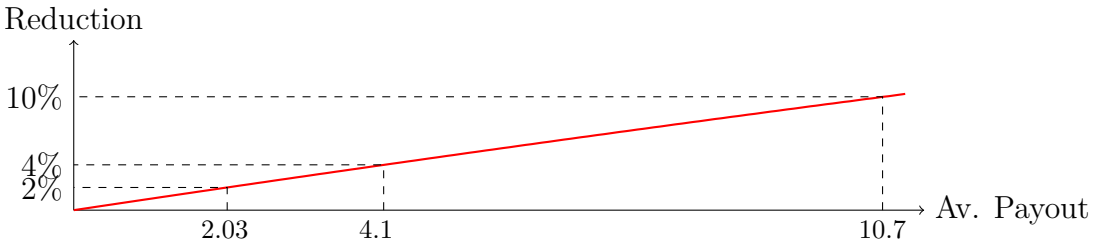


Figure 4: Expected reduction as a function of the expected payout.

Contests. We use our model estimates to simulate energy consumption in a contest. The

contest's prize equals a per-household prize times the number of households in the contest, $V = v \times N$.

We simulate contests for different sizes for different values of per-household expected payout. Table 8 shows that for our model estimates contests dominate contracts. For instance, with an expected payout of 0.74 dollars per household, an optimal contract achieves an expected monthly consumption of 389.36, whereas grouping households in 50-household contests achieves an expected monthly consumption of 385.01. We also find that larger contests achieve larger gains. In the last column of the table, we simulate contests using all the households of each type; on average, there are 180 households per type.

	Optimal 1-Contract	50-Contest	N_κ-Contest	10,000-Contest
Av. Payout ($)	Av. kWh monthly	Av. kWh monthly	Av. kWh monthly	Av. kWh monthly
0.00	392.48	392.48	392.48	392.48
0.36	390.92	388.85	388.10	386.26
0.74	389.36	385.01	383.47	379.69
1.14	387.73	380.98	378.59	372.77
1.54	386.14	376.94	373.72	365.85
1.94	384.52	372.90	368.85	358.94
2.41	382.80	368.16	363.12	350.81
2.86	381.13	363.62	357.64	343.03
3.34	379.39	358.77	351.79	334.73
3.81	377.68	354.03	346.06	326.61
4.29	375.98	349.18	340.22	318.31
9.62	358.46	292.65	275.28	226.15

Table 8: Optimal Contract versus Contests

Increasing Energy Price. We study what is the impact on price reduction by increasing energy prices. In our baseline model, the energy price is 11 cents per kWh. Table 9 shows the energy consumption for different prices for energy consumption in kWh.

Price ($/kWh)	Av. consumption (kWh, monthly)
0.11	392.48
0.12	388.71
0.13	384.94
0.14	381.17
0.15	377.40
0.16	373.63
0.17	369.86
0.18	366.09
0.19	362.32
0.20	358.55
0.21	354.78
0.22	351.01
0.23	347.24
0.24	343.47
0.25	339.70

Table 9: Energy reduction due to increases in energy prices.

6 Optimal Policy Design and Welfare Implications

Our structural model estimates provide us with a cost function for energy savings. In addition, we will collect administrative data from the utility to measure the benefit function of energy savings, including reduced energy production costs, carbon emissions reduction, and the prevention of blackouts and system failures. Using the cost and benefit functions of energy savings, we can evaluate different policies and their effects on welfare, and provide recommendations for an optimal policy.

7 Conclusions

8 References

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9 Appendix: Proofs

Proof of Proposition 1

Proof. Without an incentive to reduce energy, each household solves:

$$\max_{e \geq 0} -(e - S)^2 - ce + \sigma^2.$$

The solution to this optimization problem is given in the proposition. □

Proof of Proposition 2

Proof. Let $u(e) = -\gamma(\tilde{e} - S)^2 - c\tilde{e} + \sigma^2$ and

$$V(e, W(\cdot)) = u(e) + \int W(\hat{e}) f(\hat{e} - e) d\hat{e}$$

At the optimal solution we have $V_e(e^*, W^*(\cdot)) = 0$.

Consider the relaxed problem

$$\min_{e, W(\cdot)} e$$

subject to

1. $V_e(e, W(\cdot)) \leq 0$,
2. $W(\hat{e}) - B \leq 0$ for all $\hat{e}$,
3. $-W(\hat{e}) \leq 0$ for all $\hat{e}$,
4. $-e \leq 0$.

The Lagrangian of this problem is

$$\mathcal{L} = e + \lambda \left(u'(e) - \int W(\hat{e}) f_e(\hat{e} - e) d\hat{e} \right) + \theta(\hat{e})(W(\hat{e}) - B) + \eta(\hat{e})(-W(\hat{e})) + \mu e$$

where $\lambda, \mu, \theta(\hat{e}), \eta(\hat{e}) \geq 0$.

Taking FOC w.r.t. $W(\hat{e})$ we get

$$\frac{\partial \mathcal{L}}{\partial W(\hat{e})} = -\lambda f_e(\hat{e} - e) + \theta(\hat{e}) - \eta(\hat{e}).$$

At the optimal solution we have $\frac{\partial \mathcal{L}}{\partial W(\hat{e})} = 0$. Since $f_e(\hat{e} - e) \neq 0$ a.e. we cannot have $\theta(\hat{e}) = \eta(\hat{e}) = 0$ simultaneously when $\lambda > 0$. This means that either $W(\hat{e}) = B$ or $W(\hat{e}) = 0$ for all $\hat{e} \geq 0$. Moreover, $W(\hat{e})$ is non-increasing, since the principal wants to minimize energy consumption. Lastly, at the optimum incentive compatibility requires $V_e(e^*, W^*(\cdot)) = 0$, so $\lambda > 0$ satisfies complementary slackness. □

Proof of Proposition 3

Suppose there are N agents competing in a static contest. Agents exert costly effort to reduce their energy consumption, and the household with the largest reduction wins the contest. We use the same notation as before: A household chooses expected consumption and its actual consumption is

$$\hat{z}_i = e + \varepsilon_i.$$

Agents are ranked according to their reduction (from the largest reduction to the lowest one), where energy reduction is given by $\hat{z}_i - z_i^{past}$ (difference in log consumption). With a single prize, V, agent i wins the contest if

$$\hat{z}_i - z_i^{past} < \hat{z}_j - z_j^{past} \text{ for all } j \neq i.$$

This expression is the same as

$$e_i + \varepsilon_i - z_i^{past} < e_j + \varepsilon_j - z_j^{past} \Leftrightarrow e_i - e_j + z_j^{past} - z_i^{past} + \varepsilon_i < \varepsilon_j.$$

Let us consider a symmetric equilibrium, where $z_i^{past} = z^{past}$ for all i, and each agent optimally

chooses $e_i = e^*$. Fixing ε_i, player i wins with probability

$$\psi(e_i, \varepsilon_i, e^*) \equiv (1 - F(e_i + \varepsilon_i - e^*))^{N-1}.$$

Player i chooses her effort before knowing the realization of the shock ε_i. Then, the optimal choice of e_i solves

$$\max_{e_i \geq 0} V \int \psi(e_i, \varepsilon_i, e^*) f(\varepsilon_i) d\varepsilon_i + E_{\varepsilon_i}[U(e_i, \varepsilon_i)].$$

The FOC yields

$$-V \int \frac{\partial \psi(e_i, \varepsilon_i, e^*)}{\partial e_i} f(\varepsilon_i) d\varepsilon_i + E_{\varepsilon_i}[U'(e_i, \varepsilon_i)] = 0.$$

In a symmetric equilibrium we must have $e_i = e^*$. Thus, the contests creates an incentive to reduce energy consumption, I, given by

$$I = V \int (N-1)(1 - F(\varepsilon_i))^{N-2} f^2(\varepsilon_i) d\varepsilon_i.$$

The optimal energy consumption solves

$$e^* = S + E[\varepsilon] - \frac{(c + I)}{2\gamma}. \tag{9}$$

Intuitively, spending energy becomes "more costly" when there is a prize for being the household with the lowest consumption.