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The Role of Advance Notice in Shaping Industrial Response toTime-Varying Electricity Prices

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Abstract: Time-varying electricity prices is pivotal for efficient electricity demand management, particularly when supply is inflexible. Utilities often issue advance notices during peak demand periods to alert users of imminent price hikes. However, the extent to which such notices influence demand response (DR) effectiveness has been understudied, either theoretically or empirically. This paper investigates the impact of advance notifications periods on industrial responses to fluctuating electricity prices. It posits that for users with a lower rate of inter-temporal elasticity of substitution, DR efficacy wanes as advanced warnings of peak prices lead to more homogenized consumption patterns over time. Empirical evidence from an industrial DR program in Japan substantiates this theory. Furthermore, the paper explores the economic rationale behind utilities' decisions to issue advance notices, despite their potential to lessen DR impact.

Keywords: Demand Response; Critical Peak Pricing; Advance Notice; Constant-elasticity of Substitution;

JEL classification: D12, L94, Q41, Q42

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1 Introduction

Demand response (DR) is the adjustment of electricity consumption by users in response to external signals, often rooted in price-based incentives (The Brattle Group, 2015). This approach involves higher charges during times when electricity generation and delivery are more costly, and conversely, reduced rates when generation is less expensive (US Energy Information Administration, 2020; Federal Electricity Regulatory Commission, 2020). Such pricing strategies can include models like time-of-use (TOU), real-time pricing (RTP), critical peak pricing (CPP) [1] and its variant that offers rebates (Critical Peak Rebate, CPR).[2] With the growing prominence of non-dispatchable renewable sources like wind and solar, regulating electricity demand has become imperative to ensure continuous balance with an increasingly variable electricity supply.

Many DR pilot programs have primarily focused on residential customer responses to time-varying pricing models. These experiments, as surveyed in Faruqui and Sergici (2013) and Harding and Sexton (2017), differ significantly, and some factors influencing their outcomes are not fully understood. A notable variable among them is the length of advance notice provided.

Day-ahead advance notice is prevalent in these experimental settings. However, a seminal work by Jessoe and Rapson (2014) observed demand reductions in response to DR events given a 24-hour warning, but found no noticeable response when only a 30-min warning were provided. This disparity might suggest that the duration of the notification period significantly influenced the cost of adjusting consumption, with shorter durations leading to substantially higher costs. (Jessoe and Rapson, 2014). Extended advance notice would thus allow for more electricity consumption adjustments, reducing the costs associated with curtailing consumption.

Yet, evidence remains scant regarding how the availability and duration of advance notice affects DR's effectiveness, especially when considering inter-temporal substitution of electricity consumption. This paper addresses this gap from two distinct angles. Firstly, we conduct a theoretical exploration of the relationship

[1] According to Harding and Sexton (2017), TOU pricing features predetermined rates that vary based on the time of day, day of the week, or week of the year. Unlike other models, TOU rates remain constant in the short run and do not fluctuate in response to generation costs. In RTP, rates typically change on an hourly or 30-minute basis to reflect the real-time costs of generation. CPP, meanwhile, involves flat rates with a predetermined increase for specific periods when generation costs reach or exceed designated threshold levels.

[2] Under CPR, a rebate is calculated based on the extent to which a user's consumption falls below a predetermined reference level during critical peak periods. Conversely, with CPP, users are charged at a higher CPP rate for their entire consumption during these peak periods. Given that the rebate represents an opportunity cost of forgone profit should users exceed the reference level, the rebate value under CPR is effectively equated with a price under CPP. In this paper, we thus use the terms "price" and "rebate" interchangeably, except where distinctions are necessary to avoid confusion. For a more detailed comparison of how CPR and CPP could lead to different incentives in a DR program, refer to footnote 4.

between the availability and duration of advance notices and reactions of electricity consumption to price spikes. By integrating early notifications into an inter-temporal choice model, we demonstrate that the impact of DR, whether enhancing or diminishing, is closely tied to the rate of inter-temporal elasticity of substitution.

Secondly, we shift our focus to industrial users, a segment often adapting to varied operational changes in response to DR indicators. Despite the limited literature on industrial DR, the sector's substantial contribution to total electricity demand makes understanding its DR potential pivotal. For instance, in the U.S., commercial and industrial entities account for 60% of electricity consumption, with a peak reduction potential nearly eight times that of residential users (Kholerdi and Ghaemi-Marzbali, 2021). This pattern is reflected globally, with countries like Japan and Germany showing similar trends (Richstein and Hosseinioun, 2020).[3] Leveraging a unique case study, we examine the impact of advance notice on industrial electricity consumption, offering new insights into how industrial entities strategically respond to the spectrum of early notifications.

This paper examines a price-based DR program in Japan, focusing on critical peak rebates (CPR) aimed at industrial electricity users and implemented by the country's major utilities in 2016 and 2017. Unlike many studies based on field experiments, this program was executed in a real-world setting. The CPR framework provides rebates to users proportionate to their consumption reductions compared to a predetermined reference level during critical peak periods (Federal Electricity Regulatory Commission, 2020). The rebate under CPR is designated to reflect the opportunity cost of foregone benefits if consumption exceeds this reference level, thereby aligning the rebate value with the pricing structure seen in CPP (Faruqui and Sergici (2013, 2011), Wolak (2010, 2011)).[4] In our case study, the rebate rate under CPR was set at a value 2.5 times the fixed rate applicable during non-critical periods.

CPR became increasingly prevalent, following the 2016 liberalization of Japan's electricity sector. This

[3] An additional advantage for concentrating on the industrial sector is its comparatively straightforward response dynamics. In contrast to the residential sector, where diverse cognitive biases, such as limited attention, can significantly influence demand response behaviors (Harding and Sexton, 2017), industrial entities may be driven by profit motives, resulting in more immediate and predictable reactions to price changes. While firms may not be perfectly free from behavioral biases (Aguirregabiria and Jeon, 2020), their focus on profitability might mitigate the impact of the kind of biases typically seen in residential electricity consumption patterns. Behavioral bias in residential sector under CPR is discussed in, for example, Ito, Ida, and Tanaka 2018 and Murakami, Shimada, Ushifusa, and Ida 2022.

[4] Under CPR, users are charged standard fixed rates if their consumption remains above the set reference level, in contrast to the higher rates under CPP. Thus, while facing similar marginal prices, CPR might be less effective than CPP in inducing demand reduction, as CPR provides an 'option to quit' (Wolak, 2010) to the users. Although this paper does not directly test this 'option to quit' hypothesis, the DR effectiveness observed could have been more pronounced under CPP. Faruqui, Sergici, and Akaba 2014 reported evidence consistent with this hypothesis. Ito 2015 studies the California 20/20 rebate program, a variant of the CPR.

shift was, in large part, a reaction to the aftermath of the Fukushima nuclear disaster, which left utilities striving to secure financing for new generation capacities. In particular, our study spans the summer of 2017 and winter of 2018, representing the pioneering large-scale deployment of industrial DR, introduced as a countermeasure to the void left by nuclear power cutbacks.

The DR program under our study offers a range of advance notifications, including instances with no notification. These notifications, set by utilities, can vary from two hours warning to more extended pre-event notice. Figure 1 illustrates the dataset used in this study, highlighting the relationship between the duration of advance notifications and their subsequent DR effectiveness. On the horizontal axis, we measure advance notification in terms of hours leading up to the critical peak event. The vertical axis indicates DR effectiveness, quantified as the proportional reduction in electricity consumption compared to a predefined reference level. Section 2 details the DR program and explains the methodology for defining the reference level and its robustness. The figure reveals that, under an identical price surge, industrial users curtail their consumption by 15% with no prior notices, compared to a more modest 11% reduction when notified nine hours in advance. This indicates that the earlier the notification is given prior to peak periods, the more diminished the impact of the DR program during those peak hours. In Section 3, we conduct regression analyses using instrumental variables and confirm our finding in Figure 1.

The aforementioned finding appears to diverge from the observation of Jessoe and Rapson (2014). In their study in Connecticut, residential users (as opposed to the industrial users in our research) demonstrated greater reductions in consumption when provided with longer advance notifications for the same price incentive. In Section 4, we introduce a constant electricity of substitution (CES) demand function, and reconcile these divergent insights. The model posits that the magnitude and direction of DR's impact, whether increasing or decreasing, hinge on the rate of inter-temporal elasticity of substitution in consumption. Specifically, users characterized by sub-unitary elasticity (i.e., elasticity less than one), exhibit an aversion to demand fluctuations caused by rising prices. [5] As the duration of advance notice – i.e., the lead time before an upcoming price hike – increases, they reduce consumption in advance, thereby diminishing the DR program's effectiveness in cutting peak loads. In contrast, users with super-unitary intra-day substitution elasticity (i.e., elasticity exceeding one) are more accommodating to changes in demand, responding more flexibly to price increases. Their demand reduction in response to higher prices is directly related to their elasticity, high-

[5] As noted in footnote 2, we use the terms "price" and "rebate" interchangeably throughout this paper. Both CPR and CPP offer users similar monetary incentives, barring the exception discussed in footnote 4.

lighting their responsiveness to price signals. Section 4 delves deeper into the implications of the duration of advance notice on DR effectiveness, expanding the analysis to include a multi-period model. Building upon our theory model, we estimate a parameter of the CES demand function in Section 5. The estimates indicate a substitution elasticity below one, corroborating our theoretical premises.

If advance notices diminish the effectiveness of the DR program for industrial users in Japan, who are estimated to have sub-unitary elasticity of substitution, electric utilities might be reluctant to employ such notifications. This hesitancy could be further amplified by the increased risk of forecast inaccuracies as to when DR events occur, a direct consequence of the increasing reliance on renewable energy sources. Section 6 investigates this issue, examining the utilities' motivations of issuing advance notices through a cost-benefit perspective. Our investigation uncovers a trade-off in the decision-making process within the utilities, balancing the additional costs and potential revenue gains. On the one hand, issuing advance notifications incurs costs associated with arranging supplementary backup supplies, aiming to compensate for the diminished impact of DR. On the other hand, these notifications present an opportunity for utilities to generate additional revenue from consumers who value the flexibility they provide. This perceived advantage would increase the appeal of the DR program to industrial users. Our findings suggest that the overall social surplus generated by offering advance notice remains positive, despite the accompanying costs. This implies that utilities might deem it beneficial to continue providing advance notifications, despite the diminished impacts of DR program.

Related Literature This paper contributes to the literature investigating the effectiveness of DR programs within the electricity sector. Our primary emphasis is on the relatively untapped area of how advance notice of impending price hikes influences the decisions of industrial users. While it is often perceived as naturally intuitive that earlier advance notice leads to more effective demand reduction during peak hours, the theoretical and empirical foundations supporting this notion are not well-grounded. Theoretically, Taylor and Schwarz (2000) is an exception, albeit offering a simplified assumption that advance notifications inherently enhance elasticity by calibrating a model. Although this work corroborates the efficacy of advance notice in DR program, it fails to furnish a theoretical framework to underpin the observations highlighted in Figure 1. Empirically, Jessoe and Rapson (2015) provides insights but limited in scope, drawing conclusions based on just two durations of advance notifications: 24-hour and 30-minute intervals. Our research seeks to bridge these theoretical and empirical voids.[6]

Utilizing the inter-temporal CES demand framework, we determine that the impact of advance notifications on demand varies depending on the rate of inter-temporal elasticity of substitution in consumption. Extended notification periods either enhance or diminish the DR program's effect, contingent on the elasticity being high or low, respectively. This interpretation aligns with the prior findings of Jessoe and Rapson (2015) and Taylor and Schwarz (2000), assuming a supra-unitary intra-day elasticity of substitution.

On the empirical front, we delve deeper into how industrial users react to time-varying prices. While the literature is replete with studies on residential users, insights into commercial and industrial (C&I) DR remain sparse. Initial studies spotlight varied reactions across industries (Schwarz, Taylor, Birmingham, and Dardan 2002) and across firms (Herriges, Baladi, Caves, and Neenan 1993). A more recent study by Jessoe and Rapson (2015) on TOU pricing for U.S. C&I users found limited DR effectiveness. Chen and Zhu (2023) examined the experience of steel makers in Taiwan with demand response through auctions.

Another distinctive feature of our study is the consideration of endogeneity concerns arising from the potential correlations between the timings of DR events, advance notice issuance, and electricity demand shocks. Our study diverges from the existing literature by leveraging a real-world DR program implemented during peak demand periods to reduce system strain, coupled with the proactive dissemination of DR event notifications. The anticipation of DR events by electricity users might pose an upward bias in the estimated effect of the DR initiative, a concern that similarly pertains to the timing of advance notifications. To address these concerns, we introduce two novel sets of instruments previously unexploited in this field of study, The first set involves the accuracy of utilities' forecasts for variable renewable energy outputs, and the second relates to the incident of unplanned outages among utilities' generators. In the context of increasing reliance on renewable energy sources and the rapid transition away from fossil fuels, these two variables are becoming more significant for system reliability, Given that this information is not readily accessible to electricity consumers in a timely manner, it is improbable that they could anticipate these factors, making these variables appropriate instruments for alleviating the concerns of endogeneity. Our demand estimates align with the findings of earlier research involving randomized experiments with industrial users (Herriges et al. (1993), Cochell, Schwarz, and Taylor (2012), Schwarz et al. (2002), and Taylor, Schwarz, and Cochell

[6] 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 thus takes the advance notice, not as a means of screening consumers, but as a means of effectively altering inter-temporal consumption patterns of electricity.

(2005)), thereby reinforcing the empirical robustness of our findings in relation to the existing body of literature.

Structure of the paper The reminder of this paper is organized as follows. Section 2 presents an overview of the industry under our empirical application and describes the DR program employed in this study. Section 3 conducts a reduced-form analysis to verify the robustness, particularly examining whether the provision of advance alerts about imminent price surges during peak periods diminishes the efficacy of the DR program. These empirical observations are further supported by the theoretical framework introduced in Section 4, where we utilize a CES demand model. Initially, Section 4 explores a two-period model to assess the impact of advance notice availability, and subsequently extends this to a multi-period model to investigate how the duration of advance notice affects demand. Section 5 estimates the CES demand model, aiming to corroborate the theoretical implications discussed in Section 4. Section 6 offers a quantitative examination of the utilities' incentives to provide advance notifications, despite potential reductions in the effectiveness of their DR programs. The paper concludes with Section 7.

2 Background and Data

This section elucidates the study's backdrop, emphasizing the instrumental role of industrial DR programs in Japan's evolving energy landscape. Section 2.1 delves into Japan's energy trajectory, particularly post the Fukushima crisis. It underscores Japan's proactive shift towards renewable energy adoption. However, the transition has not been without its challenges. The intermittent nature of renewable energy sources accentuates the need for innovative solution, with industrial DR emerging as a significant strategy. Section 2.2 describes the data sourced from an industrial DR program that is central to this study. This subsection clarifies the program's structure. It also details the determination of the reference level of demand, wherein users are incentivized with rebates for consumption that falls below this benchmark. Additionally, it reveals an intriguing pattern: when provided with advance notice, the reduction in demand from the reference level tends to be smaller. The unique features of the DR program presented here set the stage for the modeling approach discussed in the subsequent section.

2.1 Brief Overview of Japan's Energy Landscape

The Fukushima nuclear crisis on March 11, 2011, marked a significant turning point in Japan's energy strategy. Before this catastrophic event, nuclear power accounted for nearly 30% of the country's electricity. The sudden halt in nuclear operations created a noticeable gap in Japan's energy supply. In response, Japan introduced the Feed-in Tariff (FIT) system in 2012. This policy supported the adoption of renewable energy by ensuring producers a set price for the electricity they fed back into the grid, making renewable energy investments more economically appealing. Benefiting from this policy, solar power saw a rapid growth, and by 2020, Japan achieved a notable distinction with one of the highest solar installation densities in flatland areas worldwide (Agency for Natural Resources and Energy, 2021, p.65).

However, despite the significant progress in renewable energy adoption, there remained challenges in fully compensating for the energy deficit caused by nuclear cutbacks. Solar energy's reliance on sunshine hours presents inherent limitations, as it does not generate power during nighttime or cloudy conditions. This intermittency underscores the need for reliable backup or balancing power sources to maintain grid stability.

Following the 2016 liberalization of Japan's electricity market, another issue surfaced: the conventional load-following power sources began phasing out at an accelerated pace. This development further complicated the task of aligning the unpredictable supply from renewables with demand. In this context, DR has been identified as a potential solution. The industrial sector, in particular, is seen to hold a significant DR potential. The expectation is that an expanded industrial DR can complement the dwindling traditional power sources, ensuring a steady electricity supply. Given these developments, major power companies began rolling out substantial industrial DR programs from 2017 onward. This study zeroes in on one such program, undertaking a detailed empirical examination in the context of advance notification of surged prices during critical peak periods.

2.2 Industrial DR Program under Study

This section outlines the data sourced from an industrial DR program implemented by major incumbent utilities in one of Japan's largest metropolitan areas, focusing predominantly on manufacturing-sector facilities. The dataset spans two critical periods of the respective three months: winter (December 2017 to February 2018) and summer (June 2018 to August 2018). These intervals are significant as they mark the early stages of price-based DR initiatives, designed to offset the reduction in nuclear energy, a context elaborated in Section 1.

Over the six-month study period, 604 plants voluntarily participated in the program. Our analysis utilizes a subset of this dataset, specifically focusing on 100 plants that were randomly selected by the utilities from the pool of participants in the DR program within the specified timeframe. This selected dataset details their electricity consumption patterns, recorded in half-hourly intervals, amassing a total of 466,186 observations. Table 1 demonstrates that the industrial composition of our dataset is representative of the larger population of 604 plants, and further, it aligns with the industrial distribution observed in the 2016 Census data.

Table 2 outlines the details of our dataset. The data categorizes industrial plants into three distinct types based on their tariff rate schedules, as detailed in the upper section of Table 2. Tariff rates are stratified by firm size, delineated by voltage type (6kV, 20kV or greater). The category with the lowest voltage is further divided based on contract capacity (kW). The variable per kWh charges integrate an external fuel cost adjustment and a renewable energy surcharge under the FIT system, both determined outside the purview of the utilities' influence. [7]

The table shows the DR program outcomes, segmented by tariff rate. Naturally, the average quantity consumption (kWh per 30 min) correlates with the firm size. The program's design mandates the application of rebates, the rate of the rebate at the peak period being 2.5 times higher than the average fixed kWh rate shown in Table 2.[8] Note that the rebate represents an opportunity cost of forgone profit should users exceed the reference level defined below, the rebate value under CPR can effectively be equated with a price under CPP. The duration of the peak period was 2.8 hours per event, and the critical peak period is in total 45.5 hours during the study period.

During the study period, sixteen DR events occurred, each with an average duration of three hours. Participation among firms varied, with 20 percent of the 100 firms opting exclusively in one season – either summer or winter. Specifically, 7 firms participated exclusively in four DR events during the summer of 2018, while 17 firms took part in the rest in the winter. Statistical characteristics of the DR program remained stable across these seasons. To ensure robustness in our analysis, we have controlled for variations across months, days of the week, and times within the day, identifying 48 half-hour intervals per day, in the subsequent estimation sections.

[7] The fuel cost adjustment is influenced by the prices of imported oil and gas, while the renewable energy surcharge is algorithmically ascertained by FIT based on the volume of installed renewable resources.

[8] The rebate amounts cannot be disclosed due to a confidentiality agreement with the utilities from which the data was sourced.

Note that a peak hour was not known to industrial users with certainty ahead of time, with about 60 percent (8.50 out of 14.04) of the events during the study period being preceded by advance notifications. A unique characteristic of the program under study was the variability in the lead-time – specifically, the duration of advance notice issued by the utilities. This lead-time could range from a full 24 hours prior to a DR event, down to no advance warning at all. An essential aspect of our empirical analysis involves employing instrumental variables to mitigate the potential endogeneity linked to users' foresight of critical peak events – regardless of whether advance notifications were issued – and the anticipation of the timing for such notifications. We detail the instrumental variables and additional controls in the lower portion of Table 2, and provide an in-depth discussion in Sections 3 and 5. This approach ensures a robust assessment of the impact and effectiveness of the DR program while addressing potential biases in user responses.[9]

A crucial aspect of the DR program is determining the reference level of demand, which would exist without the influence of the DR program. For this purpose, we employ the *High 4 of 5* methodology, endorsed by the US Federal Energy Regulatory Commission (Goldberg and Agnew 2013). The method designates the five non-peak weekdays immediately preceding the peak event to serve as a baseline. Of these, the four days exhibiting the highest electricity consumption during the same hour as the upcoming peak event are identified. The average electricity volume across these selected days sets a preliminary reference level. Subsequently, we calculate the average deviation between the actual load and this initial reference in the hours preceding the peak event, specifically during the four hours from five hours before two hours before the DR event. This deviation, averaged over the specified period, is added to the preliminary reference to determine the final reference level for each peak event. It is crucial to note that this reference level varies among users, preventing potential manipulation of the predetermined reference and ensuring a more accurate depiction of demand without DR influences.

The integrity of the DR program, and consequently, the validity of our findings as depicted in Figure 1, critically relies on the accuracy of the reference level estimation. In an unpublished appendix, we affirm the robustness of the *High 4 of 5* methodology compared to an alternative method for establishing the reference level, corroborating the observations presented in Figure 1.[10]

It's worth noting in Table 2 that the estimated demand curtailed during peak hours was about 5% less

[9] In the paper, the terms "users" and "plants" are used interchangeably.

[10] The alternative method involves projecting demand levels in the absence of DR interventions and extending these projections to periods when DR measures are in effect. The key insight from Figure 1, that earlier notification of DR events reduces the program's effectiveness remains substantiated.

when industrial users were forewarned of the event, a pattern previously supported by Figure 1. Interestingly, this trend stands in contrast to previous research, such as that by Jessoe and Rapson (2014), which posited that more extended advance notifications lead to greater reductions in electricity consumption. In the subsequent section, we propose a model to harmonize these seemingly conflicting insights.

3 Regression Analysis

In this section, we perform a reduced-form analysis to capture the responses of industrial plants to advance notifications in our DR program. The regression analysis herein aims to corroborate the findings in Sections 1 and 2, which suggest that the presence of advance alerts about impending price surges during peak periods undermines DR efficacy. This empirical observation is substantiated by the theoretical framework delineated in Section 4.

Empirical Setup Consider an industrial electricity user, denoted as plant i. This plant consumes electricity, quantified in kilowatt-hours (kWh) as q_{it} at a specific time t, based on its day-long production agenda. The consumption is expressed as follows:

$$q_{it} = \delta_0 D_{it} + \delta_1 D_{it} \times A_{it} + \delta_2 (1 - D_{it}) \times A_{it} + \gamma x_{it} + v_{it}, \tag{1}$$

where D_{it} is a binary indicator, set to 1 if plant i is subjected to the critical peak period, C, at time $t \in C$, and 0 otherwise. Another binary indicator, A_{it}, represents the issuance of an advance notice, being 1 when such a notice has been provided to the plant at time t and 0 in its absence. We also distinguish between the different durations of advance notices in A_{it} later in our analysis.

We assume that t is measured in half-hour intervals, ranging from 1 to 48, which correspond to the times 0:00 and 24:00 of a given day. This assumption posits that plants allocate production resources within a single day, rather than spanning multiple days. While this intra-day framework might seem restrictive – suggesting each 24-hour day operates independently and potentially overlooking factors like day-ahead advance alerts – it aligns with our data, where advance notices predominantly surfaced on the day of DR event. We treat the day-ahead advance notice as issued at 0:00 on the day of the DR event. To ensure robustness of our findings, we later relax this intra-day constraint in our empirical analysis. Estimation results in this section suggest that this modification does not significantly influence our primary findings.

Let the critical peak period for plant i be defined as $C_{it} = [c_{i1}, c_{i2}]$, and the advance notice be issued at time c_{i0}. The timeline of the relationship between D_{it} and A_{it} can be illustrated in Figure 2. Note that price variation is inherently captured by the binary indicator, D_{it}; specifically, we observe only two distinct prices: p_{it}, the standard price when $D_{it} = 0$, and $p_{it} + r$, an elevated opportunity cost when $D_{it} = 1$. In the absence of advance notice, c_{i0} is by definition equal to c_{i1}. The lead time of the notice before the DR event is given by $c_{i1} - c_{i0}$.[11] For some specifications presented below, we will estimate the effect of the duration of advance notices by replacing the variable A_{it} with $A_{it} \cdot (c_{i1} - c_{i0})$ in equation 1.

The vector x_{it} contains a series of control variables. These include dummy variables specific to months, days of the week, 30-min intervals within a day (broken down into 48 segments spanning from 0:00 to 24:00), respectively. Additionally, to account for plant heterogeneity such as size indicated in Table 2, we integrate plant-specific dummy variables into the vector. The error term is denoted by v_{it}.

The parameters to be estimated include δ_0, δ_1, δ_2 and γ, each offering insights into the effects of DR and advance notifications. Specifically, δ_0 quantifies the impact of DR on peak demand in the absence of advance notice, while δ_1 delineates the effects of DR when advance notices are provided. Lastly, δ_2 characterizes the impact of advance notices on off-peak hours, i.e., $t \notin C$.

Identification In estimating equation (1), our analysis addresses variables potentially endogenous to demand shocks: the DR-event dummy, D_{it}, and the advance-notice variables, A_{it} and $A_{it} \cdot (c_{i1} - c_{i0})$. Unlike the prevailing research, which utilizes field experiments disconnected from electricity system stress, our study leverages a real-world program. Here DR measures are activated during peak hours to alleviate electricity demand and avert system overload. This contextual difference suggests a likely positive correlation between D_{it} and the electricity demand shock, v_{it}. Likewise, the presence and duration of advance notices, A_{it} and $A_{it} \cdot (c_{i1} - c_{i0})$, respectively, may also demonstrate correlations with demand shocks. This correlations arises particularly if the timing of issuing advance notices for DR events plays a crucial role in mitigating stress on the electricity supply and demand balance.

To address anticipated endogeneity, we employ two sets of instruments. The first set is based on the forecast errors by utilities concerning solar and wind power outputs. As the share of solar and wind power in total generating capacity has rise markedly (from 0.6% in 2011 to 6.3% in 2017), the reliability of power system has become increasingly dependent on the accuracy of these renewable energy forecasts. Larger

[11] In defining the lead time, we utilized the starting point of C_{it}. However, employing c_{i2} would yield qualitatively identical results.

forecast errors pose a higher risk to system reliability, thereby making it more probable for both D_{it} and A_{it} to be equal to 1. However, these forecast errors are unlikely to be directly correlated with electricity demand since users are typically unaware of utilities' forecasting methodologies. Hence, the forecast inaccuracy for solar and wind power outputs are deemed appropriate instruments for D_{it}, A_{it}, and by extension, $A_{it} \cdot (c_{i1} - c_{i0})$.

Our analysis also incorporates a second set of instruments: the instances of unplanned generator outages, as reported to the Japan Electric Power Exchange (JEPX). Utilities are mandated to report any unplanned outage of generators with a unit capacity exceeding 100MW. We have compiled data on unplanned outages within the electrical power supply area relevant to our DR program. An increase in the frequency of unplanned generator outages intensifies demand-supply imbalances, thereby increasing the likelihood of DR events and the issuance of advance notifications. However, it is improbable that most users attentive to or aware of the specifics of these unplanned outages, rendering this variable likely uncorrelated with v_{it}. The summary statistics for these instrumental variables are presented in the lower section of Table 2.

Estimation Results Five sets of estimates are shown in Table 3. All contain dummy variables specific to month, days-of-the-week, intra-day half-hour intervals, along with plant dummies. The first two models (3-1) and (3-2) are obtained by ordinary least squares (OLS). The difference between the two models concerns the treatment of the advance notice variable; the first incorporates A_{it}, whereas the second uses $A_{it} \cdot (c_{i1} - c_{i0})$. The findings indicate that DR effectively reduces electricity usage during critical peak times. While advance notices do not show a statistically significant effect, there appears a reduction in electricity usage during peak hours when notices are provided.

The remaining models use the two-stage least squares (2SLS) methods. As discussed prior in this section, we use two sets of instrumental variables: utilities' forecast errors from solar and wind power outputs, and units of unplanned generator outage. For all the models discussed below, the Durbin test rejects the null hypothesis that both the DR and the advance-notice dummies are exogenous. The Sargan test does not reject the hypothesis that the instruments are orthogonal to the error.

The estimates in (3-3) and (3-4) suggest that the use of instrumental variables effectively mitigate the upward bias observed in the DR dummy variable, reducing it by approximately 240 percent in (3-3) and 80 percent in (3-4). The results demonstrate a significant reduction in peak demand by 316.6 kWh and 221.9 kWh per half hour in (3-3) and (3-4), respectively. This reduction corresponds to approximately 21.4%

and 15.0% of the average peak demand subject to DR during our study period, which amounts to 1481 kWh. Furthermore, the interaction terms involving the advance-notice dummy variable, A_{it}, in (3-3) suggest that the provision of advance notice would undermine the effectiveness of DR during peak hours by 52%. Although not statistically significant, the advance notice is observed to decrease electricity demand by 61.6 kWh every half hour during off-peak periods. These estimation results align with the observations in Figure 1, highlighting that advance notifications may diminish the effectiveness of DR.

In model (3-4), the interaction between the DR dummy variable and the lead-time of advance notice, $A_{it} \cdot (c_{i1} - c_{i0})$, is negatively signed, indicating a diminishing return on DR effectiveness with earlier advance notifications. For instance, an average duration of three hours for advance notices would result in a reduction of peak demand by 135 kWh ($= -221.87 + 14.41 * 6$), which represents 9% of the peak demand. This analysis suggests that a three-hour advance notice would decreases DR effectiveness by 39.16%. While the impact of advance notice on increasing off-peak demand is noted, it remains statistically insignificant.

In model (3-5), we reassess the intra-day assumption related to advance notice, specifically focusing on notices issued on the same day as the DR event. While this approach captures a significant proportion of advance notices, it may introduce a potential censoring issue. Similar to the findings in (3-4), the coefficients for both DR and advance notice in this model exhibit comparable magnitudes and signs concerning the effectiveness of DR; while the estimate for the interaction term between D_{it} and the advance-notice variable nearly half that observed in (3-4), the impact of a three-hour advance notice on peak demand is 11.9%, a slight increase from the 9% effect noted in (3-4).[12]

4 Modeling the Effect of Advance Notice on DR

Preliminary observations from Figure 2 and our prior empirical analysis hinted that earlier notifications about the peak prices may diminish DR efficacy. This contrasts with findings from studies such as Jessoe and Rapson (2014), which argue the reverse. To reconcile these observations, this section presents a model that can accommodate both standpoints. Section 4.1 introduces a two-period model to elucidate how the presence or absence of advance notifications influences DR efficacy. Employing a CES demand model, we explore consumption substitution between the two periods. A salient outcome of our model is that the effect of advance notice on DR efficacy is contingent on the inter-temporal elasticity of substitution. When

[12] We also sought to include the number of DR events per plant in our analysis. However, due to the inability to obtain precise estimates, this aspect is further discussed in an unpublished appendix.

elasticity is greater than unity, advance notifications enhance DR effectiveness. On the other hand, for sub-unitary elasticity, such notifications dampen DR's impact.

In Section 4.2, we extend the two-period model to capture multiple periods. This adaptation allows us to move away from a binary setting, where advance notice is either provided or not. Instead, we delve into a more nuanced examination of how the duration of advance notifications impacts DR efficacy. Again, the elasticity of substitution emerges as a pivotal factor. When this elasticity exceeds unity, longer advance notifications can bolster DR effectiveness. Conversely, with sub-unitary elasticity, extended warning intervals lower the impact of DR, reducing its efficacy in influencing consumption behaviors during peak demand periods.

Note that, in the regression analysis discussed in Section 3, the model in Section 4.1 corresponds to the specification where the advance notice is represented by A_{it}, and the model in Section 4.2 addresses the lead-time of advance notice prior to the DR event, as $A_{it} \cdot (c_{i1} - c_{i0})$.

4.1 Two-period Model of Electricity Demand

In this section, while we retain the notations from Section 3, we modify time t to assume only two values, 1 and 2, within a day for this subsection. We extend this two-period framework to a multi-period model in Section 4.2. We proceed under the assumption that a plant's allocation of production resources is concentrated within a single day, rather than spread across multiple days. As discussed in Sections 2 and 3, the majority of advanced notifications in our data set were issued on the same days as the DR events. The results discussed in the preceding section indicate that the estimates derived under the intra-day assumption are comparable to those obtained when applying an inter-day assumption. This similarity suggests minimal potential impact of the assumption choice on our overall estimates.

While the dataset spans plants from various sectors, each with its unique production modality, all rely on electricity as a fundamental factor of their operational inputs. However, depicting the nuances of each sector's production processes proves challenging due to their heterogeneity and limited data availability. Thus, for the purposes of this study, we shift our focus on the consumption side. We view each plant as an electricity user and, under this lens, assume that plants derive utility from electricity consumption in accordance with a CES function. Subject to a budget constraint on electricity expenditure, denoted I_i, plant i maximizes its utility to determine the electricity consumption, q_{it}, for periods $t = 1, 2$. The optimized consumption for $t = 1$ is given by

$$\max_{q_{i1}, q_{i2}} \left(\beta_{i1} q_{i1}^{\frac{\sigma-1}{\sigma}} + \beta_{i2} q_{i2}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{2}$$
$$\text{s.t. } p_{i1} q_{i1} + \tilde{p}_{i2,1} q_{i2} \leq I_i,$$

where the parameter β_{it} captures the plant's marginal utility with respect to q_{it}, and σ symbolizes the elasticity of substitution between q_{i1} and q_{i2}. The CES utility typically demands that $\sigma > 0$, $\beta_{it} > 0\ \forall i$ and $\forall t$, and $\sum_{t=1}^{2} \beta_{it} = 1\ \forall i$. The unit retail price of electricity is pre-set for plant i in our study, and represented by p_{it} (expressed in JPY per kWh). We assume that plants are aware of the current price at time t, but they are uncertain about whether a DR event will occur – either raising the retail price to $p_{it} + r$ or leaving it unchanged at p_{it}. Let $\tilde{p}_{i\tau,t}$ be the electricity price at time τ as predicted by plant i based on information available at time t, where $\tau > t$.

We solve equation (2) backward starting from $t = 2$. Suppose that the optimal consumption volume at t is q_{it}^*. Note that q_{i2}^* is obtained by the budget constraint, which is expressed as $p_2 q_{i2}^* \leq I_i - p_{i1} \overline{q}_{i1}$, where $\overline{q}_{i1}$ is determined at $t = 1$. Accordingly,

$$q_{i2}^*(q_{i1}) = \frac{I_i - p_{i1} q_{i1}}{p_{i2}}, \tag{3}$$

As formulated in equation (2), the optimization over q_{it} is contingent on both p_{it} and $\tilde{p}_{i\tau,t}$. Putting equation (3 back into equation (2), we obtain:

$$q_{i1}^* = \frac{\beta_{i1}^{\sigma} p_{i1}^{-\sigma} I_i}{\beta_{i1}^{\sigma} p_{i1}^{1-\sigma} + \beta_{i2}^{\sigma} \tilde{p}_{i2,1}^{1-\sigma}}. \tag{4}$$

Equations (3) and (4) underscore that the interplay between the effects of advance notice on electricity consumption and the influence of DR, which is largely determined by the inter-temporal elasticity of substitution. To elucidate this, we turn our attention to three scenarios for plant i concerning DR and advance notifications (Below, we drop the subscript i unless there is confusion).

- **Scenario 0**: This scenario represents a situation devoid of the industrial DR program. Here, the plant is subjected to the electricity price p across both periods, denoted as $p_1 = p_2 = p$.

- **Scenario A and Scenario NA**: Both scenarios feature the critical peak hours in the second period, represented by $p_2 = p + r$, where r is a predetermined rebate applicable during peak period. The difference between these scenarios lies in the provision of advance notice at $t = 1$ about the second-period price. In **Scenario A**, the plant receives an advance notice, providing it with precise information about whether DR event will occur at $t = 2$. In contrast, **Scenario NA** depicts the situation where the plant is uninformed at $t = 1$ regarding the impending DR event. In this scenario, it is assumed that the plant predicts the upcoming period's price as follows:

$$\tilde{p}_{2,1} = p + \Pr(D_2 = 1|x_1) \cdot r. \tag{5}$$

Here, $\Pr(D_2 = 1|x_1)$ represents the probability of the plant facing a critical peak period $D_2 = 1$, given the set of information available to the plant at time 1, denoted by x_1.

We define the solutions of equation (3) and (4) for scenarios 0, A, and NA as q_t^{0*}, q_t^{A*}, and q_t^{NA*}, respectively. The discrepancy between q_1^{NA*} and q_2^{NA*} indicates the influence of industrial DR on electricity consumption in the absence of advance notice, represented as $\Delta^{NA} \equiv q_2^{NA*} - q_1^{NA*}$. Meanwhile, the difference between q_1^{A*} and q_2^{A*} presents the difference of providing an advance notice, denoted by $\Delta^A \equiv q_2^{A*} - q_1^{A*}$. We can establish the relationship between Δ^A and Δ^{NA}, which we present as Proposition 1:

Proposition 1. *With a two-period CES demand model with the elasticity of substitution,* $0 < \sigma$, *and with a positive critical peak rebate,* $0 < r$,

$$\begin{aligned} &\Delta^A < \Delta^{NA} \quad \textit{when } 1 < \sigma, \\ &\Delta^A \geq \Delta^{NA} \quad \textit{otherwise.} \end{aligned}$$

Proof. Utilizing equations 3 and 4, $\Delta^A - \Delta^{NA}$ is calculated as:

$$\begin{aligned} \Delta^A - \Delta^{NA} &= \left\{ \frac{I - p_1 q_1^{A*}}{p_2} - q_1^{A*} \right\} - \left\{ \frac{I - p_1 q_1^{NA*}}{p_2} - q_1^{NA*} \right\} \\ &= \left(\frac{p}{p+r} + 1 \right) \left(q_1^{NA*} - q_1^{A*} \right) \\ &= \left(\frac{p}{p+r} + 1 \right) \frac{\beta_1^\sigma \beta_2^\sigma p^{-\sigma} \left((p+r)^{1-\sigma} - p^{1-\sigma} \right) I}{\left(\beta_1^\sigma p^{1-\sigma} + \beta_2^\sigma p^{1-\sigma} \right) \left(\beta_1^\sigma p^{1-\sigma} + \beta_2^\sigma (p+r)^{1-\sigma} \right)}. \end{aligned}$$

Consequently, the sign determining the comparative effectiveness of DR with advance notice versus without it hinges on the numerator of the right-hand side of the equation, which is:

$$\operatorname{sign}\left(\Delta^{A}-\Delta^{NA}\right)=\operatorname{sign}\left((p+r)^{1-\sigma}-p^{1-\sigma}\right)$$

This leads to the conclusion that $\Delta^{A}<\Delta^{NA}$ in cases where $1<\sigma$ and $0<r$. In other scenarios, the relationship is $\Delta^{A}\geq\Delta^{NA}$. □

The proposition underscores the pivotal role of the inter-temporal elasticity of substitution in determining the influence of advance notifications on DR efficacy. Figure 3 graphically represents the essence of the proposition. Specifically, users with an elastic substitution ($1<\sigma$) show a heightened sensitivity to demand adjustments in response to price changes. These users, adept at reshaping their consumption patterns, react more acutely to price spikes. Their demand adjustments, aligned with increasing opportunity costs at the peak periods, resonate with their elasticity level. This trend is evident in the right-hand side panel of Figure 3, where $\Delta^{NA}<\Delta^{A}$, echoing the finding of Jessoe and Rapson (2014).

Conversely, users with inelastic substitution (where elasticity less than one) resist dramatic demand shifts driven by price increments. When presented with early alerts about looming price hikes, these users proactively moderate their consumption, often before the actual price increase, as shown in the left-hand side panel of Figure 3. Such preemptive reductions can potentially undermine the anticipated effectiveness of DR in alleviating peak loads, indicated by $\Delta^{A}<\Delta^{NA}$. Their behavior, characterized by complementary inter-temporal electricity consumption, is evident when, even with early price alerts, they decrease usage in anticipation rather than in direct reaction to price elevations.

Providing advance notifications of impending critical peak hours benefits electricity users by offering greater flexibility in their temporal consumption allocation. However, dispensing such alerts may not invariably serve as the optimal tactic to reduce demand during peak intervals, especially when dealing with users who exhibit inelastic inter-temporal substitution behaviors.

4.2 Extending to Multi-period Model

In the preceding subsection, we investigated the impact of simply having or not having advance notifications on DR efficacy, using a two-period CES demand model as our primary framework. Building on this foundation, in this subsection, we aim to understand the effects of different duration of early notifications on DR outcomes. To address this, we transition from a two-period model to a broader multi-period model.

For this extended model, we continue to employ the CES demand function, with a modification that t is no longer restricted to the binary values but encompasses a range, specifically $t \in \{1, \ldots, T\}$. As a result, the optimal electricity consumption is derived from the following utility function:

$$\left(\sum_{t=0}^{T} \beta_{it} q_{it}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \tag{6}$$

Note that equation (6) collapses into a two-period model when $T = 2$. As in Section 4.1, we assume that $\sigma > 0$, $\beta_{it} > 0\ \forall i$ and $\forall t$, and $\sum_{t=1}^{T} \beta_{it} = 1\ \forall i$.

Plant i faces a sequence of future prices in the determination of its optimal consumption. Suppose that the peak price $p_{it} + r$ is imposed during the critical peak period $C_{it} = [c_{i1}, c_{i2}]$, and the price at the off-peak period ($\tau \notin C_{it}$) is p_{it}. The advance notice of the DR event is announced at time c_{i0}, where $c_{i0} \leq c_{i1}$. As we assumed in Section 4.1, plant i estimates the probability of encountering a critical peak period, $\Pr(\tau \in C_{it} | x_{it})$. This estimation is based on the available data, x_{it}, which represents the information available to plant i at time t. In summary, the predicted price, $\tilde{p}_{i\tau,t}$, is defined as follows:

$$\tilde{p}_{i\tau,t} = \begin{cases} p_{it} + \Pr(\tau \in C_{it} | x_{it}) \cdot r, & t < c_{i0} \\ p_{it}, & c_{i0} \leq t \text{ and } \tau \notin C_{i0} \\ p_{it} + r, & c_{i0} \leq t \text{ and } \tau \in C_{i0} \end{cases} \tag{7}$$

Note that in the absence of the advance notice, c_{i0} must be equal to c_{i1}, in that the plant gets to know that the DR takes place only when DR is executed. At each t, plant i maximizes its utility, equation (6), given its past consumption $\{q_{i1}, \ldots, q_{it-1}\}$ and the sequence of predicted prices, $\{\tilde{p}_{i1,t}, \ldots, \tilde{p}_{iT,t}\}$, subject to the budget constraint, $\sum_{\tau=t}^{T} \tilde{p}_{i\tau,t} q_{i\tau} \leq I_i - \sum_{\tau=1}^{t-1} p_{i\tau} q_{i\tau}$. The optimal consumption is given by:

$$q_{it}^{*}(q_{i1}, \ldots, q_{it-1}) = \frac{\beta_{it}^{\sigma} p_{it}^{-\sigma}}{\sum_{\tau=t}^{T} \beta_{i\tau}^{\sigma} \tilde{p}_{i\tau,t}^{1-\sigma}} \left(I_i - \sum_{\tau=1}^{t-1} p_{i\tau} q_{it\tau} \right). \tag{8}$$

Using equation (8), we examine how the duration of the advance notice affects the effectiveness of DR, in comparison with no advance notification. The following proposition shows that the parameter of inter-temporal substitution plays a pivotal role (We drop the subscript i again unless there is confusion):

Proposition 2. *In a multi-period CES demand model with the constant elasticity of substitution σ, as the duration of the advance notice (given by $\Delta c \equiv c_1 - c_0$) increases:*

$$\Delta_c^A - \Delta_c^{NA} \textit{ increases for } \sigma > 1,$$
$$\Delta_c^A - \Delta_c^{NA} \textit{ decreases for } \sigma \leq 1,$$

where $\Delta_c^A \equiv q_c^{A*} - q_{c_0}^{A*}$ and $\Delta_c^{NA} \equiv q_c^{NA*} - q_{c_0}^{NA*}$ for all $c \in C$.

Proof. For simplicity, the proof specifically addresses the case of $c = c_1$, though it is applicable to all $c \in C$. The duration of an advance notice is defined as $\Delta c \equiv c_1 - c_0$, which corresponds to the time difference between the DR execution time (c_1) and the issuance time of the notice (c_0). The effectiveness of DR in the presence and absence of advance notice, denoted by Δ_c^A and Δ_c^{NA} respectively, is calculated utilizing equation 8 as follows:

$$\begin{aligned}\Delta_{c_1}^A =& \frac{\beta_{c_0+\Delta c}^{\sigma}(p+r)^{-\sigma}}{\sum_{\tau=c_0+\Delta c}^{T}\beta_\tau^\sigma(p+r)^{1-\sigma}}\left(I - \sum_{\tau=1}^{c_0+\Delta c-1} pq_\tau^{A*}\right) \\ &- \frac{\beta_{c_0}^\sigma p^{-\sigma}}{\sum_{\tau=c_0}^{c_0+\Delta c-1}\beta_\tau^\sigma p^{1-\sigma} + \sum_{\tau=c_0+\Delta c}^{T}\beta_\tau^\sigma(p+r)^{1-\sigma}}\left(I - \sum_{\tau=1}^{c_0-1} pq_\tau^{A*}\right),\end{aligned}$$

$$\Delta_{c_1}^{NA} = \frac{\beta_{c_0+\Delta c}^{\sigma}(p+r)^{-\sigma}}{\sum_{\tau=c_0+\Delta c}^{T}\beta_\tau^\sigma(p+r)^{1-\sigma}}\left(I - \sum_{\tau=1}^{c_0+\Delta c-1} pq_\tau^{NA*}\right) - \frac{\beta_{c_0}^\sigma p^{-\sigma}}{\sum_{\tau=c_0}^{T}\beta_\tau^\sigma p^{1-\sigma}}\left(I - \sum_{\tau=1}^{c_0-1} pq_\tau^{NA*}\right).$$

Therefore, the comparative effectiveness of DR with advance notice, as opposed to without it, is expressed as:

$$
\begin{aligned}
&\Delta^{A}_{c_1} - \Delta^{NA}_{c_1} \\
&= \left\{ \frac{\beta^{\sigma}_{c_0+\Delta c}(p+r)^{-\sigma}}{\sum_{\tau=c_0+\Delta c}^{T} \beta^{\sigma}_{\tau}(p+r)^{1-\sigma}} - \frac{\beta^{\sigma}_{c_0} p^{-\sigma}}{\sum_{\tau=c_0}^{c_0+\Delta c-1} \beta^{\sigma}_{\tau} p^{1-\sigma} + \sum_{\tau=c_0+\Delta c}^{T} \beta^{\sigma}_{\tau}(p+r)^{1-\sigma}} \right\} \left(I - \sum_{\tau=1}^{c_0-1} p q^{A*}_{\tau} \right) \\
&\quad - \left\{ \frac{\beta^{\sigma}_{c_0+\Delta c}(p+r)^{-\sigma}}{\sum_{\tau=c_0+\Delta c}^{T} \beta^{\sigma}_{\tau}(p+r)^{1-\sigma}} - \frac{\beta^{\sigma}_{c_0} p^{-\sigma}}{\sum_{\tau=c_0}^{T} \beta^{\sigma}_{\tau} p^{1-\sigma}} \right\} \left(I - \sum_{\tau=1}^{c_0-1} p q^{NA*}_{\tau} \right) \\
&\quad + \frac{\beta^{\sigma}_{c_0+\Delta c}(p+r)^{-\sigma}}{\sum_{\tau=c_0+\Delta c}^{T} \beta^{\sigma}_{\tau}(p+r)^{1-\sigma}} \left\{ \sum_{\tau=c_0}^{c_0+\Delta c-1} p \left(q^{NA*}_{\tau} - q^{A*}_{\tau} \right) \right\}.
\end{aligned}
$$

Since $q^{A*}_{\tau} = q^{NA*}_{\tau}$, $\forall \tau < c_0$, the expression is simplified as:

$$
\begin{aligned}
\Delta^{A}_{c_1} - \Delta^{NA}_{c_1} &= \left\{ \frac{\beta^{\sigma}_{c_0} p^{-\sigma}}{\sum_{\tau=c_0}^{T} \beta^{\sigma}_{\tau} p^{1-\sigma}} - \frac{\beta^{\sigma}_{c_0} p^{-\sigma}}{\sum_{\tau=c_0}^{c_0+\Delta c-1} \beta^{\sigma}_{\tau} p^{1-\sigma} + \sum_{\tau=c_0+\Delta c}^{T} \beta^{\sigma}_{\tau}(p+r)^{1-\sigma}} \right\} \left(I - \sum_{\tau=1}^{c_0-1} p q^{NA*}_{\tau} \right) \\
&\quad + \frac{\beta^{\sigma}_{ic_0+\Delta c}(p+r)^{-\sigma}}{\sum_{\tau=c_0+\Delta c}^{T} \beta^{\sigma}_{\tau}(p+r)^{1-\sigma}} \left\{ \sum_{\tau=c_0}^{c_0+\Delta c-1} p \left(q^{NA*}_{\tau} - q^{A*}_{\tau} \right) \right\} \\
&= \frac{\beta^{\sigma}_{c_0} p^{-\sigma} \sum_{\tau=c_0+\Delta c}^{T} \beta^{\sigma}_{\tau} \left\{ (p+r)^{1-\sigma} - p^{1-\sigma} \right\}}{\sum_{\tau=c_0}^{T} \beta^{\sigma}_{\tau} p^{1-\sigma} \left\{ \sum_{\tau=c_0}^{c_0+\Delta c-1} \beta^{\sigma}_{\tau} p^{1-\sigma} + \sum_{\tau=c_0+\Delta c}^{T} \beta^{\sigma}_{\tau}(p+r)^{1-\sigma} \right\}} \left(I - \sum_{\tau=1}^{c_0-1} p q^{NA*}_{\tau} \right) \\
&\quad + \frac{\beta^{\sigma}_{c_0+\Delta c}(p+r)^{-\sigma} p}{\sum_{\tau=c_0+\Delta c}^{T} \beta^{\sigma}_{\tau}(p+r)^{1-\sigma}} \left\{ \sum_{\tau=c_0}^{c_0+\Delta c-1} \left(q^{NA*}_{\tau} - q^{A*}_{\tau} \right) \right\}.
\end{aligned}
$$

Consider the case where $1 < \sigma$. In the right-hand side of the equation, the first term bears a negative sign, as indicated by $\mathrm{sign}\left((p+r)^{1-\sigma} - p^{1-\sigma}\right)$. Moreover, this term increases with the lead time of the advance notice, Δc, since the denominator grows with Δc, and $\sum_{\tau=c_0+\Delta c}^{T} \beta^{\sigma}_{\tau}$ in the numerator decreases as Δc is extended. The second term on the right-hand side also increases with Δc, particularly when $q^{NA*}_{\tau} > q^{A*}_{\tau}$ where $\tau \in [c_0, c_0 + \Delta c)$. Consequently, in scenarios where $1 < \sigma$, the difference $\Delta^{A}_{c} - \Delta^{NA}_{c}$ is observed to increase with Δc. For cases where $\sigma \leq 1$, a similar approach can be employed to demonstrate that the difference $\Delta^{NA}_{c} - \Delta^{A}_{c}$ increases with Δ_c. □

Let us assume for plant i that the weight, β_{it}, depends on the characteristics vector in a following form:

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

where x_{it} is a series of time- and plant-specific dummy variables, already defined in Section 3, and ε_{it} is an idiosyncratic term, representing time-varying unobserved elements that influence electricity demand. Taking logarithm of both sides of equation(8), gives the following estimable demand function:

$$\log q_{it} = \sigma\beta x_{it} - \sigma \log p_{it} + \log\left(I_i - \sum_{\tau=1}^{t-1} p_{i\tau} q_{i\tau}\right) - \log\left(\sum_{\tau=t}^{T} \beta_{i\tau}^{\sigma} \tilde{p}_{i\tau,t}^{1-\sigma}\right) + \sigma\varepsilon_{it}. \tag{9}$$

We employ non-linear least square regression to estimate equation (9). It is worth mentioning that, given the potential respective correlations between each of the current price variables, p_{it} and $\tilde{p}_{i\tau,t}$, and the demand shock, ε_{it}, we utilize the same instrumental variables as delineated in Section 3.2. The next section delves into the estimation results.

5 Estimation Results

This section presents the estimates of equation (9). We first construct the predicted price variable as defined in equation (7) by estimating $\Pr(\tau \in C_{it} | x_{it})$. This involves regressing an indicator variable, which is assigned a value of 1 when τ is within the set C_{it} and 0 otherwise, against x_{it}. The variable x_{it} includes a range of predictors for estimating the likelihood of upcoming DR event at time t ($< \tau$). These predictors encompass temperature (in Celsius) and its squared term, rainfall (in millimeters), snowfall (in millimeters), and the proportion of sunshine hours in a 24-hour period. The estimation results derived from linear probability and probit models are presented in the unpublished appendix. A probit model is employed to construct the predicted price variable for subsequent analysis. Nonetheless, note that employing a linear probability model also yields results similar to those reported below.

Given the potential endogeneity of the electricity price variables, p_{it} and $\tilde{p}_{i\tau,t}$, we utilize the same instrumental variables as in Section 3.2: prediction errors on solar and wind power generation by utilities, and unplanned outage of generators. Table 4 shows the average of the estimated coefficients from the first-stage regression, where each of the two endogenous electricity prices are regressed onto exogenous variables, including the mentioned instrumental variables.[13]

A higher electricity price is typically associated with the utilities' underestimation of power from vari-

[13] We assume the exogeneity of lagged prices in equation (9), predicated on the inclusion of a comprehensive set of controls within our estimation model.

able renewable energy sources. Despite a modest R-squared measure, the F-statistics robustly reject the null hypothesis of weak instruments.

Table 5 reports the estimated results of the demand model. Our focus is on the parameter σ, representing the inter-temporal substitution pattern in daily electricity usage. The OLS estimates are presented in models (5-1) and (5-2), while (5-3) and (5-4) show 2SLS estimates, utilizing the first-stage estimates from (4-4) in Table 4. Each model includes month, day-of-the-week, and intra-day half-hour interval dummies, with models (5-2), and (5-4) incorporating plant-specific dummies. Both of the models account for the potential endogeneity of $\tilde{p}_{i\tau,t}$ using the same set of instruments employed in Table 4. The OLS estimate of σ in (5-2) is negative, which contradicts the principle of utility maximization. In contrast, the estimate from (5-1) suggests a considerably elastic inter-temporal substitution. However, the 2SLS estimates, incorporating plant-specific fixed effects, are positive and less than one, indicating inelastic substitution. The 2SLS estimates of elasticity corroborate the hypothesis that plants within our dataset exhibit resistance to demand fluctuations, leading to more uniform consumption patterns when provided with advance price notifications, as evidenced in Figure 1 and Table 3. This evidence of inelastic substitution is consistent with previous studies on industrial electricity demand, such as the findings of Schwarz et al. (2002) with σ estimated at 0.03, Choi and White (2011) with estimates ranging between 0.02 and 0.04, and Aleti and Hochman (2020) reporting 0.88. Diverging from these studies, our paper introduces the aspect of advance notifications to the discourse.[14]

6 Welfare Analysis of Advance Notices

This section examines the reasons why utilities might opt to issue advance notices for the DR program, despite evidence suggesting in the preceding sections that such notices reduce the effectiveness of the program for industrial users, who are estimated to have sub-unitary elasticity of inter-temporal substitution. A pertinent question arises: why would utilities, aiming to decrease peak demand, issue advance notices that potentially diminish the impact of their DR programs? Utilizing the demand estimates from the previous section, we explore the economic logic behind utilities' decisions to issue advance notices by use of welfare

[14]The estimation of σ across different industries presented challenges due to the sparse number of observations per category. Despite efforts to adjust for other variables in a manner akin to that in Table 5, the limited sample size within each industry segment hindered our ability to obtain robust estimates for σ. This constraint necessitates a cautious approach to interpreting industry-specific findings and underscores the critical need for a more extensive dataset to draw more definitive conclusions in subsequent studies.

analysis. This exercise involves simulating counterfactual scenarios to examine the impact of the presence or absence of advance notice before DR event taking place.

In Section 6.1 and 6.2, we calculate the consumer welfare associated with the option of advance notice in the DR program. Subsequently, we assess the costs incurred by utilities in sourcing alternative power resources to compensate for the reduced effectiveness of the DR program. Our analysis concludes that the benefits of providing an advance notice option outweigh the costs, suggesting that utilities might perceive a profitable opportunity to capitalize on consumer surplus through the issuance of advance notices.

6.1 Setting Up the Analysis

The analysis here centers on on January 22, 2018, a day marked by unexpected heavy snowfall that significantly hindered a large-scale solar panel power generation, thereby elevating the risk of blackouts within the supply area under examination. In response, the utilities activated the DR event for 1.5 hours during the 18:30-20:00 window. Notably, on this occasion, advance notice was not issued. This section constructs a hypothetical scenario wherein advance notice was provided, aiming to evaluate the differences in demand reduction and consumer surplus in scenarios with and without the issuance of advance notice.

For the purpose of this calculation, we postulate that advance notice would have been issued at the start of the DR event day, specifically at midnight on January 22, 2018. To simulate the electricity demand with the incorporation of advance notice, we designate c_{i0}, c_{i1}, and c_{i2} in Equation (7) to correspond to $0:00$, $18:30$, and $20:00$. In the subsequent subsections, we proceed to analyze the cost-benefit aspects of providing advance notice.

6.2 Consumer Welfare of Advance Notices

This section quantitatively evaluates the consumer surplus derived from the option of advance notice within the context of the DR program. Our findings are presented in Table 6, which shows electricity demand and consumer welfare under two distinct scenarios, using the obtained estimates (5-4) in Table 5.

Scenario A: Demand Response with Advance Notice

In this scenario, we estimate the average demand level during the DR event for 1.5 hours, in which advance notice has been issued, utilizing the estimates (5-4) from Table 5.

Actual Scenario: Demand without Advance Notice

In contrast, this scenario reflects the actual data, where the DR was implemented without providing advance notice.

As detailed in Table 6, the per-plant demand reduction with advance notice is determined by subtracting the demand observed under Scenario A (644.0 kWh) from that under the No DR scenario (769.5 kWh), where it is assumed that no DR event is anticipated by users, effectively setting $\tilde{p}_{i\tau,t} = p_{it}$ for $\forall\, t$ and $\forall\, \tau$. In a similar vein, the demand reduction per plant in the absence of advance notice is calculated by the difference between demand under the Actual Scenario (582.9 kWh) and the No DR scenario. This computation illustrates that advance notice can lead to a reduction in demand per usage exceeding 30 percent, amounting to a decrease of 61.0 kWh (= 186.6 − 125.5). With our analysis covering 100 plants, the cumulative demand reduction attributed to advance notice translates to 18.3MWh (= 61.0 kWh ∗ 100 plants ∗ 1.5 hours of the DR event). This finding is consistent with our previous observation that advance notice reduces the effectiveness of DR when the inter-temporal rate of substitution is less than one, indicating that industrial users in the manufacturing sector as a whole prefers stable production patterns.

Additionally, Table 6 presents the benefits of providing an advance notice option within the DR program. Compensating variation (CV) quantifies the monetary compensation that the plant would require to accept the DR program. We calculated the CV values both with and without advance notice as of January 22, 2018, and derived the option values for advance notification as the differences in the CV values between Scenario A (with advance notice) and the Actual Scenario (without advance notice). For Scenario A, each user i's CV, denoted as CV_i^A, is represented as

$$
\begin{gathered}
u_i^A = \max_{q_{i1},\ldots,q_{iT}} \left(\sum_{t=1}^{T} \beta_{it} q_{it}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \\
\text{s.t. } \sum_{\tau=1}^{T} \tilde{p}_{i\tau,t} q_{i\tau} \leq I_i + CV_i^A, \\
u_i^A = u_i^0,
\end{gathered}
\tag{10}
$$

where u_i^0 is user i's utility under the no DR scenario, represented as

$$
u_i^0 = \max_{q_{i1},\ldots,q_{iT}} \left(\sum_{t=1}^{T} \beta_{it} q_{it}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{11}
$$

$$\text{s.t.} \sum_{\tau=1}^{T} p_{i\tau} q_{i\tau} \leq I_i.$$

The CV for user i under Scenario A can be calculated using the estimates (5-4) in Table 5, referred to as $\hat{C}V_i^A$. Similarly, we estimate CV for user i under the actual scenario, denoted as $\hat{C}V_i^{NA}$.

It is observed that DR without advance notice necessitates greater compensation compared to DR with advance notice. This is because advance notice broadens a user's choice set by providing additional information, thereby enhancing user benefits. Consequently, the computed CV values are higher in the absence of advance notice, i.e. $\hat{C}V_i^{NA} \geq \hat{C}V_i^A \; \forall i$. The mean CV value with advance notice is $16,740$ JPY per day, compared to $20,466$ JPY without it. Therefore, the consumer surplus attributable to advance notice is calculated as a difference of $3,726$JPY per plant or 20.33JPY per kWh ($= 3,726/61.0$).

This finding is in qualitative agreement with recent literature, such as the study conducted by Harold, Bertsch, and Fell (2021). In their residential survey in Ireland, they found that respondents' willingness to pay for a 12-hour advance notice of an upcoming DR event ranged between 2.60 and 5.25 €bi-monthly. Although the values are not directly comparable due to differences in the study context and methodology, this corroborates the notion that advance notice is perceived as beneficial by electricity users.

The following section presents a calculation of the costs incurred by utilities in offering the advance notice option, juxtaposed against the welfare increase determined herein.

6.3 Cost and Benefit Analysis of Advance Notices

This section evaluates the costs associated with the provision of advance notices within the DR program. Specifically, it focuses on the necessity for utilities to secure alternative power sources to make up for the diminished effectiveness of the DR program consequent to the issuance of advance notices.

In our analysis, a variety of power sources, including renewable energy, are considered. However, particular attention is given to the most expensive source in terms of variable costs as of 2020: oil-fired generation. The variable cost of this source ranges from 14.8 to 18.1 JPY per kWh. These costs are influenced by a combination of factors, including fuel prices, operational expenditures, and expenses related to environmental measures against global warming.[15]

As determined in our previous analysis, the welfare gain per kWh due to advance notice is quantified at

[15] The data source is available at https://www.enecho.meti.go.jp/committee/council/basic_policy_subcommittee/#cost_wg.

20.33 JPY/kWh. This figure exceeds the variable costs of oil-fired generation, suggesting that the provision of advance notices can potentially enhance overall welfare in the context of the DR program.

Moreover, if utilities can effectively monetize this welfare increment, it becomes apparent that issuing advance notices is not solely about aligning with consumer preferences, but it also emerges as a potentially profitable strategy for the utilities themselves. This consideration sheds light on why utilities might be inclined to issue advance notices, even when such actions could potentially dampen the efficacy of the DR program during peak demand hours.

7 Conclusion

Numerous countries have increased their reliance on renewable energy sources, such as wind and solar power, aiming to limit global warming to 1.5 degrees Celsius, the target established in the Paris Agreement in 2015. In the United States, for instance, renewables overtook both coal and nuclear power in 2020 to become the second-largest source of electricity generation after natural gas. The inherently non-dispatchable nature of wind and solar power, coupled with the quickly phasing out of load-following conventional power plants, has made Demand Response (DR) increasingly vital for the continuous balancing of electricity supply. This is particularly crucial as expanding capacity for peak hours often requires substantial time and investment.

Given that peak hours are typically irregular and not predetermined according to renewable energy outputs, electricity users stand to benefit significantly from advance notifications of DR events. Such fore-warnings are essential for them to adapt effectively to the varying demands of the power grid. However, the existing literature predominantly focuses on day-ahead advance notices in DR programs, resulting in a gap in understanding the full impact of these notifications on DR effectiveness.

This study addressed this gap in the literature by exploring a unique case study where different lead times of advance notification are provided for DR events. It investigated the influence of these varied notification periods on industrial responses to impending price surges of peak periods. This paper theoretically demonstrates that the impact of advance notice on DR effectiveness is conditional upon the inter-temporal elasticity of substitution. Specifically, when elasticity exceeds unity, the provision and duration of advance notices are found to augment DR effectiveness. Conversely, in scenarios where elasticity is below unity, these advance notices tend to diminish the effectiveness of DR. Empirical evidence from an industrial DR program in Japan corroborates these theoretical implications, particularly for cases exhibiting sub-unitary elasticity.

Furthermore, this paper conducted a welfare analysis of advance notices, shedding light on the economic reasoning behind utilities' decisions to issue such notices, despite their potential to attenuate the impact of DR. This analysis revealed a trade-off in the utilities' decision-making processes, where they weigh the costs of securing alternative power sources against the potential benefits from consumers who appreciate advance notifications. The aforementioned cost arises as utilities need to compensate for the reduced effectiveness of the DR program resulting from the provision of advance notice.

We identify two key issues not fully addressed in our welfare analysis that warrant further exploration in future research. The first concerns the uncertainties associated with providing advance notice in DR programs. As we discussed in Section 6-2, extending the advance notice period offers customers increased flexibility in adjusting their production processes, thereby optimizing costs. However, for the utilities' perspective, an essential factor linked to advance notice is the precision of demand forecasts and predictions for outputs from variable renewable energy sources, such as solar and wind.[16] With increased notice periods, uncertainties in the projected levels of demand and renewable energy outputs at the actual time of consumption become more pronounced, potentially escalating the utility's anticipated marginal cost of service. This aspect highlights a crucial tension between the customer benefits of receiving advance notice and the operational challenges that utilities face in accurately forecasting and managing demand.

The second issue pertains to the extensive margins of our welfare analysis, particularly the oversight of how advance notice could potentially incentivize increased participation in the DR program. An expanded participant base could lead to a broader scope of electricity consumption requiring curtailment, ultimately enhancing the overall demand reduction. However, since all industrial customers in our dataset were already enrolled in the DR program, identifying potential new entrants who might have been motivated by advance notice would require a more expansive research framework. Incorporating these potential new participants into the analysis could significantly enrich our understanding of the broader benefits associated with providing advance notifications, supplementing the advantages discussed in Section 6-2. This aspect represents an important avenue for future research, as it could reveal additional dimensions of the impact of advance notifications on DR program efficacy and appeal.

[16] The first aspect of demand forecasts was discussed in Taylor and Schwarz (2000)

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Table 1: The Data and Census 2016

	Data	Original Data	Census (2016)
Industry Composition:			
Food processing	10.70%	9.42%	10.97%
Chemicals	3.28%	2.06%	4.12%
Ceramics	4.37%	6.60%	4.82%
Iron / other metals	6.02%	5.91%	3.18%
Machinery	11.46%	12.14%	14.13%
Others	64.17%	63.87%	62.78%
Num. Plants	100	604	356,752
Num. Observations	466,186	2,797,142	

Notes: The table presents a comparison of industrial composition across three datasets. The study utilizes Data from a sample of 100 plants, which were randomly selected from Original Data comprising 604 plants. This sample is then compared to the 2016 Census data.

Table 2: Summary Statistics of Industrial Consumers in the Data

Electric voltage:	6kV		20kV-	all
Contract capacity:	-499kW	500kW-		
Per-kWh rates (JPY/kWh)				
Summer	17.34	16.16	15.16	15.98
Winter	16.23	15.16	14.25	15.03
Num. Plants	33	13	54	100
Quantity consumed (kWh/30min)	220.69	462.31	1939.90	1229.50
(S.D.)	(172.40)	(446.37)	(2425.10)	(2031.35)
Average number of DR events	14.15	13.46	14.11	14.04
(W/ advanced notices)	(8.55)	(8.31)	(8.52)	(8.50)
Duration of advance notice (hours)	3.52	3.66	3.41	3.48
Estimated demand curtailed (%)	14.22	26.44	7.91	12.38
(W/ advanced notices)	(13.66)	(23.86)	(7.78)	(11.82)
Num. Observations	144,179	61,137	260,870	466,186

Controls:	Mean	Std.Dev.	Min	Max
Prediction errors (MWh) from				
Solar power outputs	-10.83	386.31	-3615.50	3341.79
Wind power outputs	3.19	13.03	-61.28	57.80
Unplanned outage (Units)	2.02	1.26	0.00	7.00
Weather conditions:				
Temperature (°C)	15.61	12.00	-3.60	37.40
Rainfall (mm)	0.09	0.63	0.00	16.00
Snowfall (mm)	0.01	0.15	0.00	4.00
% sunshine hours	28.81	41.60	0.00	100.00

Notes: The upper section of the table categorizes industrial plants into three distinct types according to their tariff schedules. The lower section provides summary statistics for instrumental variables and other exogenous variables used in the estimation. The number of observations in our data is 466,186.

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
D_{it}	-92.52 ***	-122.63 ***	-316.58 ***	-221.87 ***	-225.42 ***
	(20.37)	13.95	(81.42)	(37.54)	(39.98)
$D_{it} \times A_{it}$	-40.77 *		164.05 *		
	(23.96)		(95.58)		
$(1-D_{it}) \times A_{it}$	3.90		-61.59		
	(17.68)		(41.53)		
$D_{it} \times A_{it} \cdot (c_{i1} - c_{i0})$		-1.88		14.41 **	7.63 **
		(1.95)		(7.30)	(5.43)
$(1-D_{it}) \times A_{it} \cdot (c_{i1} - c_{i0})$		-1.22		-2.69	-1.85
		(1.77)		(5.41)	(4.46)
R-squared	0.932	0.932	0.931	0.932	0.932
Durbin chi2	-	-	11.62 ***	14.57 ***	11.38 ***
Sargan chi2	-	-	2.68	0.19	0.49
Num. Observations	20,303	20,303	20,303	20,303	20,303

Notes: The binary dummy variable, D_{it}, is assigned a value of 1 when plant i participates a DR event, and 0 otherwise. Similarly, A_{it} is valued at 1 when an advance notice is issued to plant i at time t, and 0 in the absence of such notice. The term, $(c_{i1} - c_{i0})$, represents the lead-time of advance notice given before a DR event. Our analysis incorporates fixed effects for plants, months, days of the week, and 30-minute time intervals. The models presented in (3-1) and (3-2) are estimated using Ordinary Least Squares (OLS), while subsequent models employ Two-Stage Least Squares (2SLS) for estimation. Model (3-5) relaxes the assumption that advance notices issued on the same day as the DR event. Standard errors are inside parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

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

	(4-1)		(4-2)		(4-3)		(4-4)	
Prediction errors:								
Solar power	2.77E-08	***			2.76E-08	***	2.83E-08	***
	(3.32E-10)				(3.32E-10)		(3.32E-10)	
Wind power			9.97E-08	***	7.16E-08	***	1.85E-08	***
			(1.02E-08)		(1.02E-08)		(1.02E-08)	
Unplanned outage							5.26E-03	***
							(1.12E-04)	
R-squared	0.535		0.528		0.535		0.537	
F statistics	3664.64	***	3565.07	***	3640.43	***	3648.08	***
Num. Observations	466,186		466,186		466,186		466,186	

Notes: All specifications include the dummies specific to plants, months, days of the week, and time indicating 30-mins intervals. Standard errors are inside parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

Table 5: Estimates of Inter-temporal Substitution of Electricity Consumption

	(5-1)		(5-2)		(5-3)		(5-4)	
	OLS		OLS		2SLS		2SLS	
σ	6.65	***	-0.28	***	0.58	***	0.67	**
	(0.02)		(0.02)		(0.26)		(0.27)	
Plant Dummies	No		Yes		No		Yes	
Num. Observations	466,137		466,137		466,137		466,137	

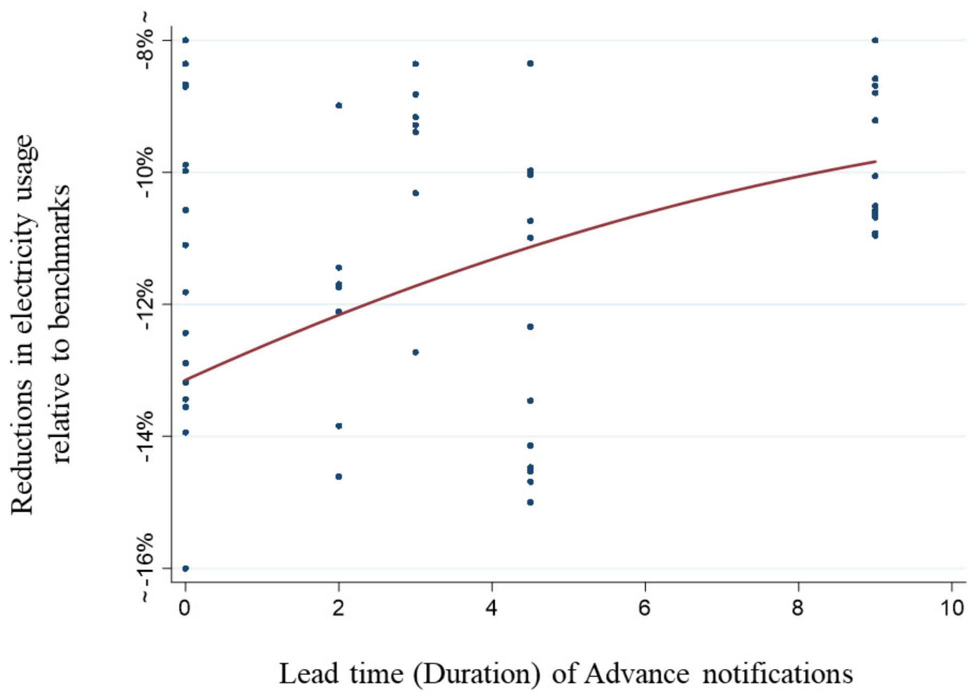
Notes: All specifications include the dummies specific to months, days of the week, and time indicating 30-mins intervals. Standard errors are inside parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

Table 6: Effects of Advance Notice on Demand Reduction

	No DR	Scenario A DR w/ advance notice	Actual DR w/o advance notice	Effects of advance notice (per plant)
Per-plant demand (kWh/30 min)				
averaged over all hours	832.8	822.9	821.2	
averaged over DR hours	769.5 (A)	644.0 (B)	582.9 (C)	
Demand curtailed per plant (kWh/30min) (#)	-	125.5 (D = A − B)	186.6 (E = A − C)	61.0 (E − D)
Total demand curtailed (MWh)	-			
= (#)× 100 plants × 1.5 hours	-	37.7	56.0	18.3
CV (JPY/day)	-	16,740	20,466	3,726

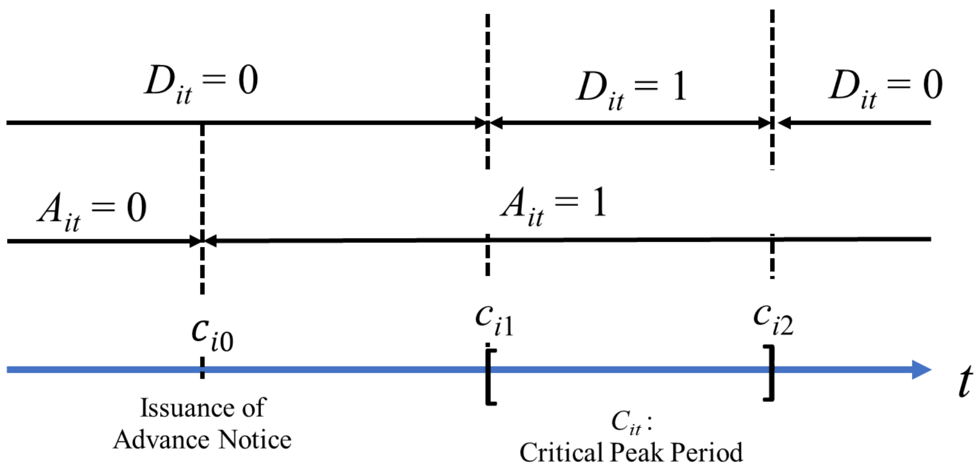
Notes: In the case study of January 22, 2018, per-plant demand was calculated for Scenario A (with advance notice) and the Actual Scenario (without advance notice), compared to the No-DR scenario. Additionally, the compensating variation (CV) was determined for both Scenarios A and the Actual Scenario. Note that no advance notice was issued on this particular date. However, under Scenario A, it is assumed that an advance notice for the DR event was issued at midnight on the date. The DR event on this date lasted for 1.5 hours, with 100 plants participating. The CV metric quantifies the monetary compensation that a plant would necessitate to be indifferent to receiving advance notice.

Figure 1: Reductions in Electricity Usage and Timing of Advance Notices



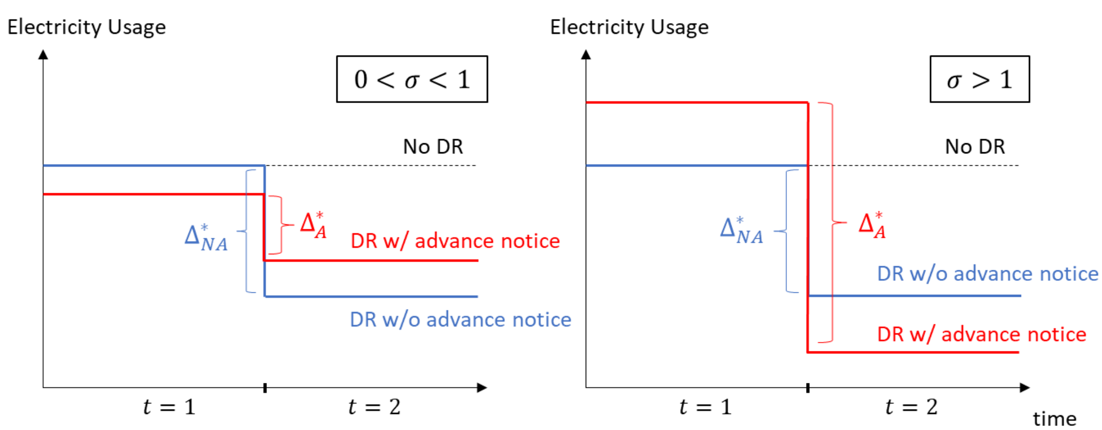
Notes: % consumption reduction on the vertical axis represents the percentage of electricity usage compared to the baseline during DR hours. The horizontal axis indicates the difference between the timing of advance notice announced to the users and the timing of DR being executed. The fitted curve is shown in red, indicating a positive relationship between the two variables.

Figure 2: Timeline of D_{it} and A_{it}



Notes: D_{it} is a binary indicator, set to 1 if plant i is subject to the critical peak period C, and 0 otherwise. A_{it} represents the issuance of an advance notice, being 1 when such a notice has been provided to the plant by t, and 0 otherwise.

Figure 3: Electricity Usage and Advance Notice



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

Unpublished Appendix

This unpublished appendix contains three sections. Section A.1 examines DR effectiveness under an alternative method to construct reference levels. Section A.2 discusses the estimates incorporating the number of DR events per plant. Finally, Section A.3 presents the estimates of the likelihood of DR event used in Section 5.

A.1 DR effectiveness under alternative reference levels

The study initially utilized the *High 4 of 5* methodology for determining the reference level of demand, indicative of the hypothetical scenario absent the DR program's influence. In pursuit of the methodological robustness, this section introduces and evaluates an alternative approach to the *High 4 of 5* for establishing the reference level.

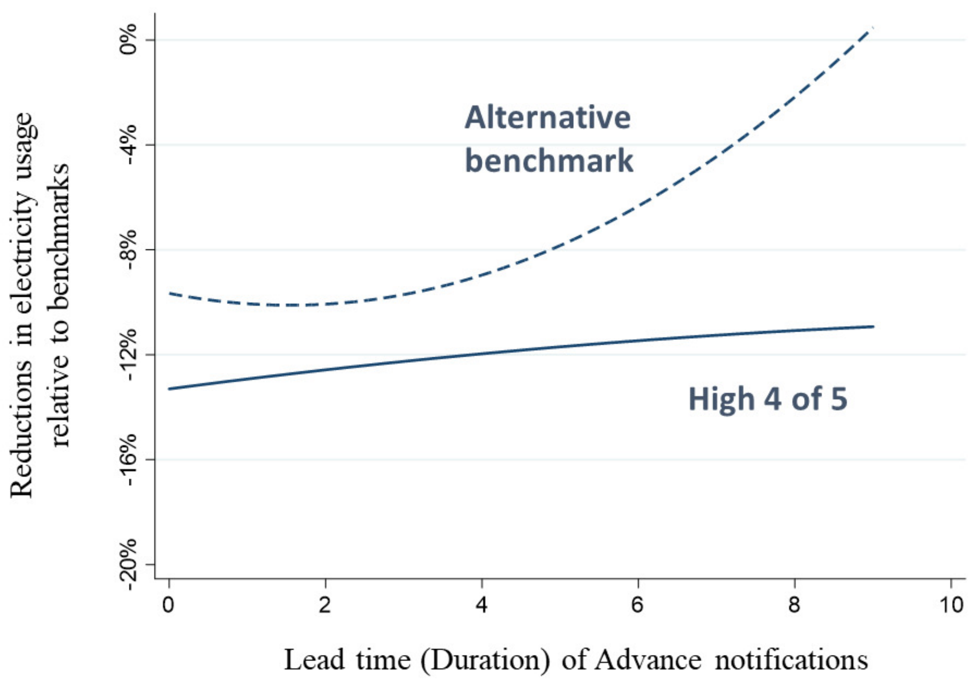
The alternative methodology leverages electricity consumption data from periods not affected by DR events, projecting demand levels in the absence of DR interventions. The regression model incorporates a variety of explanatory variables to accurately estimate non-DR period demand. These variables include the temperature (in Celsius) and its squared term, to account for non-linear effects of temperature on electricity demand, rainfall (in millimeters), and the percentage of sunshine hours, capturing the impact of weather conditions on demand. Additionally, the model includes dummy variables for plants, months, days of the week, and 30-minute intervals within a day, to control for fixed effects that might influence electricity usage patterns.

Upon this estimation, we extrapolate the projections to periods affected by DR interventions to establish an alternative reference level. The disparity between the actual demand and this reference quantifies the DR program's estimated effectiveness using the alternative method. Figure A.1, serving a parallel purpose to Figure 1, employs this alternative methodology to gauge demand reduction during DR interventions. Importantly, Figure A.1 reaffirms the pivotal finding of Figure 1: the premise that advance notification of DR events compromises the effectiveness of the program is robustly supported.

A.2 Estimates incorporating the number of DR events per plant

We endeavored to include the number of DR events experienced by each plant in our analysis. Given the challenge in obtaining precise estimates, we proceeded under the assumption that the advance-notice

Figure A.1: Reductions in Electricity Usage Using Alternative Methodology



Notes: % consumption reduction on the vertical axis represents the percentage of electricity usage compared to the baseline during DR hours. The horizontal axis indicates the difference between the timing of advance notice announced to the users and the timing of DR being executed. The solid blue line represents the fitted curve using the *High 4 of 5* methodology, while the dashed blue line represents the fitted curve using the alternative methodology.

variables (A_{it} and $A_{it} \cdot (c_{i1} - c_{i0})$) are exogenous in this estimation framework. Initially, we verified that the estimates under this exogenous assumption remain largely consistent with those in model (3-4), as depicted in equations (A1-1) and (A1-2). Subsequently, we introduced three variables interacting with the cumulative number of DR events encountered by plant i up to time t, denoted by $\#DR_{it}$ in (A1-3); D_{it}, $D_{it} \times A_{it}$, and $D_{it} \times A_{it} \cdot (c_{i1} - c_{i0})$. Model (A1-4) also explores the replacement of A_{it} with $A_{it} \cdot (c_{i1} - c_{i0})$. The analyses in (A1-3) and (A1-4) reveals that the coefficients for D_{it}, $D_{it} \times A_{it}$, and $(1 - D_{it}) \times A_{it}$ are significantly larger than those in the baseline estimates of model (3-4) presented in Table 3.

While caution is thus required in interpreting these results, an estimated positive coefficient for $D_{it} \times \#DR_{it}$ suggests that the load-reducing effect of DR weakens with an increasing number of DR events. Conversely, the coefficient for $A_{it} \times \#DR_{it}$ is negative, implying a trend where the quantity of load reduction dimnishes with advance notice. The magnitude of the coefficients for $D_{it} \times \#DR_{it}$ and $D_{it} \times A_{it} \times \#DR_{it}$ are nearly identical, suggesting that for DR events with advance notice, the amount of load reduction does not alter with repeated occurrences. In model (A1-4), no statistically significant results were obtained for $\#DR_{it}$.

A.3 Estimates of the likelihood of DR event

To compute the predicted price, $\tilde{p}_{i\tau,t}$, we need to obtain the estimated probability of plant i encountering a critical peak period, $\Pr(\tau \in C_{it} | x_{it})$. This estimation leverages the available data, x_{it}, encapsulating information accessible to plant i at time t. The variables within x_{it} are assumed to encompass temperature and its squared term, rainfall, snowfall and the proportion of daylight hours in a day. The estimates are provided in Table A.2, and are used to estimate (7),

Table A.1: 2SLS Estimates with the Number of DR Events

	(A1-1)		(A1-2)		(A1-3)		(A1-4)	
D_{it}	-306.05	***	-223.42	***	-7419.06	**	-180.45	**
	(81.02)		31.03		(3292.66)		(92.01)	
$D_{it} \times A_{it}$	173.72	*			7094.18	**		
	(95.31)				(3210.52)			
$(1-D_{it}) \times A_{it}$	-75.49	*			-163.94	**		
	(40.01)				(64.32)			
$D_{it} \times A_{it} \cdot (c_{i1} - c_{i0})$			9.02	*			9.55	
			(4.99)				(12.34)	
$(1-D_{it}) \times A_{it} \cdot (c_{i1} - c_{i0})$			-6.09	**			-6.93	
			(2.93)				(3.54)	
$D_{it} \times \#DR$					457.63	**	-4.06	
					(210.55)		(8.70)	
$D_{it} \times A_{it} \times \#DR$					-446.93	**		
					(205.64)			
$D_{it} \times A_{it} \cdot (c_{i1} - c_{i0}) \times \#DR$							0.10	
							(1.25)	
R-squared	0.931		0.932		0.931		0.932	
Durbin chi2	10.06	***	13.62	***	19.21	***	22.91	***
Sargan chi2	4.23		1.06		0.46		1.28	
Num. Observations	20,303		20,303		20,303		20,303	

Notes: The binary dummy variable, D_{it}, is assigned a value of 1 when plant i participates a DR event, and 0 otherwise. Similarly, A_{it} is valued at 1 when an advance notice is issued to plant i at time t, and 0 in the absence of such notice. The term, $(c_{i1} - c_{i0})$, represents the lead-time of advance notice given before a DR event. The number of DR events that plant i experiences up to time t is denoted by $\#DR_{it}$. Our analysis incorporates fixed effects for plants, months, days of the week, and 30-minute time intervals. Model (A1-4) relaxes the assumption that advance notices issued on the same day as the DR event. Standard errors are inside parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

Table A.2: Estimation results of $\Pr(\tau \in C_{it}|x_{it})$

	Linear		Probit	
Temperature	-1.01E-02	***	-8.49E-01	***
	(9.50E-05)		(8.91E-03)	
$(\text{Temperature})^2$	1.87E-04	***	2.31E-02	***
	(2.17E-06)		(2.63E-04)	
Rainfall	1.13E-03	***	2.04E-01	***
	(2.66E-04)		(1.65E-02)	
Snowfall	4.56E-02	***	-9.69E-01	***
	(1.09E-03)		(2.58E-02)	
% sunshine hours	4.56E-02	***	7.32E-01	***
	(1.09E-03)		(2.99E-02)	
R-squared	0.081		0.501	
Num. Observations	531,268		97,770	

Notes: ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.