INFORMATION ON TOP OF INCENTIVES: HOW PRICE INFORMATION INFLUENCES HOUSEHOLD RESPONSE TO THE PEAK-TIME REBATE

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Overview

The classic assumption that agents are perfectly informed when they make choices is often challenged in modern empirical studies. When consumers are paying for services, not for energy directly, and possibly confront intermittent billing combined with tiered tariffs, the full information assumption is even harder to hold. Consumers may not comprehend how much electricity is required for a certain service (e.g., one hour cooling via electric air-conditioner), how costly it is to use electricity for the service at the margin, and how much benefit the service generates. Such information problems lead to inefficiency in the consumption of electricity. The examples include gasoline use for travel, energy and water consumption, and cell-phone usage [1-3]. Previous studies have demonstrated that choice and demand behaviour of the consumers can be affected considerably by the completeness of information available to them [4]. As such, any policy intervention should identify whether or not the consumers make fully informed decision, and, if not, the extent to which their behaviour can be modified by the provision of some additional information. Another consideration to give is that well-designed information programs may generate synergistic coupling with pre-existing price instruments, whereas ill-founded information measures may not serve the originally intended goals or even harm the consumer welfare [3, 5].

The role of information in modifying household electricity use is receiving renewed attention with the diffusion of Advanced Metering Infrastructures (AMI), the electricity meter with featuring, monitoring and controlling functions connected to communication networks [6]. This is because the AMI enables new electricity services, such as dynamic pricing and real-time feedbacks. In this regard, several studies have assessed the load impact of dynamic pricing schemes in various market arrangements (e.g., [7, 8]). However, little research has investigated or at least controlled for the effect of information provision on demand response under a dynamic pricing setting—see [2] for a notable exception. To fill in the research gap, our research pursues the following research questions: (i) How would the different levels of information (incentive only versus incentive plus price information) influence the households' response to the peak-time rebate program? (ii) To what extent would the information treatments moderate the households' peak-time response and overall electricity consumption patterns? To answer these questions, we have conducted a large-scale field experiment of the peak-time rebate program permitting different levels of information treatment. A total of about 1,500 Korean households have been recruited and approached with a face-to-face survey to collect the individual households' detailed socio-demographic and techno-economic characteristics. To the recruited households, ten peak-time rebate events were called in August and September of 2017. Some preliminary results are presented below, although more comprehensive analysis and model estimations are underway.

Methods

Recruitment. Candidates for our experiment have been randomly selected from the registry of households installed with the AMI according to a stratified random sampling procedure. The candidates were a priori assigned to one of the three experimental groups—Control, Treatment I (event notice only), and Treatment II (event notice plus price information)—and given a chance to participate into the experiment upon their agreement through on-site visits, such that the possible sample selection bias could be minimized. The recruitment has been performed until each of the three groups forms a panel of 500 households, so that a total of 1,500 households eventually participated in our field experiment. Compared to households in the treatment groups who receive either type of information treatment during the experiment and are rewarded financially based on their performance in load reductions in event-day peak hours, households in the control group neither receive the information nor rewarded based on performance. A face-to-face survey was conducted to all of the recruited households regardless of their group assignment in order to collect their detailed socio-demographic information.

Experiment Design. Households in either treatment group receive a SMS-based critical peak event alert a day before each event day. The alert consists of event hours (2pm-6pm) and peak-time incentive rate applied, which is held fixed to KRW1,000 per kWh of abatement achieved. In particular, the households are rewarded based on the amount of electricity usage reduced relative to their customer baseline loads (CBL) during critical peak hours in event days. Households in Treatment II received additional information on their marginal price of electricity under the prevailing Increasing Block Tariff (IBT). Both of the two treatment groups are also notified with usage abatement scores for each critical peak event several days after the event. A total of ten peak-time rebate events were called in August and September of 2017.

Results

Three models are proposed for our preliminary analysis. Model 1 is used to identify the standard average treatment effects (ATEs), where $AFTERTREAT_t$ indicates whether time t is after the announced start time of the pricing experiment, and $EVENTPEAK_t$ indicates whether time t is on critical peak hours in event days. The model is to identify what we call 'participation effect' and 'incentive effect.' The participation effect captures the difference in the load impact of the commencement of the experiment between the control group and either of the two control groups. The coefficient for the interaction term, $TREAT_g \times AFTERTREAT_t$, thus represents this participation effect. The incentive effect indicates the difference in the load impact of the peak-time rebate between the control group and either of the two treatment groups in event days. The coefficient for the interaction term, $TREAT_g \times EVENTPEAK_t$, represents the incentive effect. Model 2 estimates how these two treatment effects would vary with the requirement for cooling, for which a six-hour moving average of cooling degree hours is used with the reference temperature of 24°C (indicated as $m6CDH$). Model 3 compares response patterns among the experimental groups according to the overall usage levels of individual households. For all models, household-specific fixed effect (α_i), hour-of-the-day fixed effect (τ_h), and climate variables (μC_t) are employed as the control variables.

$$\begin{aligned} log(USE_{it}) = {} & \alpha_i + \tau_h + \gamma(AFTERTREAT_t) + \beta_{0g}(TREAT_g \times AFTERTREAT_t) \\ & +\phi(EVENTPEAK_t) + \delta_{0g}\left(TREAT_g \times EVENTPEAK_t\right) + \mu C_t + \epsilon_{it} \end{aligned} \qquad (Eq.1)$$

$$\begin{aligned} log(USE_{it}) = {} & \alpha_i + \tau_h + \gamma(AFTERTREAT_t) + \left(\beta_{0g} + \beta_{1g} \times m6CDH\right)\left(TREAT_g \times AFTERTREAT_t\right) \\ & +\phi(EVENTPEAK_t) + (\delta_{0g} + \delta_{1g} \times m6CDH)(TREAT_g \times EVENTPEAK_t) + \mu C_t + \epsilon_{it} \end{aligned} \qquad (Eq.2)$$

$$\begin{aligned} log(USE_{it}) = {} & \alpha_i + \tau_h + \gamma(AFTERTREAT_t) + \left(\beta_{0g} + \beta_{2gl} \times USELEVEL_l\right)\left(TREAT_g \times AFTERTREAT_t\right) \\ & +\phi(EVENTPEAK_t) + (\delta_{0g} + \delta_{2gl} \times USELEVEL_l)(TREAT_g \times EVENTPEAK_t) + \mu C_t + \epsilon_{it} \end{aligned} \qquad (Eq.3)$$

Our estimation results indicate first that, compared to the control group, both treatment groups exhibit statistically significant participation and incentive effects (see Model 1 in Table 1). Treatment II (event notice plus price information) presents greater incentive effect but smaller participation effect than Treatment I (event notice only). Second, both treatment groups exhibit smaller participation effects with higher cooling requirement but greater incentive effects with higher cooling requirement (see Model 2). Third, while mid- and high-use households in Treatment I present significantly smaller incentive effects than low-use households, mid- and high-use households in Treatment II do not exhibit statistically different incentive effects than low-use households– approximately 2.8% compared to control group households. Mid- and high-use households in Treatment I show greater participation effects than that of low-use households, the trend of which is shown less by households in Treatment II (see Model 3).

Table 1 Coefficient Estimates of Models

	Model 1		*Model 2*		*Model 3*	
	Est.	Std.dev	Est.	Std.dev	Est.	Std.dev
TREAT1*AFTERTREAT	-0.012	(0.001)***	-0.038	(0.001)***	0.027	(0.003)***
TREAT1*AFTERTREAT*m6CDH			0.016	(0.000)***		
TREAT1*AFTERTREAT*MIDUSE					-0.026	(0.003)***
TREAT1*AFTERTREAT*HIGHUSE					-0.068	(0.003)***
TREAT2*AFTERTREAT	-0.004	(0.001)**	-0.033	(0.001)***	0.023	(0.003)***
TREAT2*AFTERTREAT*m6CDH			0.018	(0.000)***		
TREAT2*AFTERTREAT*MIDUSE					-0.018	(0.003)***
TREAT2*AFTERTREAT*HIGHUSE					-0.049	(0.003)***
TREAT1*EVENTPEAK	-0.012	(0.005)*	0.020	(0.009)*	-0.058	(0.011)***
TREAT1*EVENTPEAK*m6CDH			-0.017	(0.002)***		
TREAT1*EVENTPEAK*MIDUSE					0.044	(0.012)***
TREAT1*EVENTPEAK*HIGHUSE					0.063	(0.012)***
TREAT2*EVENTPEAK	-0.026	(0.005)***	0.010	(0.009)	-0.028	(0.012)*
TREAT2*EVENTPEAK*m6CDH			-0.019	(0.002)***		
TREAT2*EVENTPEAK*MIDUSE					-0.003	(0.012)
TREAT2*EVENTPEAK*HIGHUSE					0.011	(0.012)
Adj. R-Squared:	0.1706		0.1720		0.1709	

* P<0.05, ** P<0.01, *** P<0.001

Conclusions

Our study presents distinctive households' responses under different information treatment in peak-time rebate program. In our experiment, when households get price information along with event notice, their load reduction in event-day peak hours is greater than the reduction of the households who get only event notice. Those households who get event notice only, however, have greater load reduction impact after the commencement of the experiment that the reduction of the households with event notice plus price information. Though our study already suggests some meaningful insights, more thorough analysis supported by detailed and rich survey information is needed to address the effect of information provision on peak-time demand response. Our study is, thus, expected to provide deep and overarching insight for information facilitating demand response program design.

References

1. Stillwater, T. and K.S. Kurani, *Goal Setting, Framing, and Anchoring Responses to Ecodriving Feedback*. 2012.
2. Jessoe, K. and D. Rapson, *Knowledge is (less) power: Experimental evidence from residential energy use.* The American Economic Review, 2014. **104**(4): p. 1417-1438.
3. Grubb, M.D. and M. Osborne, *Cellular service demand: Biased beliefs, learning, and bill shock.* American Economic Review, 2015. **105**(1): p. 234-71.
4. Gabaix, X., *A sparsity-based model of bounded rationality.* The Quarterly Journal of Economics, 2014. **129**(4): p. 1661-1710.
5. Allcott, H. and S. Mullainathan, *Behavior and energy policy.* Science, 2010. **327**(5970): p. 1204-1205.
6. NETL Modern Grid, *Advanced metering infrastructure.* US Department of Energy Office of Electricity and Energy Reliability, 2008.
7. Allcott, H. and T. Rogers, *The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation.* The American Economic Review, 2014. **104**(10): p. 3003-3037.
8. Houde, S., et al., *Real-time feedback and electricity consumption: A field experiment assessing the potential for savings and persistence.* The Energy Journal, 2013. **34**(1): p. 87.