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Role of Advance Notice on High-priced Hours: Critical Peak Pricing on Industrial Demand*

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Abstract: This paper evaluates the impact of advance notice of demand curtailment events on inter-temporal consumption patterns of industrial electricity consumers. The empirical analysis focuses on a demand-response program offered in Japan, which has the same incentive structure as critical peak pricing (CPP). CPP imposes known higher prices at times that are not announced ahead of time, but the uncertainty of high-priced hours presumably limits the extent to which demand flexibly responds to the price intervention. Estimates of inter-temporal constant-elasticity-substitution preference indicate that advance notice weakens, not strengthens, the effectiveness of CPP for those industrial users who have lower rates of intra-day substitution of electricity consumption. The electricity demand turns significantly less elastic when the timings of CPP are announced in advance, compared to when they are kept unknown. This is largely because industrial electricity users in the Japanese manufacturing sector prioritize stable utilization of production facilities. Finally, the estimates imply that providing advance notice would encourage the participation of the demand curtailment program.

Keywords:
Demand Response; Critical Peak Pricing; Advance Notice; Inter-temporal Constant-elasticity Demand
JEL classification: D12, L94, Q41, Q42

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1 Introduction

Many countries have expanded electricity supply from renewable sources, such as wind and solar power, to limit global warming to aim for 1.5 degrees to adapt to the impacts of changing climates. For example, US renewables overtook both coal and nuclear in 2020, and became the second largest electricity generation behind natural gas. Since wind and solar are not dispatchable in a timely manner, and load-following conventional power plants are gradually phased out, controlling for electricity demand plays a greater role of continuously matching with electricity supply, whose capacity often takes time to build for expensive peak hours.

Demand response (DR) refers to customers actions that are taken to change their metered electricity demand in response to an activation signal (The Brattle Group, 2015). Signals that activate customer reactions can stem from both energy prices and system reliability. Price-based DR charges higher prices during hours when it is more expensive to generate and deliver electricity, and lower when it is less expensive to do so (US Energy Information Administration, 2020; Federal Electricity Regulatory Commission, 2020)

How much of electricity demand responds to a DR activation signal depends not only on information content of the signal (for example, the price level of the signal for a price-based DR), but also on the timing at which the signal is notified to the user. Given the information content the activation signal carries, earlier the signal is notified in advance, the users would have more time to modify patterns of their electricity usage, including the timing and the level of electricity demand. The availability of advance notice thus would enhance the welfare of users who enroll the DR program. This paper takes as a case study an early price-based DR program introduced to industrial customers in Japan after the Fukushima nuclear disaster.

We use electricity consumption data at a granular level of industrial customers in Tokyo, who subscribed to a price-based DR program, economically equivalent to a critical peak pricing (CPP), [1] offered by the largest incumbent utilities in the supply territory. Japan restructured and liberalized the electricity market in 2016, and the Japan's utilities found it difficult to finance on new generation capacity, to fill the void of nuclear retirements, following the 2011 earthquake and subsequent Fukushima nuclear disaster. The study period of this paper, the summer of 2017 and the winter of 2018, is the first time when a large-scale DR became available as a reliable and lower-cost peaking resource, alternative to conventional generation

[1] Price-based DR program includes CPP and real time pricing. The DR program in this study is a peak-time rebate, where a user is given a rebate per each kWh on the reduced consumption during pre-specified peak periods. As indicated by Earle, Kahn, and Macan 2009, industrial users are reasonably characterized as loss neutral, and we assume in this paper that the DR program equivalent to a CPP program.

capacity. Note that the paper focuses on the early stages of introducing price-based DR into the resource mix, when both the utilities and the participating industrial users must have experimented and learned how to effectively make out of the new demand-side resource.

In the DR program under the study, the utilities notified the users in advance of two to twenty-four hours before the CPP event takes place.[2] As discussed in Section 4, we find that CPP is more likely to occur at the time when the margins of prediction errors become larger on wind and solar generations. However, the timing of advance notice is little correlated with the magnitude of the prediction errors, which is consistent with the exogenous assumption that the utilities dispatched the notice rather haphazardly in this early stage of DR in Japan.

Figure 1 plots the relationship between the number of hours the advance notice was sent to the users prior to the CPP event, and the adjusted volumes of electricity consumed at the peak price. Note that the peak price is pre-determined and set at the same level [3] regardless of the severity of anticipated system stress during the study period. Since the consumption could differ by time and by user type, the adjusted volumes at the vertical axis is obtained by controlling for by time dummies (namely, the dummy variables specific to years, months, days-of-the-week, and intra-day hours (48 half-an hour intervals starting from 0:00 to 24:00)) and plant-specific dummy variables. The horizontal axis shows how many hours in advance the CPP event was notified to the participating industrial users. The figure implies that the users respond less elastically to the price hike, as they are notified the event earlier in advance. In other words, the earlier the users know with certainty that the peak period would come at time t, the more the users consume electricity at t.

This finding is contrary to an intuition that users reduce more of their electricity usage with the receipt of earlier advance notice, as they have more time to prepare shifting their load. This paper provides an answer to this puzzle by building a simple two-period demand model, and show that the finding is theoretically consistent with small inter-temporal elasticity of substitution in consumption.

We then proceed to an empirical examination on the role of advance notice in the CPP program of our study. While advance notice is dispatched in an exogenous manner by the utilities (PG), the industrial users participating to the DR program may have been able to predict the CPP event by use of weather forecast and other external information available to the electricity users. To control for this possible endogeneity concern, we use prediction errors in the respective outputs of solar and wind power and construct instrumental

[2]To be more precise, the power transmission and distribution company (PG hereafter) notified the electricity retailer (EP hereafter), and then the retailer passes on the information to the users.

[3]The level of the critical peak price is available for the study subject to confidential agreement.

variables. Each of the prediction errors is calculated by taking a difference between the day-ahead predicted value reported by the utilities and the actual output of the respective power. The reduced-form estimates point to the evidence consistent with the finding implied in Figure 1.

A demand of constant elasticity of substitution (CES) is used for structural estimation. The demand expands a simple model of two period to a model allowing for general intra-day substitution patterns. The estimates obtained by use of the instruments show that the elasticity of substitution is less than one, supporting the aforementioned theoretical implication. We also find heterogeneous price responses of intertemporal consumption patterns across industry sectors.

If advance notice helped little reduce the peak load at the time of system stress, the utilities would not be willing to adopt advance notice, as the notice only increased risk exposure to the utilities brought by increased forecast errors. The paper examines whether and to what extent the presence of advance notice would attract electricity users to participate the DR program. The paper finds that the advance notice would encourage industrial users to enroll to the extent that the participation effect outweighs the attenuation effect observed in Figure 1.

Advance notice of prices has been widely observed, for example in the airline and hotel industries, sometimes as a way of price discrimination (Gale and Holmes 1993, and Dana 1998). In this study, advance notice is applied exogenously to all participating users in the DR program. This paper takes the advance notice, not as a means of screening customers, but as a means of effectively altering inter-temporal consumption patterns of electricity. (add?—implemented taken place on industrial users in Japan, to explicitly evaluate how users respond to varying degrees of advance notices of dispatch price signals.)

This paper extends to the previous literature estimating electricity demand of intertemporal substitution from consumption data (Herriges, Baladi, Caves, and Neenan (1993), Cochell, Schwarz, and Taylor (2012), Schwarz, Taylor, Birmingham, and Dardan (2002) and Taylor, Schwarz, and Cochell (2005))[4], by incorporating the features of advance notice of prices in the demand model. While the paper finds that the parameter estimate of inter-temporal substitution is in a similar range to those reported in the literature, the existing work has not examined empirical implications on effectiveness of advance notice of price information. The paper finds that the advance notice would reduce the effectiveness of the price-based DR program, in which the DR participants on average has less elastic inter-temporal substitution of intra-day electricity demand.

[4]Another example is Jessoe and Rapson (2015), which exploits a natural experiment and estimate the price effects on overall usage, peak usage and peak load.

The average participating firms prefer stable utilization of production, and thus the advance notice would alter their consumption behavior prior to the CPP event actually taking place. This feature of electricity demand is perhaps due to the fact that our study period is in the early stage of introducing DR in Japan. Should the electricity users be accustomed to CPP, their electricity usage patterns would be more flexible and elastic across time.

While there are many types of benefits DR could bring about, our primary focus of this paper is to quantify the impacts of CPP and the role of advance notice on inter-temporal electricity usage patterns. Another important benefit of DR is on a financial aspect; that is to avoid or defer the need for new generating capacity. Also in any evaluation of a DR resource, we should weigh the benefits against the cost of the program, including participation incentive payments, equipment costs, and marketing expense. Evaluating these benefits and costs would be a valuable future reserach activity.

The rest of the paper is organized as follows. In section 2, we provide an overview of the industry under our empirical application and describe the CPP program employed in the field. We present a simple two-period CES model in Section 3 and discuss how the presence of advance notice affects the patterns of electricity consumption. In Section 4, we introduce the full-fledged estimable demand model, and discuss the identification of the demand parameters. Estimation results are discussed in Section 5. In Section 6, we evaluate the role of advance notice by use of simulation of the estimated model. The paper finds as discussed above that the presence of advance notice would not hold down the peak demand as much as in the absence of advance notice. In the meantime, advance notice would encourage new entry to the participation of DR program. Overall effects of the advance notice is found to be similar to those without the notice in our application. Section 7 concludes.

2 Background and Data

The data used in this paper are at the level of plant in the manufacturing sector located in the region, Kanto, which overlaps with the greater Tokyo metropolitan area, the size little smaller than New York City. Electric power is supplied predominantly by the incumbent utilities, TEPCO (Tokyo Electric Power Company)[5] in Kanto. The plants in the data were tailored specifically for our study, randomly sampled from those subscribed to TEPCO's DR program in 2017 and 2018.

[5] TEPCO is one of the nine incumbent utilities, and the first to supply electricity in Japan.

Subscription to the program was not mandatory, and the total number of the participating plants were 604 during the sample period. While our analysis on advance notice is based on the treated sample, the composition of industries well matched with that in the Census, as shown in Table 1.

In the end, the data contains 100 plants with electricity consumption at 30-minute intervals. The data cover the period of winter (from December 2017 through February 2018) and summer (from June 2018 through August 2018) with the number of observations of 466,186. The two periods have been marked by high rates of demand curtailment events, due to considerably unpredictable weather, little comparable to those in the past several years.[6]

The data contain four types of industrial plants[7] according to tariff rates schedule, as presented at the upper portion of Table 2. The tariff rates are segmented by firm size, represented by voltage type (6kV, 20kV and 60kV), and the lowest voltage type is further broken into two by contract capacity (kW). TEPCO offered a two-part tariff, consisting of a fixed per-kW and a variable per-kWh charges. The latter includes additional fuel cost adjustment and renewable energy surcharge, both set exogenous to the utilities[8]. According to the table, two major industrial categories of our plants are small-sized food processing and large-sized machinery.

The lower portion of the table shows by tariff rates type the outcomes of CPP program. The average quantity consumed (kWh per 30 minutes) naturally correlates with firm size. The CPP program is supposed to charge pre-specified peak prices during the peak hours. The duration of the peak period is half an hour per event, and the plants in the data received at maximum 76 CPP events. The peak period was not known to industrial users with certainty ahead of time. However, for approximately 60 percent (=42.56/64.61) of the events, the users were notified of when the peak would be in advance of the CPP event taking place. As pointed out in Section 1, advance notice of the CPP program is a feature sought by users (Harold, Bertsch, and Fell 2021), and was welcomed by TEPCO (EP) users. We quantitatively evaluate how the advance notice increased the number of CPP subscribers in the analysis that follows.

It is interesting to note in the lower part of Table 2 that the estimated volume of demand curtailed at the peak period is found smaller on average by 5 percent when the event was notified in advance.[9] This finding

[6]Triggered by the high rates of CPP in 2017 and 2018, the government initiated R&D programs to improve predictive accuracy of weather forecast by the nine electric utilities.

[7]We use the terms, users and plants, interchangeably in this paper.

[8]Fuel cost adjustment is determined by imported (CIF) prices of oil and gas, and renewable energy surcharge is automatically calculated by the volume of renewable resources installed.

[9]To estimate the volume of curtailed demand, we need to calculate a baseline demand, the level at which the demand would have been in the absence of CPP. We rely on the *High 4 of 5* method, recommended by Federal Energy Regulatory Commission

is consistent with the finding in Figure 1, and we now turn to a model that explains the puzzle.

3 Preliminary Analyses on the Role of Advance Notice

This section describes a two-period model of an industrial electricity user responding to CPP. The simple model discussed herein serves to illustrate how advance notice of peak-hour prices affects within-day electricity consumption patterns. It concludes with a modeling implication that effectiveness of peak pricing depends critically on the elasticity of intertemporal substitution in electricity consumption. This implication would hold in a full estimation model discussed in Section 4.

3.1 A Simple Two-stage Model

Let us assume plant i as an industrial electricity user consumes electricity with the amount of q_{it} at period t, according to its production plan of the day. The day is divided into two periods. We assume that a plant considers the allocation of its production resource within the day, but not across days nor over a longer period.[10]

The plant derives its utility from electricity consumption according to a constant elasticity of substitution (CES) function, often used in the empirical literature on inter-temporal electricity consumption of industrial users.[11] With the constraint on the maximum usable expenditure on electricity, I_i, plant i maximize its utility to decide the consumption volume q_{it} at time $t = 1, 2$. The optimal consumption volume at $t = 1$ is given by

$$q_{i1}^{*} = \arg\max_{q_{i1}, q_{i2}} \left(\beta_{i1} q_{i1}^{\frac{\sigma-1}{\sigma}} + \beta_{i2} q_{i2}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

$$\text{s.t. } p_1 q_{i1} + \tilde{p}_{i12} q_{i2} \leq I_i,$$

where the parameters β_{it} capture plant's marginal utility with respect to q_{it}, and σ is the elasticity of substitution for plant i between q_{it}'s. The CES often imposes the conditions without loss of generality that $\sigma > 0$,

(Goldberg and Agnew 2013). The method consists of following three steps: (1) all non-CPP weekdays within the past 45 days prior to the CPP event are designated as the reference period. Five days closest to the CPP event day are chosen from the reference period. (2) Among the five days defined above, four days are chosen with order of higher electricity usage for the same hour as that will be dispatched by the CPP event. Take the mean of the electricity volumes over the four days, and call it a temporary baseline. Calculate the mean difference between the actual load and the temporary baseline during the pre-CPP hours (between 5 hours and 2 hours prior to the hour at which the CPP will be dispatched) of the CPP event day. (3) Add the calculated mean difference to the temporary baseline. The obtained value is the baseline corresponding to the CPP under study.

[10] This may sound a stronger assumption to make in the manufacturing sector under our study. Incorporating between-day behavior would require a complicated intertemporal nested structure, and we leave the exercise for a future research agenda.

[11] For example, see Herriges et al. (1993) and Schwarz et al. (2002).

$\beta_{it} > 0$ for $\forall i$, and $\sum_{t=1}^{2} \beta_{it} = 1$. An actual unit price of electricity offered by the utilities is uniform for all i's and denoted by p_t (JPY per kWh). The plant at time t observes the current price, but cannot accurately predict future prices, p_τ, where $t < \tau$. The future price predicted by plant i at time t is denoted by $\tilde{p}_{it\tau}$. As in Eq. (1), q_{it} is determined by not only p_t but also $\tilde{p}_{it\tau}$.

The optimal consumption volume at $t = 2$ is easily obtained by use of the budget constraint, $t = 2$, $p_2 q_{i2} \leq I_i - p_1 q_{i1}^*$ as:

$$q_{i2}^* = \frac{I_i - p_1 q_{i1}^*}{p_2}. \tag{2}$$

Now consider the following three scenarios. Scenario 0 is where plant i faces the same electricity price, p, for the two periods, namely $p \equiv p_1 = p_2$. Scenarios A and NA correspond to the ones in which CPP is in place at the second period, $p_2 = p + r$, where r is a pre-specified surcharge at the peak period, and assumed positive. The scenarios A and NA differ by whether the advance notice of future prices is available to users. In scenario A, plant i receives the advance notice, which enables the plant to have perfect foresight on the future price, namely $\tilde{p}_{i12} = p + r$. In scenario NA, the advance notice is not available, and thus the plant has to forecast the future price on its own. There are a number of ways of forecasting, including a naive forecast, according to $\tilde{p}_{i12} = p$. We assume naive forecasting hereafter in this paper. Note that this assumption would overestimate the effects of the advance notice if users rely on other forecasting techniques.

Denote the solution of Eq. (1) and (2) under the respective scenarios by q_{it}^{0*}, q_{it}^{A*} and q_{it}^{NA*}. The difference between q_{i1}^{NA*} and q_{i2}^{NA*} indicates the effect of CPP on electricity usage without the advance notice ($\Delta_{NA} \equiv q_{i2}^{NA*} - q_{i1}^{NA*}$), and that between q_{i1}^{A*} and q_{i2}^{A*} shows the effect with the advance notice ($\Delta_A \equiv q_{i2}^{A*} - q_{i1}^{A*}$).

Solving Eq. (1) gives

$$q_{i1}^* = \frac{\beta_{i1}^{\sigma} p_1^{-\sigma} I}{\beta_{i1}^{\sigma} p_1^{1-\sigma} + \beta_{i2}^{\sigma} \tilde{p}_{i12}^{1-\sigma}}. \tag{3}$$

Eq. (2) and (3) show that the relative impact of advance notice on electricity usage, to that of CPP, differs according to the values of the inter-temporal elasticity of substitution, namely:

- $0 < \sigma < 1 \Rightarrow q_1^{AN*} < q_1^{A*} = q_1^{0*}$ and $q_2^{A*} < q_2^{AN*} < q_2^{0*}$
- $\sigma > 1 \Rightarrow q_1^{AN*} > q_1^{A*} = q_1^{0*}$ and $q_2^{AN*} < q_2^{DR*} < q_2^{0*}$

Figure 2 illustrates how the consumption volumes differ by the scenarios. The availability of the advance notice of the future price lessens the effectiveness of CPP when the inter-temporal electricity usage of the plant is complement (namely, $0 < \sigma < 1$), whereas it enforces when the electricity consumption is inter-temporally substitute ($\sigma > 1$). Plants that prefer stable utilization of production would fit to the case of $0 < \sigma < 1$, whereas those that could easily shift the intensive hours of production across times falls into the case of $\sigma > 1$. Note that while the advance notice of future prices would be beneficial to electricity users in either case, it does not appear to be a good strategy for the utilities to make the advance notice available in the former case.

3.2 Preliminary Reduced-form Regressions

We conduct regression analyses using a simple linear demand model that would capture plant's response to CPP event with and without advance notice. Plant i's electricity consumption in terms of kWh at time t on day d, denoted by q_{idt}, is presented as:

$$q_{idt} = \alpha D_{idt} + \beta_1 N_{idt} * D_{idt} + \beta_2 N_{idt} * (1 - D_{idt}) + \gamma x_{idt} + v_{idt}, \tag{4}$$

where D_{idt} is a dummy variable, which takes the value of 1 when plant i receives CPP at time t, and 0 otherwise. The dummy variable N_{idt} takes 1 in the presence of advance notice, and 0 in the absence of it. A vector of control variables x_{id} includes plant dummies, month-day dummies and time dummies. Parameter α captures the effects of CPP on peak demand without the advance notice, Δ_{NA} in Section 3.2, and parameter β_1 captures the effects with the advance notice, Δ_A. Parameter β_2, on the other hand, corresponds to the impact of advance notice on off-peak demand, which is shown as difference between two horizontal lines at $t = 1$ in Figure 2. With $\sigma < 1$, CPP with the advance notice can reduce not only peak consumption, but pre-peak consumption.

In estimating Eq. (4), we control for endogeneity of the CPP dummy variable. CPP is typically used at system stress when electricity demand and supply is severely tight, and thus D_{idt} would positively correlate with the error in the electricity demand, v_{idt}. We employ supply-side variables as instruments for this endogeneity. In particular, the respective prediction errors of solar and wind powers in the Kanto region are used to control for D_{idt}.[12] Note that power changes dispatched by renewable energy, which is unanticipated by the utilities (PG), would not have little correlation with electricity demand, but would sometimes lead to

[12]The utilities (PG) make its day-ahead prediction of solar and wind powers available on the public domain. We take the difference between each of the predicted values and the actual outputs of solar and wind powers to construct the instruments.

the system under stress, triggering CPP in a worst case.[13]

We treat the advance notice dummy N_{idt} as exogenous. This is because the timing of advance notice little correlates with the magnitude of the prediction error during the study period. Figure 3 presents two panels of scattered plots, indicating the relationship between the number of hours in advance the CPP event is notified, and prediction errors of solar power (on the LHS) and wind power (on the RHS). Both panels witness virtually no correlation between the variables, consistent with the exogenous assumption of advance notice.

Four sets of estimates are shown in the first four columns of Table 3. All contain the dummy variables specific to month, days-of-the-week, Half-an-hour time, and plants. The first two specifications (3-1) and (3-2) are obtained by the ordinary least squared (OLS), and the remaining (3-3) and (3-4) by the two-stage least squared (2SLS) methods. All specifications have the CPP dummy variable, and (3-2) and (3-4) add the term interacting with the advance-notice dummy variable. The Durbin test would reject the null hypothesis that the CPP dummy variable is exogenous in the 2SLS estimates. The Sargan test would not reject the hypothesis that the instruments used in the estimation are orthogonal to the error in the main estimates of (3-4).

The 2SLS estimates in (3-3) and (3-4) indicate that the use of the instrumental variables appears to successfully eliminate the upward bias in the CPP dummy variable by the magnitude of about 80 percent. They show that CPP significantly contains the peak demand by the range from 615 to 702 kWh per half an hour, which corresponds to roughly from 50 to 53% of peak demand. The interactions of the advance-notice dummy variable in (3-4) indicate that advance notice would kill the effectiveness of CPP in the peak hours by 46 percent, and reduce the electricity demand in the off-peak period by the amount of 73.90 kWh per 30 minutes. These estimation results are consistent with the case of $0 < \sigma < 1$ in Figure 2.

We additionally investigates the effect of repeated DR in the remaining columns of Table 3. At each DR event, participants had experienced different numbers of events before, which could alter the impact of DR and advance notice. Interestingly, the 2SLS estimates in (3-5) and (3-6) indicate that the effects of CPP and the advance notice gradually gradually diminished.

[13] For example, we observe events during the study period, where unpredictably large quantities of snowfall caused solar power outputs far lower than anticipated by the utilities.

4 Full Estimation Model

This section constructs a structural model capturing customer's decision-making on electricity use. The model enables us to evaluate the effects of the CPP program under the study. It is an expanded version of the model discussed in Section 3.1. We first specify a utility from electricity consumption, and then derive an electricity demand function. The model allows us to consider intertemporal substitution pattern in electricity usage, the analysis comparable to the existing work including Herriges et al. (1993) and Taylor et al. (2005).

We construct a single agent finite-horizon dynamic model to describe a decision making of a plant's electricity consumption choice. Plant i is assumed to choose its electricity consumption q_{idt} at $t \in \{1, \ldots, T\}$ of day d to maximize the following utility:

$$u_{id} = \left(\sum_{t=1}^{T} \beta_{idt} q_{idt}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}},$$

where t is of 30 minutes interval, and thus T takes 48 per day. The parameter β_{idt} captures plant's marginal utility at t, and σ is the elasticity of substitution common across plants. Note that we allow for heterogeneous σ in Section 5. Following the usual convention, both σ and β_{idt} are assumed positive, and $\sum_{t=1}^{T} \beta_{idt} = 1$.

At each t, plant i faces the sequence of future prices of day d. Let $\tilde{p}_{idt\tau}$ be an electricity price at τ perceived by plant i at t. As for the past, this perceived price is identical to the actual price; i.e. $\tilde{p}_{idt\tau} = p_{id\tau}$ if $\tau \leq t$. In addition, the customers here faces a constant price p during non-DR periods, which coincides with the perceived price. On the other hand, the perceived prices during DR periods depends on whether the DR is notified in advance. If a DR during $[t_2, t_3]$ is notified at t_1 $(\leq t_2)$ on day d, the perceived prices are summarized as follows.

$$\tilde{p}_{idt\tau} = \begin{cases} p, & \forall t < t_1, \tau, \\ p, & \forall t \geq t_1, \tau \notin [t_2, t_3], \\ p + r, & \forall t \geq t_1, \tau \in [t_2, t_3], \end{cases}$$

where r is a monetary incentive (JPY/kWh) for this DR program.

With i's maximum expenditures for electricity on day d, I_{id}, customer's decision making corresponds to a finite-horizon utility maximization problem with budget constraint. At each t, customer i chooses q_{idt} that maximizes its utility given its past electricity usage $\{q_{id1}, \ldots, q_{idt-1}\}$, the maximal expenditures I_{id}, and the sequence of perceived prices at t, $\{p_{idt1},\ldots,p_{idtT}\}$. In summary, the maximization problem is given as

$$q^*_{idt} = \underset{q_{idt},q_{idt+1},\ldots,q_{idT}}{\arg\max} \left(\sum_{t=0}^{T} \beta_{idt} q_{idt}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \quad \forall t,$$
$$\text{s.t.} \sum_{\tau=t}^{T} \tilde{p}_{idt\tau} q_{id\tau} \le I_{id} - \sum_{\tau=1}^{t-1} \tilde{p}_{idt\tau} q^*_{id\tau}.$$

The CES functional form enables us to represent optimal electricity consumption explicitly. Customer i's consumption at $t=1$ is

$$q^*_{id1} = \frac{\beta^{\sigma}_{id1} p^{-\sigma}_{id1} I_{id}}{\sum_{\tau=1}^{T} \beta^{\sigma}_{id\tau} \tilde{p}^{1-\sigma}_{id1\tau}},$$

At $t \ge 2$, given customer's past electricity consumption $q_{id\tau},\ \tau \in \{1,\ldots,t-1\}$, the optimal consumption is

$$q^*_{idt} = \frac{\beta^{\sigma}_{idt} p^{-\sigma}_{idt}}{\sum_{\tau=t}^{T} \beta^{\sigma}_{id\tau} \tilde{p}^{1-\sigma}_{idt\tau}} \left(I_{id} - \sum_{\tau=1}^{t-1} \tilde{p}_{idt\tau} q^*_{idt\tau}\right). \tag{5}$$

Based on these equations, we estimate primitive parameters, $\{\beta_{idt}\}$, σ and $\{I_{id}\}$. As for the utility function parameters β_{idt}, we assume

$$\log \beta_{idt} = \beta x_{idt} + \varepsilon_{idt},\ \forall i,d,t,$$

where ε_{idt} is an idiosyncratic term. Taking logarithm of both sides of (5), we obtain

$$\log q_{idt} = \sigma\beta x_{idt} - \sigma \log p_{idt} + \log\left(I_{id} - \sum_{\tau=1}^{t-1} \tilde{p}_{idt\tau} q_{idt\tau}\right) - \log\left(\sum_{\tau=t}^{T} \beta^{\sigma}_{id\tau} \tilde{p}^{1-\sigma}_{idt\tau}\right) + \sigma\varepsilon_{idt}. \tag{6}$$

We estimate the model by use of non-linear least squares regression. In the estimation, we need to control for endogeneity of electricity prices. As the price correlates with the demand error, ε_{idt}, we employ the same instrumental variables used in Section 3.2 as supply-side shocks.

5 Estimation Results

This section presents structural estimates of the demand model (5). Table 4 reports the first-stage regression, projecting the endogenous variable of electricity price onto the exogenous variables, including the two instrumental variables proposed in Section 3.2. The F statistics reject the null hypothesis that the instruments used in the estimation are not weak and have enough explanatory power.

Table 5 shows estimates of the demand model. The estimate of our interest is σ, the parameter that determines the inter-temporal substitution pattern of electricity usage within day. The OLS estimates are under (5-1) and (5-2), whereas the 2SLS estimates using the instruments discussed in Table 4 are shown in (5-3) and (5-4). The estimate of σ under (5-2) is negative with the plant dummy variables, the result that is inconsistent with the utility maximization principle. Both the 2SLS estimates are 0.4, consistent with the implications discussed in Figure 1 and Table 3, the estimates lie inside the unit interval. The estimates fall in the range similar to the findings in the past literature.[14]

We also estimate Eq. (6) separately by industry. The estimates are shown in Table 6. The estimates σ are not statistically different from zero for four out of the five industries, and statistically and significantly below one for chemical and machinery industries. The elasticity of substitution is higher than one for the food industry at the significance level of 95 percent, indicating that the advance notice of CPP would help the demand curtailment more effective.

6 Simulating the Effect of Advance Notice on Electricity Demand

This section employs the estimates obtained in the previous section and evaluates the effects of advance notice on electricity demand. To do so, we examine intensive and extensive margins of the advance notice. In Section 6.1, we quantify the effects of intensive margin, by focusing on the users who participated the program. We then turn to Section 6.2 to assess extensive margin by looking at incentives for potential users to enrol in the program. For this purpose, we identify the users who used to participate the CPP program, but would have stopped the subscription in the absence of the advance notice.

The analyses in this section utilize simulation exercises. We restrict our attention to a specific day, January 22nd, 2018, when record-breaking unanticipated heavy snowfall stopped power generated from solar panels, increasing the likelihood of blackout in Kanto area under study. The utilities (PG) decided to use CPP during the period from 18:30 to 20:00. In the subsequent analyses, we simulate outcomes under three scenarios. We consider how each of the scenarios influence on electricity demand. Scenario A assumes that CPP was not used, whereas scenarios B and C considers CPP was used with and without advance notice.

[14] For example, Schwarz et al. (2002) estimates σ to be 0.03, while Choi and White (2011) reports the estimates in the range from 0.02 to 0.04, and Aleti and Hochman (2020) finds 0.88.

Note that CPP was used in the data without advance notice.

6.1 Intensive Margin

Table 7 summarizes the results of intensive margins. The table lists three results. In scenario A, we calculate electricity demand in the absence of CPP executed, by using the obtained estimates (5-4) in Table 5 under the assumption that $r = 0$. We compare this calculated demand level with another counterfactual scenario where the advance notice had been available, in that $\tilde{p}_{idt\tau}$ takes the value of $p + r$ when $t \geq t_1, \tau \in [t_2, t_3]$ in Eq.(4). We assume that the CPP times were notified the day, i.e. $t_1 = 1$. The demand curtailed is obtained by subtracting the demand under scenario B from the corresponding value under A. The same applies to the actual scenario that CPP was executed without advance notice and we obtain the simulated value of electricity demand under Scenario C. The CPP reduce per-user average demand by 20 percent when advance notice was available, and more than 30 percent in the presence of the notice. This finding is consistent with our previous observation in that the advance notice attenuates the effectiveness of CPP, when the inter-temporal rate of intra-day substitution is less than one, indicating that industrial users in the manufacturing sector as a whole prefers stable production pattern.

6.2 Extensive Margin

We now investigate the extensive margin, namely how the presence of advance notice would have encouraged the participation of CPP program. All industrial customers in our data participated CPP program, and it is difficult to directly identify potential entrants, who were not in the program, but would have participated with advance notice. Instead, we employ a strategy to identify potential exiters for assessing extensive margin.

For this purpose, we derive compensating variation (CV) with and without advance notice, where the original utility is that in the absence of CPP. Figure 4 show the distribution of CV. The mean of CV is 16,749 JPY/day with advance notice and 20,476 JPY/day without it. The latter is higher because advance notice is beneficial to users if other conditions are equal. The maximal value is 159,030 JPY/day in the left figure, which means that at least 159,030 JPY per user is required to be paid for keeping all users to participate in the program. We assume that this amount of incentive was paid to each user. Focusing on CV without advance notice, CV is larger than this amount for two plants. These plants are those most likely to exit from CPP without advance notice, and we identify them as potential exiters.

Excluding the potential exiters, the last column in Table 7 reports total demand curtailed. In our data, the two plants contributed a lot to reducing demand, and excluding them greatly reduce the effectiveness of DR. As a result, overall effects of the advance notice is found to be similar to those without the notice in our application.

7 Conclusion

Electric utilities used to charge regulated rates, which are often specified well in advance. Consumers were often offered a limited set of price schedules, the set which is determined by the level of voltage subscribed by the consumers. As many countries ventured into liberalizing and restructuring their electric industry, the utilities have begun to offer various services to electric consumers. Among them, real-time prices (RTP) is particularly useful to the users who can easily shift demand from high-priced peak period to off-peak periods. This is often achieved by real-time price signals transmitted through advanced meters. While RTP is well perceived, it has been pointed out in the literature (first by Mak and Chapman 1993, and most recently by Harold et al. 2021) that advance notice of prices is highly appreciated by users. This empirical paper studies values of varying advance notices of RTP, with an application to industrial users in Japan.

This paper is the first to evaluate the impact of advance notice of demand curtailment event on inter-temporal consumption patterns of industrial electricity customers. Critical peak pricing (CPP) imposes known higher prices at the times that are not known ahead of time, but the uncertainty of high-priced hours presumably limits the extent to which demand flexibly responds to CPP. Estimates of inter-temporal constant-elasticity-substitution preference indicate that the advance notice attenuates, not strengthens, the effectiveness of CPP for those industrial users who have lower rates of intra-day substitution of electricity consumption. The electricity demand turns about significantly less elastic when the CPP times are notified in advance, rather than kept unknown. This is largely because industrial electricity users in Japanese manufacturing sector prefer stable utilization of production facilities. Finally the paper finds that the presence of advance notice would encourage the participation of the demand response program.

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Table 1: Comparison between our data and Census (2016)

	Data	Census (2016)
Industries:		
Food processing	10.70%	10.97%
Chemicals	3.28%	4.12%
Ceramics	4.37%	4.82%
Iron / other metals	6.02%	3.18%
Machinery	11.46%	14.13%
Others	64.17%	62.78%

Notes: The industrial composition of our data is compared with that of 2016 census data.

Table 2: Summary statistics on Tariffs and Volumes

Electric voltage:	6kV		20kV	60kV	ALL
Contract capacity:	-499kW	500kW-			
Per-kW rates					
(JPY/kW)	1269.0	1782.0	1630.8	1576.8	1502.2
Per-kWh rates (JPY/kWh)					
Summer (July-Sep)	17.05	15.87	15.07	14.83	15.69
Other seasons	15.94	14.87	14.14	13.92	14.74
Additional charges (JPY/kWh)					
Fuel cost adjustment	-2.48		-2.45		-2.48
(S.D.)	(0.54)		(0.53)		(0.50)
Renewable energy surcharge	2.77				2.77
(S.D.)	(0.14)				(0.14)
No. Plants	33	13	3	51	100
Industrial composition (%)					
Food processing	15.15	7.69	33.33	7.84	10.70
Chemicals	3.03	7.69	0.00	1.96	3.28
Ceramics	3.03	15.38	33.33	1.96	4.37
Iron / other metals	3.03	15.38	0.00	5.88	6.02
Machinery	9.09	0.00	0.00	15.69	11.46
Others	66.67	53.85	33.33	66.67	64.17
Quantity consumed (kWh/30min)	220.69	462.31	1036.96	1997.54	1229.50
(S.D.)	(172.40)	(446.37)	(727.26)	(2494.82)	(2031.35)
Average number of dispatches	64.48	60.77	47.00	66.54	64.61
(W/ advanced notices)	(42.85)	(41.15)	(29.00)	(43.37)	(42.56)
Estimated demand curtailed (%)	14.22	26.44	9.55	7.81	12.38
(W/ advanced notices)	(13.66)	(23.86)	(10.38)	(7.57)	(11.82)
No. Observations	144,179	61,137	8,721	252,149	466,186

Notes: The duration of the peak period is half an hour per event.

Table 3: Estimates from Regressions of Electricity Usage (kWh/30 mins)

	(3-1) OLS	(3-2) OLS	(3-3) 2SLS	(3-4) 2SLS	(3-5) 2SLS	(3-6) 2SLS
CPP dummy	-121.32 ***	-88.60 ***	-614.73 ***	-702.37 ***	-833.78 ***	-1030.71 ***
	(10.81)	(15.23)	(108.35)	(116.75)	(140.55)	(166.24)
× Num of CPP events					61.05 ***	72.70 ***
					(11.71)	(12.41)
Advance notice dummy						
× CPP dummy		-27.50		376.47 ***		664.47 ***
		(17.43)		(78.20)		(114.48)
× No. CPP events						-56.08 ***
						(9.02)
×		24.82 ***		-73.90 ***		-28.32 **
		(9.68)		(21.05)		(13.03)
R-squared	0.905	0.905	0.901	0.902	0.910	0.910
Durbin chi2			21.89 ***	29.11 ***	26.19 ***	30.48 ***
Sargan chi2			4.96 **	0.17	2.76 *	0.48
No. Observations	46,806	46,806	46,806	46,806	45,514	45,017

Notes: All specifications include the dummies specific to months, days of the week, time (identifying 48 half an hour slots per day from $0:00-24:00$) and plants. Standard error is inside parenthesis. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Table 4: First-stage Estimates: Electricity prices and Instruments

	(4-1)		(4-2)		(4-3)	
Prediction errors:						
Solar power	6.66E-07	***			6.64E-07	***
	(8.00E-09)				(8.00E-09)	
Wind power			2.52E-06	***	1.81E-06	***
			(2.48E-07)		(2.47E-07)	
R-squared	0.065		0.035		0.065	
F statistics	6937.39	***	103.3	***	3495.87	***
No. Observations	466,137		466,137		466,137	

Notes: All specifications include the dummies specific to months, days of the week, time (identifying 48 half an hour slots per day from $0:00-24:00$) and plants. Standard error is inside parenthesis. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.
prediction error = prediction minus real values

Table 5: Estimation results: utility function

	(5-1)		(5-2)		(5-3)	(5-4)	
	OLS		OLS		2SLS	2SLS	
σ	6.65	***	-0.28	***	0.42	0.40	*
	(0.02)		(0.02)		(0.37)	(0.21)	
Plant Dummies included:	Yes		Yes		Yes	Yes	
No. Observations	466,137		466,137		466,137	466,137	

Notes: All specifications include the dummies specific to months, days of the week, time (identifying 48 half an hour slots per day from $0:00-24:00$).
Standard error is inside parenthesis. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Table 6: 2SLS estimates by industry

Industry:	Food processing	Chemicals	Ceramics	Iron / other metals	Machinery
σ	1.67 ***	-0.24	0.42	-0.28	-0.73
	(0.46)	(0.53)	(1.19)	(0.81)	(0.48)
No. Observations	56,620	17,379	17,302	31,808	60,422

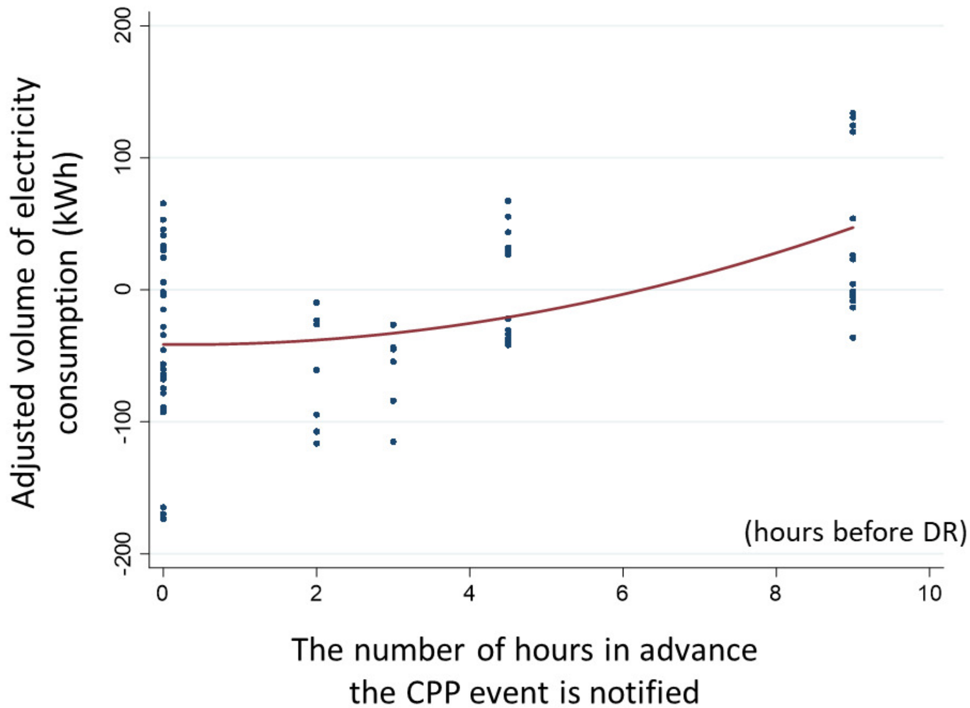
Notes: All specifications include the dummies specific to months, days of the week, time (identifying 48 half an hour slots per day from $0:00-24:00$) and plants. Standard error is inside parenthesis. $***p<0.01$, $**p<0.05$, $*p<0.1$.

Table 7: Effects of advance notice on demand curtailment

	No CPP	CPP w/ AN	CPP w/o AN
Quantity consumed (kWh/30min)	769.5	644.0	582.9
Demand curtailed (kWh/30min)	-	125.5	186.6
Total demand curtailed (MWh/30min)			
Exogenous number of users	-	35.4	52.6
Endogenous number of users	-	35.4	36.4

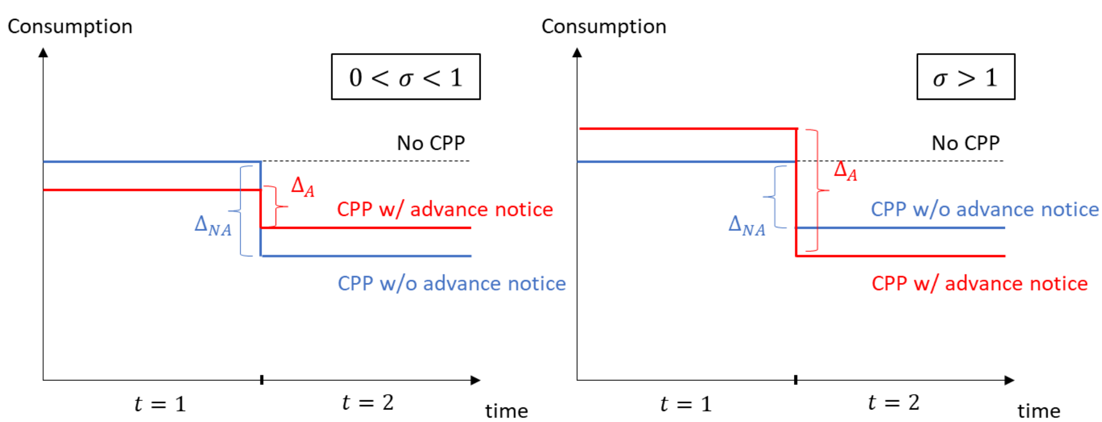
Notes: Quantity consumed in the first row reports the average consumption during CPP hours. Total demand curtailed reported in the last row reflects the changes in the participation of the demand response program.

Figure 1: Electricity usage and timing of advance notice



Notes: A value of the vertical axis is adjusted electricity usage volume. The value is the residual obtained by regressing plant-level electricity consumption onto the dummy variables specific to years, months, days-of-the-week, and intra-day hours (namely, 48 half-an hour intervals starting from 0:00 to 24:00) and plant-specific dummy variables. The horizontal axis is the difference between the timing of advance notice sent and that of DR being executed. The fitted line is shown in red, indicating a positive relationship between the two variables, with a correlation coefficient of 0.49.

Figure 2: Electricity usage and advance notice



Notes: The figure overviews the effects of advance notice on plant's consumption pattern with the CES specification.

Figure 3: Prediction errors and timing of advance notice

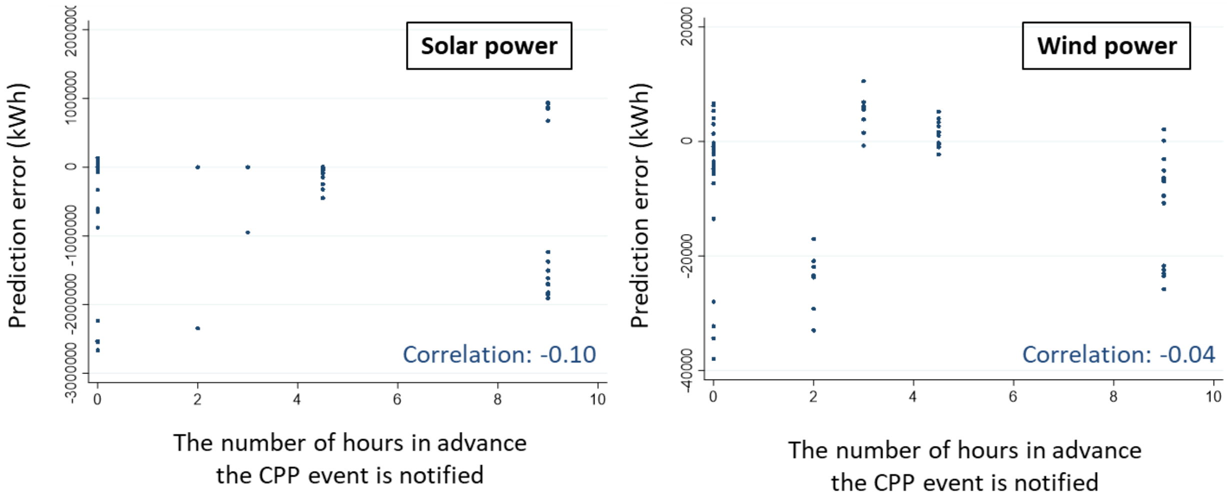
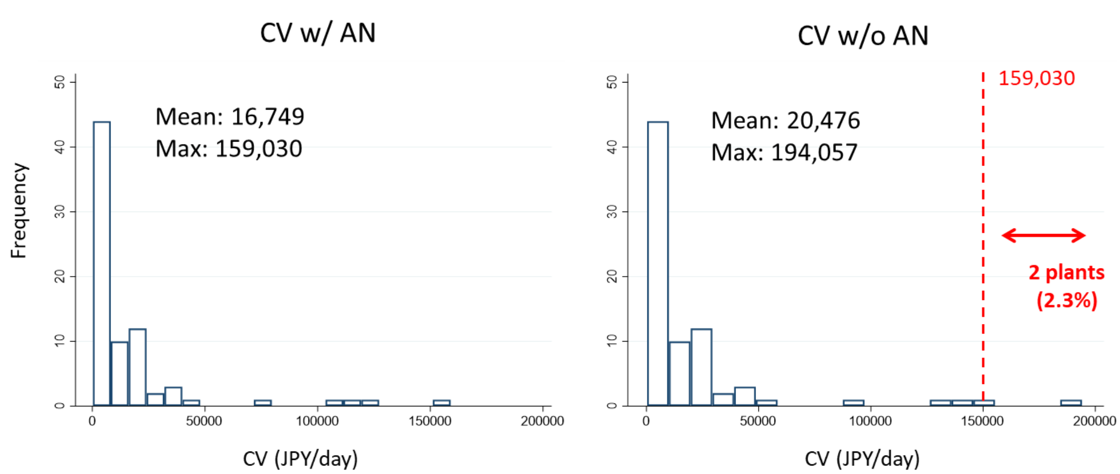


Figure 4: Advance notice and compensating variations



Notes: Two figures plot the distribution of compensating variation respectively with and without advance notice.