Do Electricity Consumers Respond to Prices or Peers? Evidence from a Novel Electricity Billing Tournament

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April 2022

Abstract

I examine an energy conservation program that instills both pecuniary and non-pecuniary incentives using a tournament among peer military households. Under the tournament, households only pay for electricity use that exceeds 110 percent of a peer-group average and receive a rebate for each kilowatt-hour below the 90 percent of the peer-group average. Before the program, no household paid for electricity. I evaluate the impacts of the program in two ways. First, I use difference-in-differences to estimate how the introduction of the program affected electricity use for those near the peer-group average (and paid/received nothing throughout) in comparison to those who received various levels of payments or rebates. Second, I examine how arguably exogenous changes in the peer-group average, driven by entry and exit of households, affected subsequent electricity use by continuing households. I find that the program causes greater conservation by high-use households that are required to make payments under the program, but that low-use households respond against their pecuniary interest and consume more, at least relative to average households. Put another way, both groups bunch toward the peer-group mean. Over time, as average use and the non-payment window shift lower, it mitigates the perverse effect from the rebate group and gradually increases the response from the payment group. Interestingly, for continuing households that switch between rebate and payment percentiles, use responds the same to both exogenous decreases and increases in the peer-group average use. These households tend to reduce electricity use if they were standing at the above-average percentiles and, in contrast, increase use if they were at the below-average percentiles regardless of the increases or decreases in the effective price. This causes bunching toward the new group mean. I discuss ways that monetary incentives and competitive psychology may be mixing to give rise to these observed impacts. (JEL D12, Q41, Q48, L94, L98)

Keywords Peer comparison, price intervention, energy conservation, electricity consumption

1 Introduction

Energy conservation has played an important part in lowering pollution emissions and mitigating climate change. Economists have traditionally considered ways in which efficient energy pricing can guide appropriate levels of demand by including, for example, the social cost of pollution emissions. Over time, however, economists have come to appreciate that behavioral factors affect choices and that these do not always

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comport with the standard model of utility maximization. For example, some studies find that residential customers facing block pricing consume electricity *as if* average price were marginal price (Ito, 2014; Liebman & Zeckhauser, 2004; Wichman, 2014) or respond to expected marginal price (Borenstein, 2009) rather than observed marginal price. Meanwhile, other studies find that even while people respond to price intervention, people may do a poor job of accounting for energy costs associated with appliance choices (Attari et al., 2010; Jacobsen, 2015; Sallee, 2014). Others have found that "nudges" or non-price interventions, which mainly involve information about consumption patterns relative to peers (Allcott, 2011; Ayres et al., 2013; Ferraro & Price, 2013; Reiss & White, 2008; Schultz et al., 2007; Wolske et al., 2020) or feedbacks on monetary savings (Abrahamse et al., 2007), can impart modestly reduced electricity use. Ferraro and Price (2013) suggest that non-pecuniary nudges provide a useful complement to pecuniary incentives because they are most effective among the group that is least sensitive to price changes.

While a large body of literature has shown the independent effects of monetary incentives and behavioral nudges, few studies have investigated how consumers respond to a combination of the two interventions. The results are mixed. Stern (1999) finds that a combination of material incentives and information provides synergistic effects on pro-environmental consumer behaviors. Jessoe and Rapson (2014) shows that providing residential electricity customers with real-time information about energy usage increases their price elasticity of demand compared to those without feedback. List et al. (2014) conduct an experiment that overlays Opower's social-comparison Home Energy Report (HER) with a rewards program that offers financial incentives for reductions in home energy use. The authors find that the combined HER and reward treatments induce greater conservation than the HER treatment alone. The conservation effects is especially substantial for low users that is not achieved by the HER alone. Studying the success of a wide range of norm campaigns, Blondeel et al. (2019) also find that problem linkages can bolster the attractiveness of a proposed new norm. For instance, the campaign to reduce environmentally harmful fossil fuel subsidies has been more effective when linked to fiscal stability. Together, they tend to have greater potential to affect policy change than either one does alone. However, using a field experiment to investigate healthy-food purchase decisions at a grocery store, List et al. (2015) shows that the simultaneous treatment of both information and pecuniary incentives do not significantly increase healthy produce purchasing compared to the pecuniary incentive alone. Similarly, Fanghella et al. (2021) and Hayes and Cone (1977) do not find evidence of synergies between monetary reward and behavioral (goal setting and feedback) interventions in optimizing energy consumption. Interestingly, Fanghella et al. (2021) find that the energy saving profile under the mix of treatments is closer to that of behavioral nudge than pecuniary, suggesting that the main driver of behavior in the mix is behavioral intervention rather than the financial incentive. All these prior studies examine the combination of information and monetary incentives that likely influence consumer behaviors in the same direction – both treatments either increase good consumption or reduce harmful behavior.

This paper contributes to the literature on energy consumer response by studying an energy conservation program that has simultaneously provided unusual pecuniary and non-pecuniary incentives which may *influence consumption in opposite directions*. The setting involves military households living on bases in Hawaii. Prior to the program, military households did not pay for electricity–it is included as a part of the housing allowance for enlisted persons and their families. To encourage conservation, the military has developed a revenue-neutral tournament. Under the tournament, households only pay for electricity use that exceeds 110 percent of a peer-group average, while households that consume below the 90 percent of the peer-group average earn a per-kilowatt-hour rebate for conservation below this threshold. Households that consume be-

tween 90 and 110 percent of the peer-group mean pay nothing. For four months prior to the actual program, households were provided information about their consumption and that of the peer-group mean, as well as the payment or rebate they would have been subject to if the program had already commenced. In a brief, households receive solely peer-comparison information during the four-month pilot period and receive both peer-comparison and monetary incentives during the actual program. Interestingly, the simultaneous treatments of peer comparison and monetary incentives may potentially affect household electricity use in either the same direction or in opposite directions. Particularly, for the payment group, both peer comparison and monetary incentives potentially reduce household electricity use. For the rebate group, the peer comparison pulls in the opposite direction of the monetary incentive. While money rebates may decrease electricity use (Azarova et al., 2020; Hayes & Cone, 1977; Slavin et al., 1981; Winett et al., 1976; Winett & Nietzel, 1975), peer comparison may increase use due to a "boomerang" effect[1]. The peer-comparison information suggests to low users that they are consuming less than typical households and that it is socially acceptable to consume more (Fischer, 2008; Schultz et al., 2007).

Peer-group comparisons in this military tournament aim to echo the use of social comparisons to "nudge" people toward lower energy consumption. Payments and rewards for deviating from the group mean add salience and economic bite to these comparisons. Thus, both psychological and economic factors are likely germane to the program's impacts, and I use a couple of strategies for trying to disentangle these effects to the extent possible and estimating the interplay between peer comparison and monetary incentives.

First, using a difference-in-difference estimator, I find households formerly consuming above 110 percent of the peer-group mean reduce use relative to the no-payment households formerly consuming near the peer-group mean. Those receiving a rebate for consuming less than 90 percent of the group average, however, actually increase electricity use relative to those near the mean. While such a pattern of crowding toward the mean has been observed in social comparison studies that lacked financial consequences, it may surprise some that this behavioral phenomenon outweighs the influence of a high marginal price. But since the reduction by those making payments is almost twice the size of the increases of those receiving rebates, on balance the program reduces electricity use.

A potential weakness of the difference-in-difference estimates is that the control—no-payment households that consume near the average—may nevertheless be influenced by the program. Thus, to complement difference-in-difference findings I consider longer-run changes over time as households enter and exit each peer group. When a high-use household moves out (e.g., their tour of duty ends) or a low-use household enters, the peer-group mean declines; conversely, when a low-use household exits or a high-use household enters, the peer-group mean rises. For continuing households, these are exogenous changes that affect the likelihood and size of payments and rebates in the tournament.

When the peer-group average decreases month-over-month – which is the usual case – making the tournament more competitive (effectively a price increase), I find that high users making payments decrease use somewhat more than average users do, while low users receiving rebates increase use much more than average. This result mirrors the bunching-toward the peer-group-mean observed in the difference-in-difference estimates. Interestingly, households' response to the reverse changes – when the peer-group mean increases – is the same: users at low-percentile increase use while users at high-percentiles decrease use. Taken together, the results indicate a powerful interaction between monetary incentives and behavioral factors that I have not

[1] A boomerang effect happens where households who have lower-than-average consumption respond to peer information by increasing their energy use.

seen documented in the prior literature.

The remainder of this paper is structured as follows. Section 2 describes background information about the military energy conservation program and data used for this study. Section 3 presents the empirical approaches. Section 4 presents the results and Section 5 provides concluding remarks.

2 Background and Data

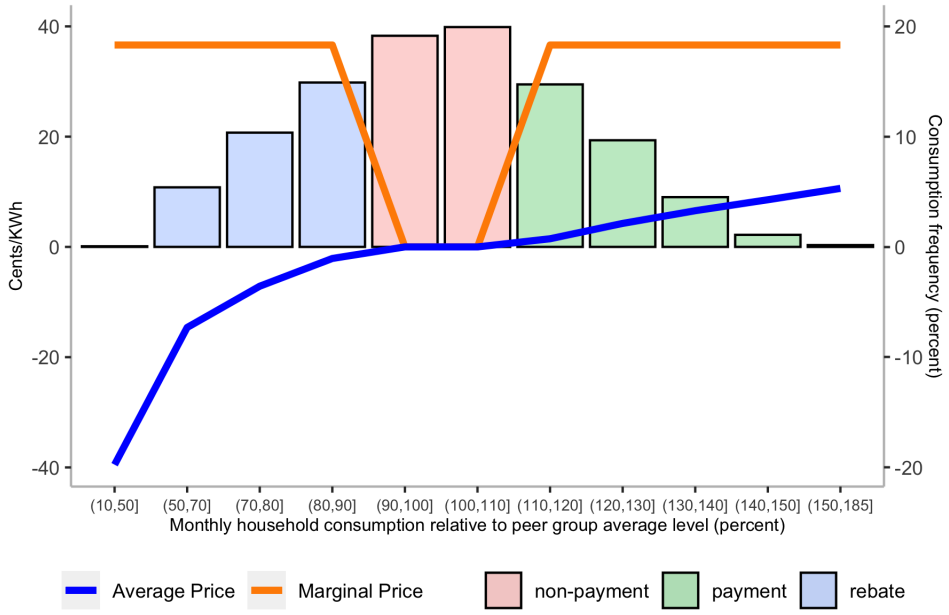
2.1 The Resident Energy Conservation Program

The Resident Energy Conservation Program (RECP) was created by the Department of Defense to increase awareness of electricity use and to reduce energy consumption. The program was designed as a revenue-neutral program and implemented based on a tournament among peer military households. RECP was initiated in Hawaii in September 2010, but the first four months is a pilot period in which households received monthly information about peer group average use and the charge they would have paid if RECP had been implemented. Households started paying or getting a rebate in January 2011. Before January 2011, military households did not pay for electricity. Under RECP, for each peer group, a buffer zone is established 10% above and 10% below the monthly average use. To calculate the group average use, RECP categorized residents into 100 different like-type groups by their home characteristics including neighborhood, size of the home, year built, construction style, and variation in the efficiency of heating and air condition systems in use. Households cannot decide which group they belong to and do not know exactly who are their groups' members. The group average use is calculated after removing the highest and lowest 5% of users in each group and homes that are not occupied for a full month. Households whose monthly use is within the resulting band still pay nothing. Those who consume above the buffer zone pay for the excess consumption, while those who consume below the buffer obtain a rebate defined by the difference of their consumption from the group average level times the electricity rate.

Figure 1 illustrates the average price and marginal price that vary by consumption level relative to the peer group average use along with distribution of electricity use after the program. In this paper, average price is defined by dividing the monthly charge, which is either positive in the payment group or negative in the rebate group, by the kilowatt-hour consumed. Marginal price is the increase in total payment or the decrease in total rebate when a household uses one additional kilowatt-hour. Under the novel pricing system, high-consuming households see a marginal price equal to the electricity rate (P) and a positive average price. While low-consuming households face the same marginal price of P, their average price is *negative*, since they receive a rebate. Households who are in the 10-percent buffer zone around average use pay zero marginal and average prices. Along with the new pricing scheme, households receive monthly utility bills with information of households' historical and current use as well as the peer group average use.

In addition to simultaneous pecuniary and non-pecuniary incentives, two features that make this program especially ideal to examine the responsiveness of consumers to price changes are that (1) Military personnel are commonly reassigned to a new station after 2-5 years, so each peer group experiences a change in member compositions almost every month. The group average use thus unpredictably changes over time, which affects who receives payments or rebates and the bill that they receive each month. This is equivalent to an exogenous change in average price and/or marginal price when households are pushed into or out of

Figure 1: Marginal price, average prices, and consumption distribution by consumption percentile after the program implementation



Notes: This figure illustrates the entire price schedule under RECP. The horizontal axis displays bins of the ratio of household electricity use to the group-average-use in percentage. The blue line presents the average price, which equals monthly bills divided by monthly kilowatt-hour used. The orange line shows the marginal price, which is either an increase in the payment for those households at above-average percentiles or a reduction in the rebate for those households at below-average percentiles when the households consume one additional kilowatt-hour. The histogram shows the distribution of consumption under RECP by household-month. The consumption within percentiles 90%-110% paying nothing for electricity are colored orange. The above-110% percentiles making payments are colored green. The below-90% percentiles receiving a rebate are colored blue.

the buffer zone. (2) The electricity rate for military residents in Hawaii, upon which the payments and rebates are based, is predetermined and fixed during a fiscal year (from October this year to September next year) regardless of their consumption level and time of use as well as market price. These two features in combination provide an unconventional block pricing structure in which both the switching points between price tiers and price changes are defined exogenously. I will exploit these natural features in developing my empirical identification in the next section.

2.2 Data

Data on military electricity billing records were assembled by a company that operates the majority of military housing communities in Hawaii. The data provide household-level monthly electricity use for more than 27,000 military households on the island of Oahu, Hawaii (Honolulu county) from October 2009 through September 2018. After I dropped households that were exempted from billing under the program, were missing data on electricity use, bill and/or assigned peer group, or were in the sample only during the pre-treatment period, I obtain an unbalanced panel data with more than 25,700 households assigned to one among 100 peer groups for the main analysis. Group size widely varies from 6 to more than 300. The homes reside in 39 neighborhoods, located in nine zip codes. The panel data is unbalanced due to the fact that military residents frequently move from one installation to another over time. The billing data includes

household monthly electricity use, the amount of payment or rebate, assigned peer group, neighborhood, zip code, and housing characteristics.

Unfortunately, size of households, demographics and income data are not accessible. Generally, a household may choose a neighborhood to reside in depending on their income and personal preferences. Therefore, neighborhood choice might partially reflect household demographics. Also, besides temperature and precipitation, other weather elements such as wind direction and humidity vary according to neighborhood locations, depending on its distance and orientation to beaches and mountains.

Table B.1 presents descriptive statistics of selected housing characteristics and billing data. Briefly, while the program in fact is revenue neutral, households on average consumed less electricity after the program implementation. Under the program, about one-quarter (25%) of households regularly get a rebate, another quarter of households frequently have to pay for their above-average electricity use, only five percent of households pay nothing, as all did before the program commenced, and the remainder (45%) fluctuate between rebate and payment over time (Figure C.2). The electricity price applied to both payments above the threshold and rebates below the threshold was relatively stable around 40 cents/kWh during the period 2011 - 2016 and reduced to less than 25 cents/kWh in the fiscal years 2017-2018 (for details, please see marginal price for the payment group in Figure 4).

Since weather variation affects the demand for electricity, some specifications include major weather elements. I use weather data from NOAA Global Historical Climatology Network (GHCN), which provides daily air temperature and precipitation observations for each station in Honolulu county. I compute daily cooling degree days (CDD) by comparing average temperatures recorded at each station to the standard temperature of 65° Fahrenheit (F) and aggregate to CDD and precipitation to monthly level. To obtain weather data at the zip code level, I first match the weather station coordinates to each zip code using spatial mapping and take a simple average of weather elements over all stations within each zip code. Weather data is merged with the main data by the zip code where each household resides.

3 Empirical strategy

3.1 Difference-in-difference estimator

To investigate how military households on either side of the non-payment zone respond to the financial motivations, I first estimate changes in electricity use under the program using a difference-in-difference (DD) estimator. The regression specification is:

$$log(use_{it}) = \beta_0 + \beta_1(Post_t * Treat_i) + \beta_2 Post_t + \beta_3 Treat_i + X_{it}\theta + \epsilon_{it}, \tag{1}$$

where use_{it} is daily electricity use by household i in month t measured in kilowatt-hours, X_{it} is a vector of home characteristics including square footage and house age, and ϵ_{it} is the error term.

The weakness of the DD approach is that RECP was not designed with a randomly assigned control group. I address this problem by selecting households that, given the way the program was implemented, were least likely to have their behavior influenced by it. In the pilot period from September to December 2010, RECP provided each household with information on their electricity use, and peer-group average use. They also

informed each household what their projected payment or rebate would have received if the tournament had been effective. Households therefore had a good understanding of their baseline position prior to program implementation. Meanwhile, their payment did not change during the pilot period: they still pay nothing for electricity use.

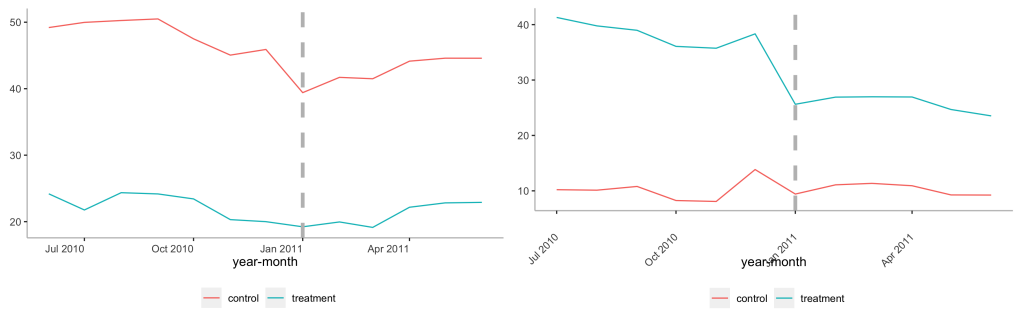
I therefore use as the control group "non-payment" households whose electricity use is always in the buffer zone throughout the sample period - both before and after the program - and was in the range of *+/-5%* from group average use in the pilot period. These households are less likely to be pushed out of the non-payment buffer zone (*+/-10%* from group average use) as long as monthly group average use does not endogenously change by a large amount. Over the longer run, this assumption could become increasingly questionable, in which case the treatment effects that I estimate are likely attenuated from their true impact, an issue I address below.

The first treatment group is comprised of "rebate" households whose consumption before the program is less than 55% of peer-group average use and are never required to pay during the whole sample period. I select 55% to ensure these households' level of consumption is far enough from the non-payment zone and so they are unlikely to be pushed to the non-payment or payment zone even if the group mean consumption slightly changes over months. Thus, these households are almost sure to face an expected marginal price equal to the full 25-40 cents per kWh, with their rebate reduced by this amount for each additional kWh consumed. The *average price* faced by these households, however, equals *minus* the rebate divided by kWh consumed, which seems more difficult to conflate with marginal price, as Ito (2014) and Wichman (2014) have found with block pricing. Households would have to believe that increasing electricity use would increase their rebate instead of decreasing it. The sign reversal and large numerical difference between these two price measures is unusual. While it seems unlikely that households would misperceive average price as marginal price in this extreme case, the substantial difference makes this a clear and testable hypothesis.

The second treatment group is comprised of "payment" households that consume more than 145% of the group average use during the pilot period and are always in the payment zone throughout the sample period. These households, like the rebate households, are almost sure to face an expected marginal price equal to the full 40 cents or 25 cents per kWh, with their payment increased by this amount for each additional kWh consumed, as they are unlikely able to reduce their electricity use as much as needed to move to the non-payment zone. While average price for these households is not negative like it is for rebate households, it is generally about one quarter the size of marginal price, since they only pay for electricity use above 110% of the average. Conflating average and marginal price seems more plausible than the rebate group, but less plausible than a typical block pricing situation. I nevertheless consider this possibility.

Figure 2: Mean seasonal adjusted electricity use by treatment status (kWh per day)

(a) Rebate versus Non-payment (b) Payment versus Non-payment

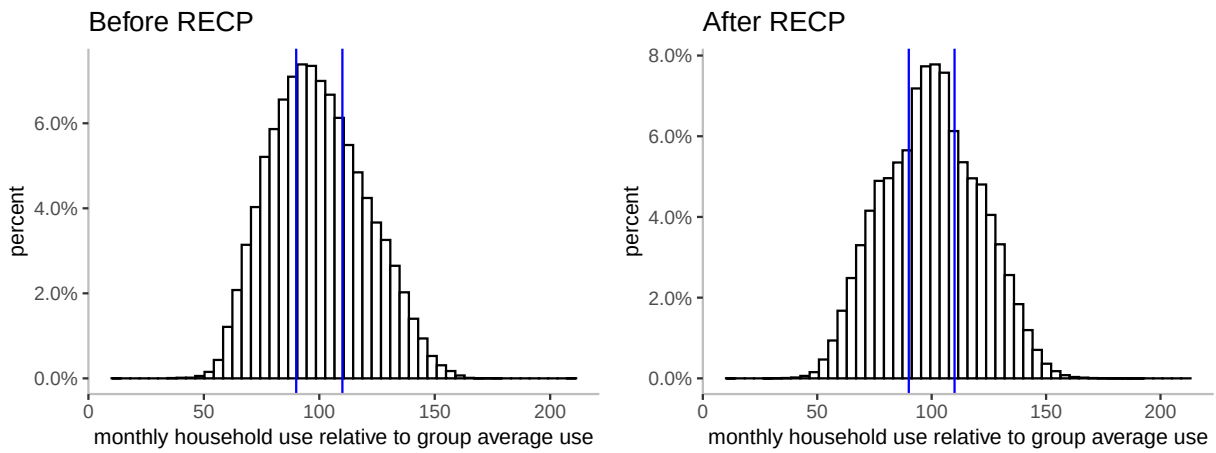


Thanks to the pilot period, households have learned about their relative position on the consumption distribution. The DD approach works assuming that households have a rational understanding of the tournament and the expected marginal prices they face and respond accordingly (Liebman & Zeckhauser, 2004). Because longer-run adjustments might change these expectations, the DD sample period is restricted to six months before and six months after the program (7/2010 - 6/2011). This selection avoids significant changes in group average use over time that might impact the behavior of households in the control group. Note that although the control group is categorized the same way in the two DD estimates, the control households included in each estimate might slightly differ. The reason is that I drop few peer groups that include only control households and no qualified treated households. Figure 2 displays mean electricity use before versus after the program by treatment status. The control group appears to slightly change its consumption after the program begins. To be conservative, I interpret differences relative to the control group, which may differ slightly from the true overall impact.

3.2 Estimating consumer response to exogenous changes in the peer-group average

A comparison between the distribution of household electricity use before versus after the program (Figure 3) shows that households respond to the billing tournament by adjusting electricity use toward the average level. In contrast to a smooth distribution of electricity use before the program, there is bunching of households at the non-payment buffer zone ($90\% - 110\%$ of the group average use) after the program. The bunching indicates that a proportion of households could manipulate electricity use to avoid being pushed out of or to move into the non-payment buffer zone. Since the monetary incentives are substantially different for under-average and above-average users, households at different consumption percentiles relative to the peer group average use might respond differently to price changes under the new billing tournament.

Figure 3: Distribution of Electricity use Before and After the program
Bunching at the average level



As mentioned in section 2.1, the electricity rate is fixed during a fiscal year regardless households' consumption level. Variation in a household's monthly payment solely depends on the difference between the household use and its peer group average use. To analyze how households respond to the new billing tournament over time, I develop an alternative design that considers how household electricity use responds to changes in peer group average use that stem from entry and exit of households from each group. Specifically, I use the peer group average fixed effect as an instrument for group average use. Since the individual fixed effect is constant over time for each household, the group average fixed effects will only change when households move into or out of the group. Since move-ins and move-outs are relatively frequent and mainly tied to tours of duty, it seems unlikely that this source of variation would be associated with any meaningful confounding factor. This feature makes the group average fixed effect an ideal instrument to measure the variation in group average use, and consequently average and/or marginal price changes induced by changes in group composition. I perform this estimate in three steps as follows:

First, I estimate individual fixed effects on log of daily use for each household i (Equation (2)).

$$log(use_{ijt}) = \alpha_i + \eta_{jt} + \epsilon_{ijt}, \tag{2}$$

where α_i is individual fixed effects, η_{jt} is a time-by-group fixed effect, to account for all time-varying weather and tournament incentives, and ϵ_{it} is the error term.

Second, I compute an average fixed effect over all households i for each peer group j in time t, excluding the extreme high or low users within each group (Equation (3)).[2]

$$G_{ijt} = \frac{\sum_{i=1}^{N_{jt}} \alpha_i}{N_{jt}} \tag{3}$$

where G_{ijt} is group average fixed effect and N_{jt} is number of households located in group j in time t.

Finally, in equation (4), I estimate the effect of group average fixed effect on household electricity use.

[2]This step follows the program practice. When computing the group average consumption level, RECP excludes top and bottom five percent in household electricity use within each peer group.

Because electricity bills arrive in the middle of the succeeding month, the lagged peer-group average use, but not contemporaneous group average use, is more likely to affect household consumption. The model includes individual fixed effects to control for heterogeneity of households in terms of their overall electricity use. Also, I include the neighborhood-by-time fixed effects to capture any changes in the neighborhood characteristics such weather or structural characteristics of the buildings or residential areas over time that may influence electricity use. The time-varying neighborhood effect would also help to control for changes in neighborhood characteristics. A peer (like-type home) group often locates in several neighborhoods and one neighborhood often include multiple peer groups. Therefore, including neighborhood fixed effects will not cause multicollinearity with the group average fixed effect predictor.

To explore the heterogeneity in consumer price sensitivity (Reiss & White, 2005) and detect the difference in consumer response to rebate versus payment incentives, inspired by Ito (2014) and Wichman (2014), I allow the effect of group average fixed effect to vary over households' consumption percentiles. The use of consumption percentile is to assess the distributional changes in consumption in response to changes in group average fixed effect. In addition, monthly consumption percentile is an appropriate indicator to predict whether households will be in the rebate, payment, or non-payment zone next month. The consumption percentile is household electricity use expressed as the percentage of its peer group average use. In each time period, I separate household consumption percentiles into bins by dividing the consumption percentiles into 10-percent intervals and by determining the percentiles that fall within each interval. Since household electricity use and group average use vary over time, one household may move from one bin to another over time. Household consumption percentiles in the treatment period ranges from 10% to 210% and are grouped into 20 10-percent bins.

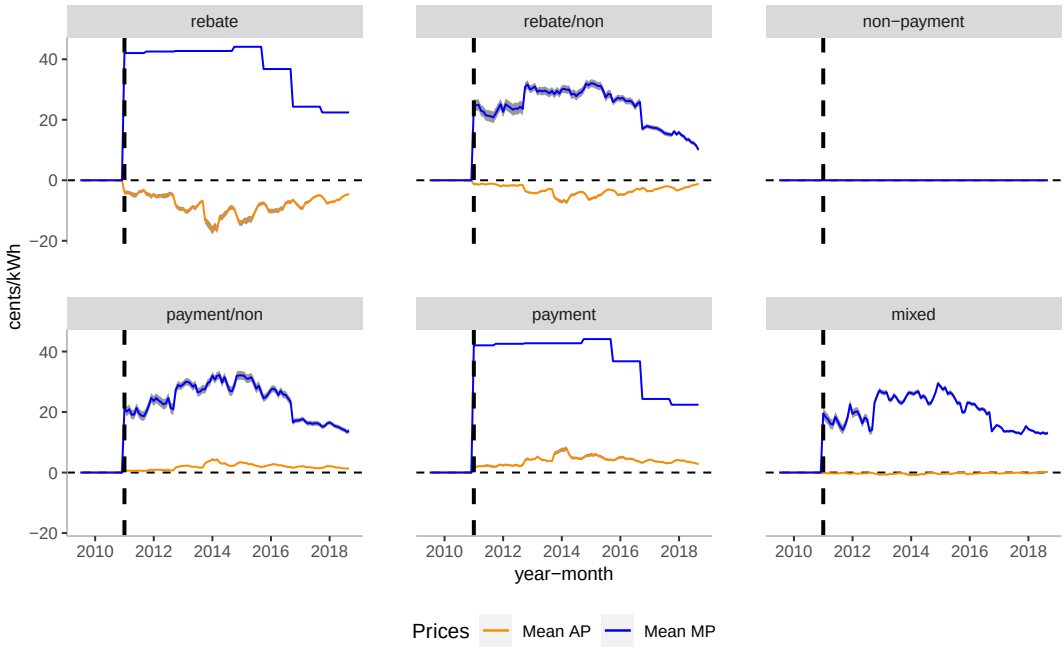
$$log(use_{ijt}) = \sum_{k=1}^{20} (\beta_k G_{ij,t-1} B_{ik,t-1}) + X_{it} + \gamma_i + \delta_{ht} + \epsilon_{ijt}, \tag{4}$$

where $G_{ij,t-1}$ is one-month lagged group average fixed effects, $B_{ik,t-1}$ is dummies which equal to 1 if household i belongs to the kth 10-percent bin in the previous month and equal to 0 otherwise, X_{it} is weather variables, including cooling degree day and precipitation at the zipcode where household i reside in time t, γ_i is individual fixed effects, and δ_{ht} is neighborhood-by-time interactive fixed effects. The coefficient β in Equation (4) shows the responsiveness of household electricity use to price changes which is caused by exogenous changes in peer group average use induced by entry and exit of households from the peer group. If the group average fixed effect decrease by one percent, ceteris paribus, household electricity use on average will reduce by β percent.

To identify how consumers respond to changes in monetary rewards (rebate) versus monetary penalties (payment) over time, instead of consumption percentile bins, I estimate the effect of peer group average fixed effects on household consumption by different types of user. I categorize households into six user types based on whether they have received a rebate or paid a payment throughout the program. Households within each user type see similar pattern of variation in monthly average and marginal prices (Figure 4 and Figure C.2). These six *user types* are: (1) the payment group includes households that always consume above the buffer zone (+/-10 percent of average use); (2) The rebate group is households that always remain below the buffer zone; (3) The non-payment group always consumes within the buffer zone and so continue paying nothing under the program; (4) The rebate/non group obtains a rebate in some months and is pushed into the non-payment zone in some months; (5) The payment/non group is, on contrast, households that

either consume within or above the buffer zone and so either receive a zero or positive charge; and (6) the mixed group includes households that frequently transverse across the buffer zone, receiving a rebate in some months, zero charge in some months, and a payment in other months. An exogenous shift in peer-group average use changes both monetary and social incentives differently between these user types. When the peer-group average use changes, households in the payment, rebate, and non-payment user types see the same monetary incentives, because the change in the peer-group average is too small to cause a shift from one zone to another. Households in the mixed user type, the rebate-to-non-payment user type, and payment/non user type may be pushed into (or out of) the buffer zone. These user types experience a change in monetary incentives, either from receiving a rebate to non-payment or making a payment, or vice versa. Note that for this estimate, I exploit the sub-sample of the post-treatment period only, 2011 - 2018. Also note that, for each household while consumption percentile bins may vary, the user types are fixed throughout the sample period.

Figure 4: Mean prices by user type



4 Results

4.1 Consumer response to monetary rewards versus monetary penalties

Table 1 shows that under the RECP monetary incentives, in comparison to non-payment households, while households in the payment group reduce consumption by about 16%, households in the rebate group surprisingly increase consumption by about 8.4%. The positive effect in the rebate group may seem surprising as it goes against pure economic incentives: the marginal price increased, so it would imply an upward sloping demand curve for a rational household. As a robust check for the increasing consumption of rebate group after the program implementation, I expand the sample to including every households in rebate and non-

payment groups, the effect slightly declines to above 4% but remains positive (Table **??**). It could be that households were responding to the decreases in average price. Alternatively, there may be another social or psychological factors at play, as these households gravitate toward to peer-group average. The response from the payment group, however, is almost double the magnitude as the rebate group and accords with pure monetary incentives. Note, however, that while average price is positive, in contrast to the negative average price for the rebate group, the magnitude of average price is much smaller than it is for the rebate group. This suggests that household do not simply respond uniformly to average price. With a similar proportion of households within payment and rebate groups, the aggregate effect of the program is to reduce electricity use.

Table 1: Difference-in-difference average treatment effects

	Dependent variable:					
	Rebate Group			Payment Group		
	Log(Usage/Day)		Usage/Day	Log(Usage/Day)		Usage/Day
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.124^{**}			-0.085		-6.235
	(0.051)					
Treat	-0.823^{***}			0.459^{***}		35.584^{***}
	(0.045)			(0.020)		(1.562)
Post*Treat	0.086^{*}	0.084^{*}	4.094^{***}	-0.161^{***}	-0.156^{***}	-13.694^{***}
	(0.050)	(0.049)	(0.898)	(0.022)	(0.024)	(1.790)
Constant	3.577^{***}	3.973^{***}	52.674^{***}	4.447^{***}	4.432^{***}	48.421^{***}
	(0.375)	(0.026)	(1.049)	(0.424)	(0.013)	(0.298)
Household FE	No	Yes	Yes	No	Yes	No
Time FE	No	Yes	Yes	No	Yes	No
Group FE	Yes	No	No	Yes	No	Yes
Seasonality	Yes	No	No	Yes	No	Yes
Observations	900	1,173	1,173	1,321	1,549	1,551
R^2	0.702	0.771	0.860	0.735	0.782	0.785
Adjusted R^2	0.692	0.749	0.846	0.728	0.760	0.763

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are two-way clustered by peer-group and time period.
Control variables include house characteristics (house square footage and house age).
Control group is households who always consume within 5% below/above the group average use.

Since RECP simultaneously implemented a new pricing scheme and peer information intervention, one may question that the increases in consumption of the rebate group was caused by a so-called "boomerang" effect rather than by economic rewards. A boomerang effect happens where households who have lower-than-average consumption respond to peer information by increasing their energy use. The peer information suggests to low users that they are consuming less than typical households and that it is socially acceptable to consume more (Fischer, 2008; Schultz et al., 2007). To our knowledge, this kind of information effect has not been simultaneously implemented with a powerful monetary incentive to reduce consumption, as does the RECP.

To investigate information about peer-group average use causes the boomerang effect in the absence of a

monetary incentive, I estimate the Equation (1) using the four-month pilot period. Table 2 shows a negative and insignificant effect of peer information provision on the low-consuming household, implying that there is no boomerang effect prior to actual implementation of the tournament. This result suggests that the positive change in low users' consumption was not caused by descriptive peer comparison alone, but only in response to the monetary reward. One possibility is that the rebate acted to make under-consuming more salient to these households. Another possibility is that some households mis-perceive the negative average price as marginal price, and mistakenly respond by consuming more. In either case, rewarding customers who are already inclined to conserve has a potentially counterproductive influence of causing them to consume more. While this response clearly goes against energy conservation goals, the economic welfare implications of this effect are difficult to pin down without a clear understanding of what causes the response, an issue that I discuss further below.

Table 2: Difference-in-difference, Descriptive norm boomerang effects

	Dependent variable:					
	Log(Usage/Day)		Usage/Day		Seasonal Adjusted Usage/Day	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.030		2.708***		−0.449	
	(0.022)		(0.606)		(1.503)	
Treat	−0.786***		−24.446***		−24.480***	
	(0.053)		(1.290)		(1.302)	
Post*Treat	−0.004	−0.009	−1.506	−1.266	−1.452	0.011
	(0.076)	(0.059)	(1.750)	(1.469)	(1.745)	(2.101)
Constant	4.080***	3.731***	59.719***	43.529***	22.714**	145.320
	(0.373)	(0.024)	(11.006)	(1.400)	(10.710)	(113.221)
Seasonality	Yes	No	Yes	No	No	No
Household FE	No	Yes	No	Yes	No	Yes
Time FE	No	Yes	No	Yes	No	Yes
Group FE	Yes	No	Yes	No	Yes	No
Observations	761	1,001	761	1,001	761	1,001
R^2	0.677	0.757	0.783	0.832	0.764	0.813
Adjusted R^2	0.664	0.730	0.774	0.813	0.758	0.794

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are two-way clustered by peer-group and time period.
Control variables include house characteristics (house square footage and house age).
'Post' is the pre-treatment period, Sep-Dec 2010.

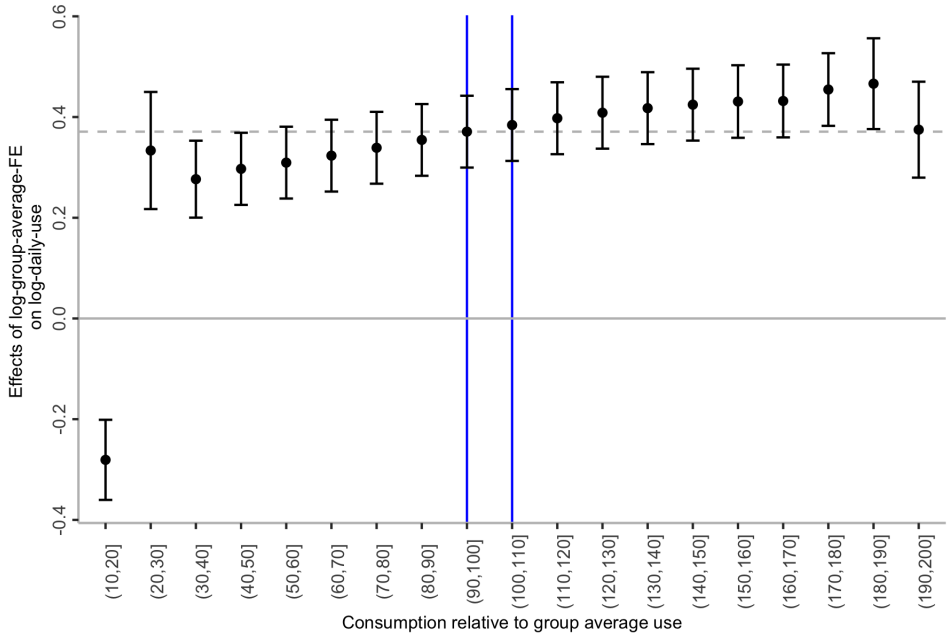
4.2 Consumer response to exogenous changes in the peer-group average

The observed data indicated that over time, on average, low users entry and high users exit will reduce group average use (Figure C.1, Table B.2). The determined level of group average use, in turn, defines who receives payments or rebates and the amounts that they will receive. Consequently, a shift of the group

average use to a lower level is equivalent to an increase in average price for all users, except those remain in the non-payment zone – consumption percentiles (90,100] and (100, 110] – both before and after the shift.

Household consumption relative to group average use varies from 10% to 210%. The result presented in Figure 5 confirms that households at relatively higher consumption percentiles respond stronger to changes in group average fixed effect. The pattern is clear and consistent, except for the highest and two lowest percentiles — probably due to lack of observations, only 4-5 observations in each bin, in the upper and lower tails of the consumption distribution. In the direction from lower to higher consumption percentiles, the responsiveness slightly increases from 0.27% to 0.47%. Hence, conditional on seeing a downward trend of group average use, households will reduce electricity use over time and high users likely save more electricity than low users. Moreover, I find that a group average fixed effect change in a given month influences household consumption not only in the succeeding month but partially last through seven months since the change. The dynamic effect estimate is presented in the Appendix A.

Figure 5: Effect of Lagged Group FE on Log(Daily Use), by Consumption Percentile



Notes: This figure displays estimates of β_k from Equation (4). Points are the coefficients on one-month lag of log group average fixed effects, vary by consumption percentile. Whiskers indicate the 95% confidence intervals for the point estimates. Two vertical blue lines indicate the boundaries of non-payment zone. The dashed horizontal line marks the β coefficient for the percentile (90,100] which includes households consuming at the group average level.

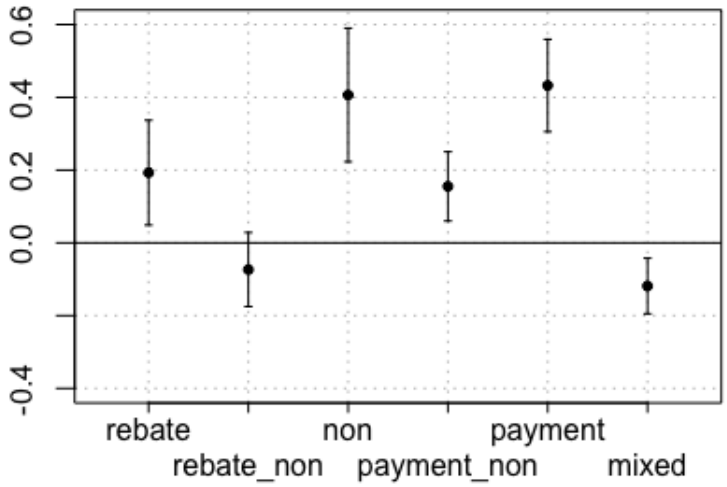
Figure 6 displays how variations in group average fixed effects influence different user types. Note again that, different from the previous estimate in which the consumption percentile is redefined each month based on the percentage of household use relative to group average use, the type of user is fixed for each household during the study period. The rebate, non-payment, and payment groups, who do not experience any changes in marginal price, all positively respond to changes in group average fixed effects and the effect is stronger when households face higher average price. Average price is respectively negative, zero, and positive for the rebate, non-payment, and payment group. When the entry/exit leads to a decrease in group average fixed effect by one percent, or equivalently a proportionally increase in average price, the payment group reduces

their electricity use by about 0.43%, which is stronger than the effect of 0.19% in the rebate group.

The effect is complex for user types who experience changes in marginal price over time. While a decrease in group average fixed effects causes an average household in the payment/non group to reduce electricity use, an average household in the mixed group will increase electricity use. The effect is insignificant for the rebate/non group. The ambiguous signs of the effects and low magnitude of the point estimates in these three user types, where households were moving back and forth between the rebate, non-payment and payment zones, suggest that different effects of negative versus positive changes in group average fixed effects might push and pull the household consumption in different directions and so make the aggregate effect tend to zero or insignificant. In the next section, I will decompose the effects of changes in group average fixed effects on household electricity use into the effect of negative changes versus positive changes for the *mixed group*.

Combining with the DD results, this estimate implies that the rebate group first increase electricity use in response to the negative average price. Over time, as average use and the non-payment window generally shift lower (Figure C.1), cause average price to increase (less negative for the rebate and rebate/non groups as shown in Figure 4), the perverse effect in the rebate group will decrease and the conserving effect in the payment group will increase. The effect in the rebate and payment groups supports the hypothesis that consumers respond to changes in average price, which is in line with (Ito, 2014; Wichman, 2014)'s findings. However, although relatively lower than in other groups, the effect in the non-payment group, who neither experience average nor marginal price changes, suggests that households may respond to another type of perceived price besides average price and/or marginal price. It can be expected marginal price (Borenstein, 2009) based on household position relative to the group average use shown in the prior electricity bills (Shin, 1985). When non-payment households see a downward shift in group average use over time, they might expect to see higher average and marginal prices in the coming months. This expectation would encourage them to reduce their contemporaneous electricity use.

Figure 6: Effect of Lagged Group FE on Log(Daily Use) by User Type



Notes: This figure presents estimates of β from Equation (4) but the β varies by user type instead of consumption percentile. Points are the coefficients on one-month lag of log group average fixed effects. Whiskers indicate the 95% confidence intervals for the point estimates. User types are defined at the end of section 3.2.

As a *robustness check*, following Alberini and Towe (2015) to deal with the absence of plausible control house-

holds, I fit the model in Equation (4) with an alternative combination of fixed effects, including household-by-month fixed effects, month-by-year fixed effects, and household-by-year fixed effects to account for all possible confounders that might influence electricity use. The effect of changes in group average fixed effects thus is identified by variation within the household–month–year cell (Table B.3, column (4)). In addition, consumer response to variation in group average fixed effects might vary depending on how large the change in household relative position from the group average use over past months. For an additional robustness check, I control for this potential effect by including the standard deviation of consumption percentile over past three months (Table B.3, column (3)). The response patterns remain similar to my main results. The coefficient for standard deviation of consumption percentile in Column (3) Table B.3 is -.0091, suggesting that households who have experienced relatively larger variation in consumption percentile tend to reduce more electricity use.

4.3 Effects of positive changes versus negative changes in the peer-group average use

Within each group, the group average fixed effects may either increase or decrease from one month to the next due to changes in the group members. To examine whether consumer behavior is different when price increases versus decreases, I estimate log use *changes* on lagged log group average fixed effect *changes* as specified in Equation (5) using the *mixed group* sample. Equation (5) presents the same specification as in Equation (4), except that I use the first difference instead of the contemporaneous variables. The purpose of using the first difference simply is to separately estimate the effect of group average fixed effect changes using two sub-samples: when the change is negative ($\Delta G_{ij,t-1} < 0$) and when it is positive ($\Delta G_{ij,t-1} > 0$). Since I use first difference estimate, the household fixed effects is dropped from the model. The coefficient β'_k is commonly expected to be positive regardless the group average fixed effect change is negative or positive[3].

$$\Delta log(use_{ijt}) = \sum_{k=1}^{20} (\beta'_k | \boldsymbol{\Delta G_{ij,t-1}} | B_{ik,t-1}) + X_{it} + \delta'_{ht} + \epsilon'_{ijt}, \tag{5}$$

where $\Delta log(use_{ijt}) = log(use_{ijt}) - log(use_{ij,t-1})$ and $\Delta G_{ij,t-1} = G_{ij,t-1} - G_{ij,t-2}$.

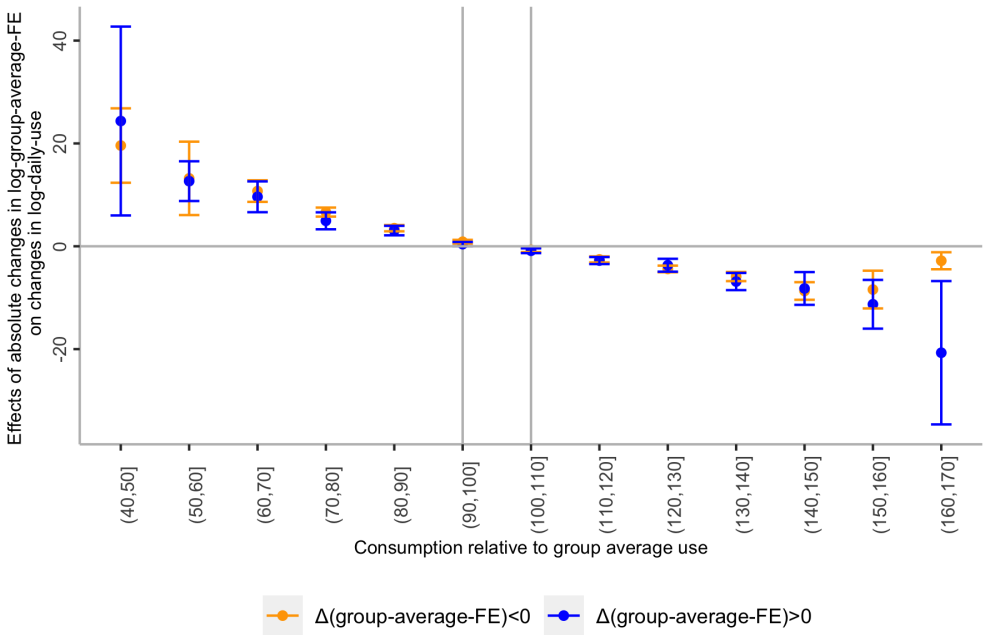
Some lowest and highest consumption percentiles ($\leq 40\%$ and $\geq 170\%$) were dropped from the estimates due to too few observations[4]. As mentioned in the section 3.2 that the mixed group includes households who receive a rebate for under-average consumption in some months and have to pay for exceed consumption in some other months. That means mixed-group households frequently move from low consumption percentiles to high percentiles and vice versa. Figure (7) shows interesting responses of households in the mixed group to negative changes versus positive changes in group average fixed effects. The estimated coefficients are *not all positive* as expected. Instead, if in previous month, households were in lower consumption percentiles – under 90% of the group average level, they tend to increase electricity use both when group average fixed effect decreases and when it increases. Namely, users from the lower percentiles increase daily use regardless of the

[3] As discussed in section 3.2, if household daily use remains unchanged over time, a decrease in group average fixed effects will cause an increase in average price for users in the mixed group, and vice versa. When lagged group average fixed effects decline, i.e. $\Delta G_{ij,t-1} < 0$, households will see an increase in their prior month bill and learn that price was increasing. Households thus commonly will decrease consumption in response to the increasing price, i.e. $\Delta log(use_{ijt} > 0$. In other words, an economist will generally expect lagged log group average fixed effect changes and log daily use changes to vary in the same direction.

[4] When I include the consumption percentiles $\leq 40\%$ and $\geq 170\%$, the regression coefficients on those percentiles are consistent with the pattern shown in Figure 7, but much larger in magnitude

average price increases or decreases. In contrast, households who learned that they were consuming more than 110% of the group average use tend to decrease electricity use in both cases of negative and positive changes in group average fixed effects. That is to say, users likely decrease contemporaneous consumption no matter how the average price changes if they were from the above-consumption percentiles. Though these households did not respond as economists would generally predict, it is in line with Jessoe et al. (2014). They find that households responded to the intervention lowered the electricity price for several months by decreasing their electricity use in those months. The result suggest that other drivers of behavior might interact with the monetary incentives to influence household usage response.

Figure 7: Effects of lagged log changes in group average fixed effects on log changes in daily use, Mixed User



Notes: This figure displays estimates of β'_k from Equation (5). The set of point estimates in *orange* color comes from the regression of the changes in log daily use on the *absolute* value of corresponding *negative* changes in log group average fixed effects. A separate same regression on the *positive* changes in log group average fixed effects provides the set of point estimate in *blue* color. Whiskers indicate the 95% confidence intervals for the point estimates. Two vertical gray lines indicate the boundaries of non-payment zone.

More interesting, the household usage response to changes in the group average fixed effects - either negative or positive - is stronger when households were in the consumption percentiles relatively further from the group average level. For instance, given that the group average fixed effect decrease 1% in the previous month, i.e, average price increased, an average household at the percentile (40,50] will increase contemporaneous use by about 20% while an average household at the percentile (80,90] increase daily use by just 3.5%. On the opposite side, if group average fixed effect increase by 1% in the previous month, i.e. average price decreased, households at the percentile (160, 170] decrease daily use by 21% while households at the percentile (110, 120] slightly decrease daily use by 2.8%. When households were within the average range (90,110], they respond to the 1% change in group average fixed effects, either negative or positive changes, by adjusting their consumption at the marginal rate, about .8%. This imply that in response to frequently changes in the group average use that have caused a large variation in household monthly bills, mixed-group households

manage to adjust the electricity use toward the group average level as if it is the norm. The further they were from the "norm" in the previous month, the harder they try this month. Households who were informed that their electricity use is abnormally high tend to engage in behavior that brings them closer to the norm (Allcott, 2011). Meanwhile, households who learned that their consumption is abnormally low tend to raise the daily use closer to the average level (Schultz et al., 2007).

The program setting does not provide information to discover the mechanism behind the unexpected response that low users increase consumption when average price increase and high users decrease consumption when average price decrease. Section 4.1 has shown that the peer comparison by itself did not cause low users to increase electricity use. This unexpected response thus might be the effects of a combination of the peer incentives (information intervention) and the monetary incentives (price intervention). By not only sending consumers the information about peer comparison but also setting the group average level as a standard to define monetary rewards and penalties, the program presumably mistakenly convey a message that residents should use electricity at the average level. This message is clearly different from the program's original purpose to encourage all households to conserve electricity regardless their current positions on the consumption distribution.

Another hypothesis might explain the driver of this unexpected response comes from the nature of household repeated decision-making. Under frequent changes in group average use, given that households see the peer comparison and learn their relative position away from the group average level every month, household monthly decision on whether to reduce or increase their use can be considered as the decision made in a multi-phase competition against others within the peer group. Huang et al. (2017) show that motivation of winning in the next round of a multi-phase competition depends on the temporary standing – whether contestants are currently ahead of behind the opponent. In the early phase, contestants concern about whether they can win and if they learn that they are in the lead then they make an effort to win since winning seem more attainable. However, in the later phase, contestants are instead driven by how much additional effort they believe they need to invest. Being ahead reduces contestants' estimate of the remaining effort needed to win, therefore, reduce their effort, which worsened their performance. The Huang et al. (2017)'s findings might explain the behavioral response of low consuming households to the group average fixed effect change. When low users realize that they were using much less electricity and winning a larger monetary rewards compared to their peers, they tend to loosen their electricity conservation effort and so consequently increase their consumption from the previous month level.

5 Discussion and Conclusion

This study has employed a unique natural experiment to document household response to an electricity conservation program that applies simultaneously price intervention and peer comparison. The price incentives to low-consuming households are perceived as a monetary reward while to high-consuming households it is a monetary penalty. Moreover, by the nature of military personnel assignments, the entry and exit of households lead to changes in the peer-group average. This change in turn implicitly causes price to increase or decrease over time. Thus, the program setting provides a unique opportunity to fully explore consumer response to different incentives (monetary rewards versus penalties), to incentive changes over time, and the interactive effects between directions of changes and incentives.

I find that monetary rewards for low users increase household electricity use while monetary penalties for high users decrease household electricity use relative to households who unlikely to receive monetary incentives. Over time, following the peer-group average use changes, which were generated by entry and exit of group members, households generally respond by changing electricity use. When the peer group average use decreases, or equivalently, the average price increases, households at all consumption percentiles generally reduce daily use. Consider the mixed group, I decompose the changes in group average use induced by household entry and exit into positive and negative changes and fine more complex effects. In the mixed group, households experience both price increases and decreases over time. When households were at the below-average percentiles on group consumption distribution, they tend to increase electricity use regardless of whether price increases or decreases. Conversely, when households were at the above-average percentiles, they reduce electricity use in response to both price increases and decreases. The further households were away from the group average use, the larger adjustment they make toward the group average level. These results indicate that the interaction between monetary incentives and behavioral factors makes the peer comparison more powerful. Thus, policymakers could use monetary incentives to foster consumer behavior toward a norm defined by a specific goal of energy conservation.

Considering the post-treatment period from January 2011 through September 2018, the program overall reduced household electricity use. The reduction comes from (i) When the program was first implemented, high-consuming households in the payment group reduce consumption while low-consuming households in the rebate group increase consumption. Since the effect of monetary penalties in the payment group is almost double the positive effect of monetary rewards in the rebate group, the aggregate effect leads to a reduction in electricity use (section 4.1); and (ii) Over time, as peer group average use and the non-payment window shift lower, with the exception of the mixed group, all users reduce electricity use. This effect mitigates the perverse effect from some in the rebate group and gradually increases the response from the payment group. With the expectation about decreasing group average use, consumers at every part of consumption distribution will reduce electricity use (section 4.2).

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Appendices

A Dynamic effects

It takes households time to change their energy consuming habits and/or to learn how changes in group average use influences their monthly bills. Since the group average fixed effects frequently change over time, which lead to frequent changes in the average price, households contemporaneous use might respond both to recent changes and earlier changes in group average use. Additionally, if households are forward-looking, they may respond in anticipation of future changes in group average use. Following Deryugina et al. (2020), I account for these dynamics by adding to the estimate of log daily use at Equation (4) a combination of lags and leads of group average fixed effects.

$$log(use_{ijt}) = \sum_{r=-L_1}^{L_2} (\sum_{k=1}^{20} \beta_{k,r} G_{ij,t-s} B_{ik,t-s}) + X_{it} + \gamma_i + \delta_{ht} + \epsilon_{ijt}, \tag{6}$$

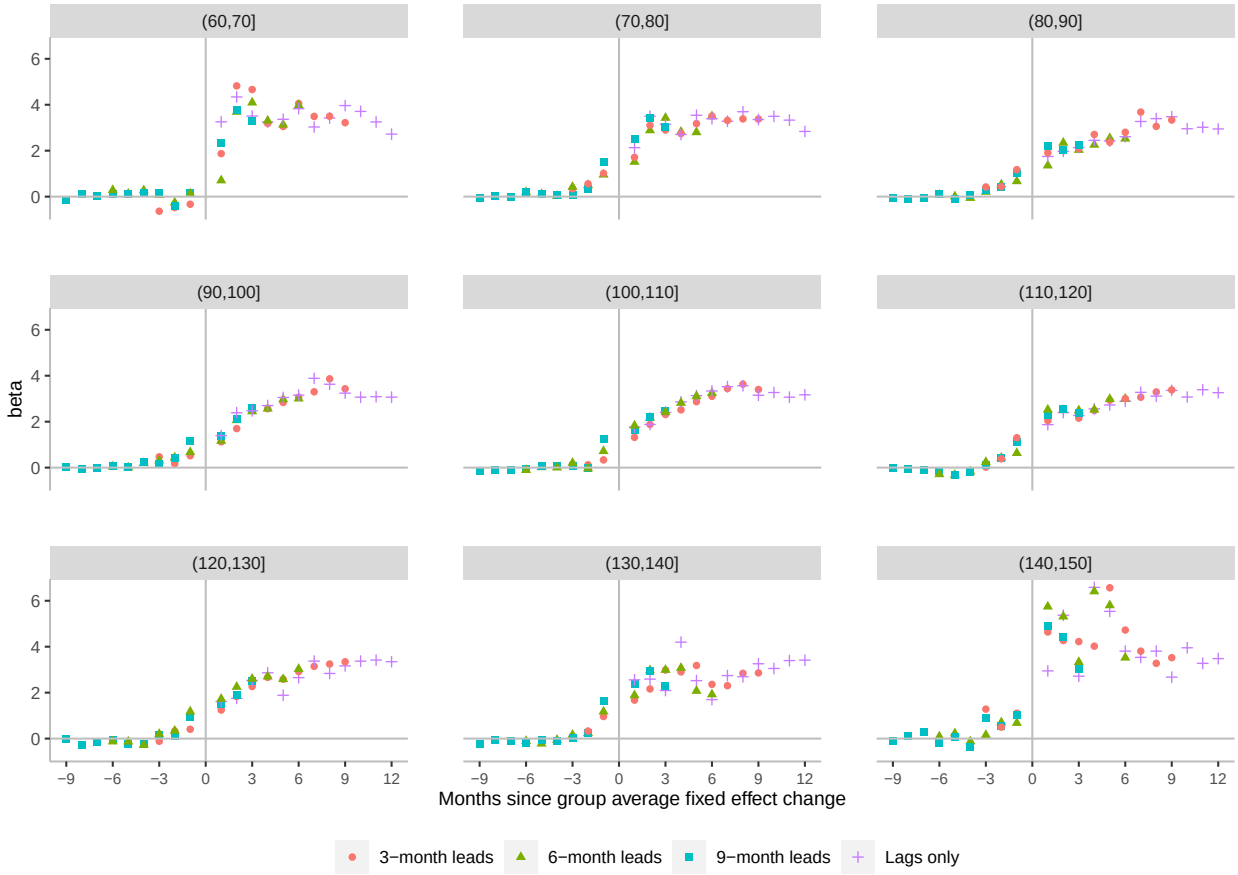
where L_1 is the number of leads and L_2 is the number of lags. To examine the dynamic effects of group fixed effect changes in the short-run, I alternately estimate Equation (6) using different sets of 12 leads and lags: $(L_1, L_2) \in \{(0,12),(3,9),(6,6),(9,3)\}$. I then take the linear cumulative sum of estimated coefficients on leads and lags to obtain the dynamic parameter (Equation 7).

$$\beta_{k,s} = \sum_{r=-L_1}^{s} \beta_{k,r}, \tag{7}$$

where s is the number of months since a change in group average fixed effect occurs. A negative s indicates that the change has not happened yet. Note that s = 0 is not the baseline when the program started but the time period that the group average fixed effect changes which frequently happens over time. Therefore, my interpretation of the dynamic parameter is slightly differ from Deryugina et al. (2020). $\beta_{k,s}$ reflects the changes in contemporaneous use of an average household in the kth consumption percentile in response to *accumulative changes* in group average fixed effects over s months.

Figure A.1 presents the dynamic effects of changes in group average fixed effect on daily use in short-run by consumption percentiles. The dynamic response patterns are quite similar across all consumption percentiles. Households seem to be able to anticipate a change in group average fixed effects and respond two months in advance of the change. The consumption percentiles that are further to the ends on the consumption distribution such as (60,70] and (140,150] respond stronger and faster to the changes, shown by the large effect in 1–3 months (β is about 5 to 6) since the changes in comparison to other percentiles that are closer to the average level (β is about 3 to 4). For most consumption percentiles, the dynamic effect is generally increasing over time and only begin to decline after the 7th month since the change. This pattern implies that household contemporaneous use is the aggregate response to changes in group average fixed effects that had happened in the recent seven months and the predicted changes in two months ahead. In other words, a change in group average fixed effects in a given month will influence household electricity use during the period from that month through seven months afterward.

Figure A.1: Dynamic Effects of log group average fixed effect on log daily use, by consumption bin



Note: Each set of markers is estimated by Equations (6) and (7) using a different set of 12 leads and lags: $(0, 12), (3, 9), (6, 6), and (9, 3)$. *The legend shows number of leads in each set.*

Table B.1: Summary Statistics

	Before	After
Monthly Electricity Use		
median	1,560	1,168
mean (sd)	1,588 ± 482	1,199 ± 368
Charge		
median	0	0
mean (sd)	0 ± 0	0 ± 46
House's square footage	1,465 ± 488	1,504 ± 438
House's number of beds	2.85 ± 0.72	2.97 ± 0.68
Cooling Degree Day		
min	54	49
max	487	570
mean (sd)	369 ± 89	341 ± 105
Number of households	3,775	25,721
Number of households*months	29,895	388,028

B Tables

Table B.2: Effects of Entry/Exit on Group Average Use
(*Group average use in turn determine the non-payment buffer zone*)

	Dependent variable:		
	Δ(Log Group Mean Individual FE)	Δ(Log Group Mean Usage/Day)	Log(Group Mean Usage/Day)
	(1)	(2)	(3)
Average Individual FE of households enter	0.063***	0.041***	
	(0.009)	(0.010)	
Average Individual FE of households exited	−0.054***	−0.053***	
	(0.006)	(0.008)	
Group Mean Individual FE			0.746***
			(0.107)
Constant	−0.078*	−0.166*	−1.214
	(0.041)	(0.099)	(0.770)
Time FE	Yes	Yes	Yes
Like-type group FE	Yes	Yes	Yes
Observations	3,569	3,569	6,739
R^2	0.425	0.792	0.903
Adjusted R^2	0.395	0.781	0.900

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are two-way clustered by group and time period

Table B.3: Robustness checks
Effects of group average fixed effect on daily use, by consumption percentile

Dependent Variable:	Log(Daily Use)			
Model:	(1)	(2)	(3)	(4)
Lagged Group mean FE × Percentile(10,20]	-0.3001***	-0.2808***	-0.2891***	-0.2534***
	(0.0405)	(0.0406)	(0.0408)	(0.0491)
Lagged Group mean FE × Percentile(20,30]	0.3125***	0.3335***	0.3308***	0.2789***
	(0.0598)	(0.0593)	(0.0614)	(0.0519)
Lagged Group mean FE × Percentile(30,40]	0.2494***	0.2766***	0.2747***	0.2831***
	(0.0380)	(0.0390)	(0.0395)	(0.0563)
Lagged Group mean FE × Percentile(40,50]	0.2774***	0.2972***	0.2912***	0.2960***
	(0.0359)	(0.0365)	(0.0368)	(0.0538)
Lagged Group mean FE × Percentile(50,60]	0.2896***	0.3095***	0.3034***	0.2994***
	(0.0358)	(0.0364)	(0.0366)	(0.0537)
Lagged Group mean FE × Percentile(60,70]	0.3039***	0.3233***	0.3171***	0.3080***
	(0.0358)	(0.0364)	(0.0365)	(0.0537)
Lagged Group mean FE × Percentile(70,80]	0.3196***	0.3390***	0.3325***	0.3173***
	(0.0357)	(0.0364)	(0.0366)	(0.0538)
Lagged Group mean FE × Percentile(80,90]	0.3352***	0.3546***	0.3478***	0.3262***
	(0.0357)	(0.0363)	(0.0365)	(0.0539)
Lagged Group mean FE × Percentile(90,100]	0.3516***	0.3710***	0.3641***	0.3362***
	(0.0357)	(0.0364)	(0.0365)	(0.0541)
Lagged Group mean FE × Percentile(100,110]	0.3649***	0.3842***	0.3772***	0.3447***
	(0.0357)	(0.0364)	(0.0365)	(0.0542)
Lagged Group mean FE × Percentile(110,120]	0.3783***	0.3976***	0.3907***	0.3535***
	(0.0358)	(0.0364)	(0.0366)	(0.0544)
Lagged Group mean FE × Percentile(120,130]	0.3893***	0.4086***	0.4017***	0.3608***
	(0.0358)	(0.0364)	(0.0366)	(0.0545)
Lagged Group mean FE × Percentile(130,140]	0.3983***	0.4177***	0.4108***	0.3666***
	(0.0358)	(0.0364)	(0.0366)	(0.0545)
Lagged Group mean FE × Percentile(140,150]	0.4052***	0.4246***	0.4180***	0.3728***
	(0.0357)	(0.0364)	(0.0365)	(0.0546)
Lagged Group mean FE × Percentile(150,160]	0.4112***	0.4308***	0.4244***	0.3774***
	(0.0360)	(0.0368)	(0.0368)	(0.0547)
Lagged Group mean FE × Percentile(160,170]	0.4118***	0.4319***	0.4223***	0.3696***
	(0.0357)	(0.0369)	(0.0370)	(0.0550)
Lagged Group mean FE × Percentile(170,180]	0.4338***	0.4546***	0.4481***	0.4009***
	(0.0355)	(0.0368)	(0.0371)	(0.0545)
Lagged Group mean FE × Percentile(180,190]	0.4470***	0.4662***	0.4597***	0.6397
	(0.0452)	(0.0460)	(0.0454)	(990.5)
Lagged Group mean FE × Percentile(190,200]	0.3549***	0.3749***	0.3706***	0.2848***
	(0.0483)	(0.0486)	(0.0474)	(0.0546)
CDD		0.0002*	0.0002	
		(0.0001)	(0.0001)	
PRCP		-0.0038**	-0.0043**	
		(0.0019)	(0.0020)	
SD(Consumption Percentile), recent three months			-0.0064***	
			(0.0011)	
Household FE	Yes	Yes	Yes	
Neighborhood-by-Time FE	Yes	Yes	Yes	
Household-by-Month FE				Yes
Time FE				Yes
Household-by-Year FE				Yes
Observations	333,868	320,139	302,756	333,868
R^2	0.86251	0.86314	0.86388	0.96204

Two-way (Household FE and Time FE) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table B.4: Robustness checks
Effects of group average fixed effect on daily use, by user group

Dependent Variable:	Log(Daily Use)			
Model:	(1)	(2)	(3)	(4)
Variables				
Lagged Group mean FE × Rebate group	0.1489*	0.1929**	0.1243	0.5754***
	(0.0866)	(0.0876)	(0.0968)	(0.1384)
Lagged Group mean FE × Rebate_Non group	-0.0744	-0.0733	-0.0917	0.1102
	(0.0592)	(0.0619)	(0.0665)	(0.0936)
Lagged Group mean FE × Non-payment group	0.3964***	0.4066***	0.4201***	0.4743
	(0.1082)	(0.1116)	(0.1516)	(0.4994)
Lagged Group mean FE × Payment_Non group	0.1569***	0.1552***	0.1522**	0.0562
	(0.0579)	(0.0579)	(0.0619)	(0.0734)
Lagged Group mean FE × Payment group	0.4294***	0.4326***	0.3539***	0.2294*
	(0.0731)	(0.0772)	(0.0877)	(0.1349)
Lagged Group mean FE × Mixed group	-0.1267***	-0.1184**	-0.1266**	0.0069
	(0.0457)	(0.0465)	(0.0485)	(0.0653)
CDD		0.0003*	0.0003*	
		(0.0001)	(0.0002)	
PRCP		-0.0033*	-0.0049**	
		(0.0019)	(0.0019)	
SD(Consumption Percentile), recent three months			-0.0091***	
			(0.0012)	
Fixed-effects				
Household FE	Yes	Yes	Yes	
Neighborhood-by-Time FE	Yes	Yes	Yes	
Household-by-Month FE				Yes
Time FE				Yes
Household-by-Year FE				Yes
Fit statistics				
Observations	384,235	368,398	320,330	384,235
R^2	0.81721	0.81767	0.82202	0.95407

Two-way (Household FE and Time FE) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

C Figures

Figure C.1: Average electricity use over time, full sample

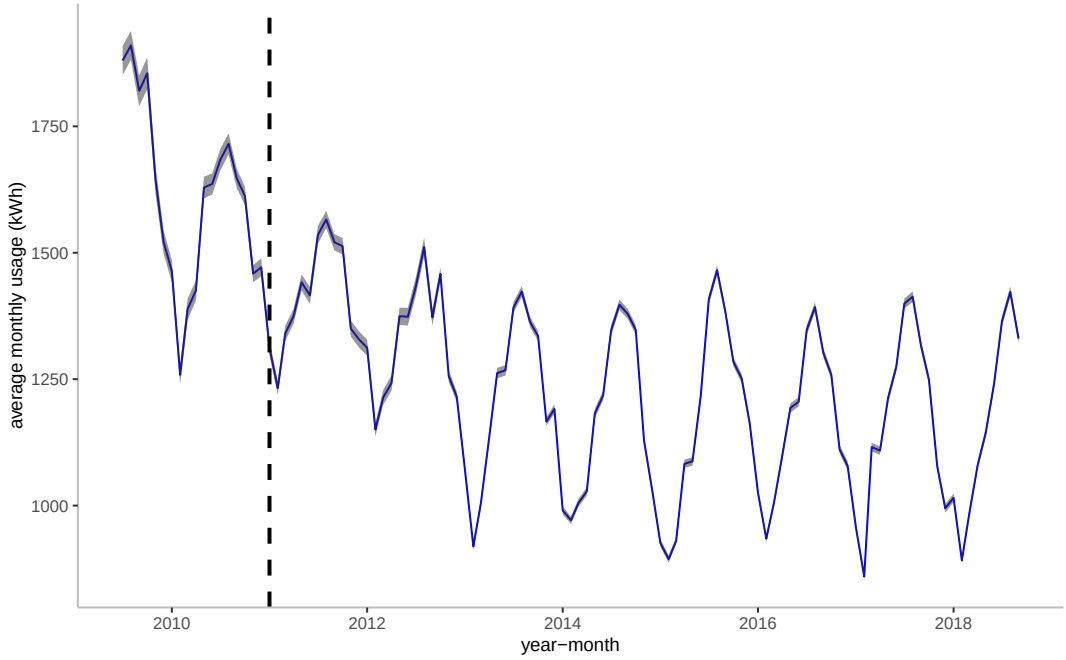


Figure C.2: Average monthly electricity use by user type