Incentivizing Demand Response Using Auctions: Evidence from Steel Producers in Taiwan*

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Abstract

This paper examines the effects of incentivizing industrial users to reduce their electricity consumption using demand response auctions, in which rewards for curtailment depend on auction outcomes. Because true baseline consumption is unobserved, firms can strategically adjust both bids and consumption, leading to upward-biased estimates of program effectiveness. Using data on bids, auction outcomes, and hourly electricity consumption from steel producers in Taiwan, this paper employs a regression discontinuity design to show that not accounting for firms' strategic bidding behavior can lead to an overestimation of electricity reductions by at least 50%.

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I Introduction

Dynamic pricing and peak-time rebate (or demand response, DR) programs both inform users about market conditions and give them incentives to reduce electricity consumption when it is in short supply. However, it is often argued that promoting DR programs based on energy reductions from an unverifiable baseline consumption not only distorts consumers' incentives but also misses opportunities to implement price-based schemes (such as real-time pricing or critical peak pricing) that accurately reflect market conditions and encourage investment [Bushnell, Hobbs and Wolak, 2009; Borenstein, 2013].

In this paper, we study the effect of incentivizing DR from industrial users using auctions (henceforth DR auctions), in which the rewards for curtailment depend on auction outcomes. Such programs are already adopted in several electricity markets.[1] While previous work in the electricity market has shown that strategic behavior exists on the supply side, and such behavior can lead to market inefficiencies [Wolfram, 1998; Hortaçsu and Puller, 2008; Schwenen, 2015], there has been little empirical evidence regarding whether strategic behavior exists on the demand side. In this paper, we explore whether industrial users bid strategically in DR auctions and whether such strategic bidding behavior results in an overestimation of their demand response.

We empirically examine how steel producers in Taiwan react to DR auctions. During our study period, many firms received over 10% reductions in their energy charges as a result of participating in DR auctions in months with high market clearing prices.[2] The DR auction in our setting operates daily (workdays only) and is structured as a pay-as-bid auction in a multi-unit procurement setting.[3] Each auction collects bids (willingness to curtail usage) and reduction targets from participants and turns DR participants into multiple 'virtual' generating units to compete with actual dispatchable generating units (such as fossil-fired or natural gas-fired power plants) in the day-ahead market. Participants with bids lower than the auction price will win the auction, and each of them will receive a reward based on the amount of its electricity reduction and their winning bid.[4] On a winning day, a participant's electricity consumption on the previous five losing workdays is used to establish its customer baseline load (CBL). The difference between the participant's CBL and its actual electricity consumption on the winning day is the load reduction defined by the program.

The ability of auction participants to submit an extremely low (or high) bid to win (or to avoid winning) an auction when their true baseline consumption is private information, known to them but unknown to the utility company, poses concerns about whether participants may exploit DR programs. This 'baseline problem', articulated in Bushnell, Hobbs and Wolak [2009], can be broken down into an adverse selection problem and a moral hazard problem in our setting.[5] Adverse selection occurs when firms strategically place bids to align DR reward days with their inherently low demand days. For example, a firm might place a low bid and consequently win an auction on a day when it has scheduled maintenance. In contrast, moral hazard occurs when firms deliberately manipulate their baseline consumption to boost their DR performance. This can happen when a firm intentionally increases its electricity consumption over five consecutive workdays on which it does not win, then places a low bid and wins in the next auction.[6] We provide a model that reflects a firm's decision problem in DR auctions and show that it is rational for the firm to bid strategically according to its load profile.

To correctly evaluate the impact of the DR program when the true baseline consumption is unobserved, one must account for the fact that firms can manipulate both their bids and load on non-winning days, which are used to construct the baseline. We exploit available data and features from the auction program to address this empirical challenge. Observing each participant's daily bids allows us to construct the cutoff for each DR auction and compare firms' electricity consumption near that cutoff, thereby using a regression discontinuity (RD) design to control for strategic bidding behavior.[7] Some features of the DR program also aid our empirical strategy. First, bids are submitted before treatment assignments (i.e., auction outcomes) are determined. Second, auction prices are determined by market conditions (such as weather or supply conditions) as well as other firms' bidding behavior, but neither auction prices nor rival bids are ever observed by firms, making auction prices difficult to predict exactly. Therefore, for observations close to the winning cutoff, treatment status cannot be directly manipulated by firms, and can be viewed as effectively random.

Our results suggest that the effect of receiving a DR request from the program is associated with a 14% load reduction, and the magnitude of the treatment effect is stronger for firms selecting larger load reduction targets and for those that pre-commit to a load reduction target. We show that our results are robust to several alternative specifications. Our estimates show that failing to account for the strategic bidding effect leads the program to overestimate its load reduction by at least 50%. The strategic bidding effect in demand response auctions is costly: not only does the utility company overpay for load reduction, but also the demand estimates based on auction results can be misleading. Inefficient participants with volatile load profiles and high marginal costs of load reduction can outbid efficient ones, further distorting incentives for future participants.

Our study is connected to the existing literature that examines the impact of time-varying pricing of electricity. A growing literature has focused on households' response to time-varying pricing of electricity, including time-of-use (TOU) pricing, critical peak pricing, and real-time pricing (RTP) [Harding and Sexton, 2017]. Households' demand elasticities of electricity implied in these studies tend to vary by program design and the technologies used to inform households about their consumption or to automate their responses [Allcott, 2011; Jessoe and Rapson, 2014; Burkhardt, Gillingham and Kopalle, 2019; Bollinger and Hartmann, 2020; Fabra, Rapson, Reguant and Wang, 2021].

Compared to studies on residential customers, evidence on commercial and industrial (C&I) customers' response to time-varying pricing is relatively scarce, and most recent studies focus on TOU or peak-time pricing.[8] Jessoe and Rapson [2015] study the first large-scale mandatory TOU pricing for C&I customers in the United States. They do not find much reduction in overall or peak usage. Blonz [2022] finds that peak pricing reduced C&I customers' usage by 13.5% on event days in California, which corresponded to a price elasticity of -0.119. Isogawa, Ohashi and Anai [2022] examine the effect of a DR program on electricity consumption among Japan's industrial users and find that the demand was less elastic with advance notice. We add to the literature by providing new empirical evidence on industrial customers' response to peak-time rebate programs. Unlike the studies above, industrial customers in our empirical setting are not price takers and are allowed to participate actively in DR auctions. To the best of our knowledge, our paper is the first to explicitly consider industrial customers' strategic bidding behavior in estimating the effect of DR auctions.

Previous studies have highlighted various disadvantages of DR programs. Bushnell, Hobbs and Wolak [2009] argue that, because the baseline consumption in DR programs is unverifiable, focusing too much on DR programs may crowd out direct price-based mechanisms. Borenstein [2013] points out that DR programs distort consumers' incentives to save energy during their baseline periods and reward consumers with volatile demand, as typical rebate programs only reward consumers who use less energy than their baseline, and never punish those who use more. Ito [2015] empirically tests the effect of asymmetric incentives and finds that such a structure weakens households' incentives to reduce electricity consumption. We contribute to this literature by showing that, without accounting for firms' strategic bidding behavior, the utility company overpaid for load reductions that would have occurred even without DR incentives.

The paper proceeds as follows. Section II describes the DR program. Section III discusses the data. Section IV introduces a model that reflects a participant's decision problem. Section V shows the empirical strategy and provides the estimation results. Section VI compares estimated and CBL-based effective electricity prices. Section VII concludes.

II Program Overview

II(i) The DR auction is part of the day-ahead market

The electricity industry in Taiwan is highly vertically integrated: the state-owned Taiwan Power Company (henceforth, the utility company) has monopoly power over the transmission, distribution, and retailing sectors, and directly controls nearly 80% of the generation sector during the period of our study.[9] The utility company internally conducts a trial run of the day-ahead electricity market in response to future industry restructuring and potential divestiture. The DR auction is part of this day-ahead market. As a result, the market-clearing price of the DR auction is determined as part of the broader day-ahead market.[10]

[Place Figure 1 about here.]

Although the utility company publishes neither its demand in DR auctions in advance nor the market-clearing price of the day-ahead market afterward, it is safe to say that they are related to market conditions in the electricity industry. Figures 1(a), 1(b), and 1(c) plot daily peak demand and supply conditions of Taiwan's electricity system, the system's reserve margin (system operating reserve divided by load), and the amount of DR requested from 2018 to 2019.[11] During this period, the electricity system's reserve margin ranges between 2.89% and 26.86%, falling below 6% on 29 days (all in 2018).[12] Overall, the DR requested by the utility company is negatively correlated with the system's reserve margin. Because the electricity system enters the emergency stage whenever its reserve margin falls below 6%, the DR requested by the utility company tends to be extremely high whenever the reserve margin is below 6%.

II(ii) DR Incentives

The primary goal of the DR program in our setting is load reduction during a designated time window (i.e., the DR window). The load of a customer during a DR window, such as from 13:00 to 17:00, is defined as the *maximum* consumption level during that period (measured in kW or MW). To establish a participant's CBL for this time window, the program calculates the average load based on the same time window across the preceding five workdays on which the participant did not succeed in the DR auctions. Load reduction is then defined as the difference between the CBL and the participant's actual load during the DR window.

After winning an auction on day t, a firm's payment depends on its submitted bid, load reduction, the length of the DR window, load reduction target, and payment type—all of which are chosen by the firm. All variables are fixed throughout the month except for the bid and load reductions, which can vary daily.[13] In essence, the firm's reward on day t is the product of its bid, load reduction and the length of the DR window. For example, if the bid is 3 NTD/kWh, load reduction is 100 kW, the length of the DR window is 4 hours, then the firm receives essentially 1,200 NTD on day t.

The actual payment schemes differ from the above simplified formula because the utility company also aims to incentivize firms to meet their load reduction target. To this end, it offers two payment plans from which firms can choose. In the *economy* plan, firms receive additional payments when their performance ratio (realized reduction divided by the target) is closer to one. This plan does not require a participant to meet its load reduction target even if it wins an auction, and so an economy participant cannot receive a negative payoff. By contrast, the *reliable* plan asks for a participant's commitment. It includes a fixed payment for meeting the target and a penalty for failing to do so. This structure ensures that the reliable plan pays more than the economy plan to participants who meet their targets, but also penalizes those who fail to do so. Figure 2 illustrates the relationship between load reduction and payments received for a given auction day. In the example, the load reduction target is 100 kW, the bid is 3 NTD/kWh, and the length of the DR window is 4 hours. Under the reliable plan, the total payment is the sum of a fixed payment and a variable payment. Figure 2 shows that the reliable plan is structured to pay more than the economy plan only when the participant meets its selected target. Additional details on the payment structures are provided in Appendix A.

[Place Figure 2 about here.]

II(iii) Decision Makers and the Timeline

Firms typically participate in DR auctions through their energy management units. Yang, Hsieh, Hung, Liu, Tsai and Peng [2019] surveyed 2,767 managers of C&I users of the Taiwan Power Company in 2019 and found that, while 72.8% of managers in the energy management unit were aware of DR programs, only 47.9% of on-site managers and 35.8% of top-level managers were aware of such programs. At the beginning of each month, each firm chooses whether or not to participate in the DR auction.[14] An auction participant next specifies its rate plan in the program, including the default bid, target for load reduction, payment type, and the length of the DR window (i.e., a two-hour or four-hour reduction).[15] Participants can submit bids up to two decimal digits, but the maximum bid is capped at 10 NTD/kWh.

For a day-ahead auction on day t, a participant is allowed to change its bid up until the auction closes at 11 am on day $t-1$. After that, the utility company collects all eligible bids and load reduction targets, turns DR participants into multiple virtual generating units, and lets them compete with its actual dispatchable generating units.[16] Participants with bids lower than the day-ahead market clearing price win the day-ahead auction and are notified before 6 pm on day $t-1$.[17] The winning notice (i.e., the DR request) includes a start time for load reduction for day t, which varies by day and by participant, and becomes known to a participant only after it wins an auction.[18] Appendix Figure A1 summarizes the timeline of an auction.

The utility company shows the previous five days' average marginal electricity price (the marginal cost from the marginal generation unit in the day-ahead market) on the DR program's website to inform participants about recent market conditions.

However, previous winners' identities, winning bids, and cutoffs used to clear the auctions are not public information. As we show below, this feature will help us identify the effect of winning DR auctions. Finally, all DR auctions are for workdays only, so all calculations referring to the previous five days' average are based on the average from the previous five workdays.

III Data

The program data from 2018 to 2019 were provided by the utility company. The auction data consist of industry codes, plans, and payments received (at the monthly level), as well as bids and auction outcomes (at the daily level) for all 1,405 participants.[19] Having the universe of all submitted bids allows us to back out each auction's price (i.e., the cutoff between losing and winning bids). Because participants selecting the two-hour reduction plan are grouped into two-hour virtual generating units and their winning cutoffs sometimes differ from those in the four-hour reduction plan, we treat two-hour and four-hour auctions as separate auctions. Appendix C provides additional details regarding how auction prices are constructed. To measure daily market conditions, we collect publicly available data, including maximum temperature, reserve margin, and previous five days' average marginal price (henceforth, recent price).

We also acquired data on hourly load and load reduction after winning an auction for a subset of participants (39 participants) in the steel industry and refer to them as 'the consumption sample' below.[20] Even though firms in the consumption sample are a subset of firms in a particular industry, these participants are important in two ways. First, the steel industry by itself accounted for 7% of total electricity consumption in Taiwan in 2019. Second, during the sample period, 59% of the program's payments went to these 39 participants. We discuss details of the consumption sample's coverage in Appendix D. Our analysis is conducted on the consumption sample. The identities of all participants are kept anonymous.

We make some restrictions on our sample. First, we exclude auctions in which there was no winner or no loser at all. This removes extreme cases where we cannot determine the auction price. Second, in rare cases, we observe that a firm lost an auction even though its bid was lower than some winners in the auction.[21] We remove five auctions where this abnormality occurred to ensure that auction outcomes are consistent with bids. Sometimes a DR request begins 15, 30, or 45 minutes after the hour. In such cases, the first and last hour in the DR window are 'partially treated'. We cannot determine whether the maximum consumption of an hour occurs in the DR window for these partially treated hours, and so our final sample excludes them. Finally, since all of the DR requests are made between 10 am and 10 pm, our main analysis is conducted during these hours. In section V, we report on the robustness of our estimates when we relax these restrictions.

III(i) Summary Statistics

Our final sample has 735 auctions, including 319 two-hour and 416 four-hour auctions. Within these auctions, we observe 11,780 bids from 39 firms. Figures 3(a) and 3(b) plot the distribution of bids and daily auction prices, respectively. While bids are allowed to have two decimal digits, the majority of bids are integers, suggesting that many firms are not sophisticated enough to submit bids at a finer level or lack the information to do so, because auction prices are not public information.

[Place Figure 3 about here.]

The auction prices at the 50th and 90th percentiles are 1.35 NTD/kWh and 3.25

NTD/kWh, respectively.[22] It is noteworthy that only 11 out of 735 auctions reached the maximum auction price of 10 NTD/kWh, and all of these instances occurred in May 2018. Interestingly, nearly 30% of bids were placed at 10 NTD/kWh, and only 4.4% of these bids were made in May 2018. This suggests that some firms submitted the maximum bid not with the expectation of winning auctions at that price. Instead, it seems that a majority of firms used the maximum bid as a strategy to avoid winning auctions, given that the observed winning probability is zero when placing a bid at 10 NTD/kWh, except in May 2018.

It might initially seem surprising that some firms would intentionally aim to lose auctions. However, it is important to recognize that firms with volatile electricity consumption can profit effortlessly from DR auctions. Specifically, if a firm's production process alternates between high and low consumption states, it can adapt its bidding accordingly. By placing a high bid during a high consumption state, it avoids winning the auction but establishes a high baseline. Then, in the following low consumption state, it can place a low bid to win the auction and benefit from its previously established high baseline.

[Place Figure 4 about here.]

Figures 4(a) and 4(b) plot the supply curve of a typical auction and the average supply curve, respectively. The price in Figure 4(a) is 1.35 NTD/kWh, which corresponds to the median of all auction prices. Note that in Figure 4(b), the y-axis is the bid-cutoff gap, defined as the bid minus the realized auction price. For each bid (or bid-cutoff gap), Figure 4 shows the auction's corresponding cumulative target (%). If firms were certain about the auction price, we would expect all winners to bid slightly below the auction price. Instead, we find that winners submit heterogeneous bids even within a single auction.

[Place Figure 5 about here.]

Figure 5 provides more evidence to show that firms do not have perfect control over their treatment status. Figure 5(a) plots the relationship between each firm's bids and auction outcomes. We sort firms by a randomly created identification number. In many cases, for a given firm, variation exists in its auction outcomes even when it places the same bid. Figure 5(b) shows the distribution of hours in the DR window on winning days by firm. With only a few exceptions, variation in treatment status (inside or outside the DR window) exists, even when looking at the same hour of the day. Our empirical strategy exploits the above sources of variation to identify the treatment effect of winning DR auctions.

[Place Table I about here.]

Table I provides summary statistics for our main sample. Given that large heterogeneity exists across firms, Table I presents the results by load reduction target and by incentive plan. Note that most firms maintain only a small number of target levels and do not change their incentive plan during the study period.[23] This stability allows us to classify firms based on their typical choices. In what follows, we refer to firms with average load reduction targets above and below the median load reduction target (1,500 kW) as high-target and low-target firms, respectively, and firms selecting the economy and reliable plans as the economy and reliable firms, respectively. Panel A presents firms' hourly load (kW). Panel B, focusing on firms' strategic bidding behavior, includes variables such as the winning probability, bid, and the bid-cutoff gap. Panel C shows variables regarding firms' load reduction behavior, including the performance ratio and an indicator variable measuring whether a load reduction target is met or not on winning days.

The average hourly load is 15,309 kW.[24] The average load of the high-target firms is higher than that of the low-target firms. High-target firms also seem to bid more sophisticatedly. Although their average winning bids are only slightly lower than those of low-target firms (1.92 NTD/kWh vs. 1.93 NTD/kWh), they have a higher average winning probability (0.24 compared to 0.22 for low-target firms), a smaller average gap between their winning bids and auction prices (0.97 NTD/kWh in absolute value, compared to 1.13 NTD/kWh for low-target firms), and a larger average gap between their losing bids and auction prices (6.14 NTD/kWh compared to 3.79 NTD/kWh for low-target firms), suggesting that high-target firms are more likely to place higher bids to 'opt out' of auctions. High-target firms also meet their targets more often (33% versus 29%) and more precisely than low-target firms: their average performance ratio (0.72) is closer to one than that of low-target firms (1.83).

Columns (4) and (5) of Table I present the results for the economy and reliable firms, respectively. We find that reliable firms consume more electricity and submit more sophisticated bids than economy firms. Reliable firms have a higher average winning probability (0.36 compared to 0.22 for economy firms), a smaller average gap between their winning bids and the auction prices (0.77 NTD/kWh in absolute value, compared to 1.07 NTD/kWh for economy firms), and a larger average gap between their losing bids and the auction prices (6.93 NTD/kWh compared to 4.81 NTD/kWh for low-target firms). Unsurprisingly, reliable firms also meet their targets more often than economy firms (95% compared to 26%), and their average performance ratio is closer to one (1.1 compared to 1.28 for economy firms).

IV Theoretical Framework

This section presents a theoretical framework that illustrates how firms determine their bids and manage load reductions in DR auctions. We begin by describing the model setup, highlighting key differences from the traditional multi-unit pay-as-bid auction. We then characterize firms' optimal bidding and load reduction decisions. Our results show that if a firm has a higher CBL or a lower scheduled load, it is more likely to lower its bid in the DR auction. In turn, a lower bid leads to a smaller load reduction effort.

While the daily DR auction resembles a multi-unit pay-as-bid auction, it differs significantly from the standard model described in the literature [Hortaçsu and McAdams, 2018] in two key respects. First, in a typical multi-unit auction, bidders submit a supply schedule. However, as described in Section II, each firm in a DR auction is restricted to submitting a single price-quantity (or bid-target) pair per auction. Second, in the standard model, prices and quantities are generally submitted simultaneously. By contrast, in DR auctions, a firm must submit its target at the beginning of each month, before submitting its daily bids, and this target remains fixed throughout the month. In addition, firms choose their actual load reduction efforts (which may differ from their targets) only after winning the auction.

Since our focus is on how firms set their bids and determine load reductions, this theoretical framework does not model their target-setting decisions.[25] Given a chosen target, firms proceed in two stages. In the first stage, they determine their bids in order to win the auction. In the second stage, conditional on winning, they choose their load reductions. For firms that do not win, the process ends after the first stage.

Specifically, in the first stage, each firm chooses its bid b with the winning probability $G(b)$, where $G(\cdot)$ is assumed to be exogenous and identical across all firms. If a firm wins the auction, it proceeds to the second stage, where it chooses the load reduction level x, incurring a curtailment cost $c(x)$. As noted in the previous section, the utility company calculates the load reduction as the difference between the firm's CBL and its actual load. Assume that the firm has a privately known scheduled level of consumption, denoted by its scheduled load SchL. Then, the load reduction calculated by the utility company is $\text{CBL} - (\text{SchL} - x)$.

We solve the firm's decision problem by backward induction, starting from the second stage. Given that a firm wins the auction with bid b, its profit maximization problem is

$$\max_x b \times [\text{CBL} - (\text{SchL} - x)] - c(x),$$

where the first term represents the payment received from the utility company. The first-order condition is $b = c'(x)$, which implies that the optimal load reduction, $x^*(b)$, is a function of the bid b. If the cost function is convex, the optimal load reduction increases with the bid.

In the first stage, the firm's profit maximization problem is given by

$$\max_b G(b) \times \left[b \times (\text{CBL} - \text{SchL} + x^*(b)) - c(x^*(b))\right],$$

where $x^*(b)$ denotes the optimal load reduction in the second stage as a function of the bid. The corresponding first-order condition is

$$b + \frac{G(b)}{G'(b)} = \frac{c(x^*(b))}{\text{CBL} - \text{SchL} + x^*(b)}. \tag{1}$$

Therefore, a firm's optimal bid and resulting load reduction depend on its privately known scheduled load.

Under the standard assumptions for the winning probability $G(b)$ and the cost function $c(x)$, there exists an optimal bid b^* for the firm at which the marginal benefit equals the marginal cost. Furthermore, a positive difference between CBL and SchL leads to a lower optimal bid for the firm, increasing its winning probability.[26] This suggests that firms with a higher CBL or a lower scheduled load are more likely to submit lower bids in the DR auction. Once a firm wins the auction, its lower bid also results in a smaller treatment effect from the auction, $x^*(b^*)$.

[Place Figure 6 about here.]

We use the following example to illustrate how a firm strategically chooses its bid in our theoretical model. In the example, the winning probability function is given by $G(b) = \Phi(1 - 0.5b)$, where Φ denotes the standard normal cumulative distribution function, and the cost function is $c(x) = x^2/2$. We fix the CBL at 30 kW, and simulate optimal bids for SchL values ranging from 20 kW to 30 kW. We present the results in Figure 6. In the figure, the blue line represents the relationship between a firm's SchL and b^*. If the firm wins the auction, it reduces its load by $x^*(b^*)$. We plot load after curtailment, $\text{SchL} - x^*(b^*)$, using the red line. The results show that firms tend to submit lower bids when they have lower SchL values, and the treatment effect, represented by the vertical difference between the blue and red lines, increases as bids become higher.

Moreover, given the auction price (shown as the vertical line in Figure 6), we use solid and dashed lines to denote observed and unobserved load, respectively.[27] Around the cutoff, comparing the observed load between just-winning and just-losing bids reveals the treatment effect, while the load reduction calculated by the utility company also accounts for the difference between SchL and CBL.

Our model assumes that curtailment cost depends only on the load reduction. In Appendix F, we extend the model to allow the curtailment cost function to also depend on scheduled load levels. The results show that when the curtailment cost increases with scheduled load, a lower scheduled load tends to strengthen a firm's incentive to bid lower.[28]

V Empirical Strategy and Results

V(i) Empirical Strategy

Our theoretical model suggests that a firm's scheduled load on winning days (which is unobserved by researchers) is correlated with its bid. Because firms can also influence their winning probabilities in DR auctions by adjusting their bids, the treatment assignment is not exogenous. As a result, simply regressing electricity consumption on auction outcomes can lead to biased estimates of the treatment effect of winning DR auctions. Fortunately, we observe bids submitted by all firms in each auction, allowing us to exploit win and lose margins at the individual firm-by-auction level to mitigate the selection problem. The idea is that since neither auction prices nor rival bids are observed by firms, for observations close to the winning cutoff, treatment status is nearly equivalent to being randomly assigned. In these cases, electricity consumption when a firm barely loses an auction can serve as the counterfactual when it barely wins an auction.

We employ electricity consumption data at the firm-by-hour level to examine the effect of winning DR auctions. The estimating equation is:

$$
\begin{aligned}
Y_{i,hdm} =& \alpha_{i,m} + \alpha_{i,h} + \beta_1 WinInWindow_{i,hdm} + \beta_2 WinOutsideWindow_{i,hdm} \\
& + f(b_{i,dm}) + \mathbf{X}'_{dm}\beta_3 + \epsilon_{i,hdm},
\end{aligned} \tag{2}
$$

where $Y_{i,hdm}$ is the hourly load of firm i (in logarithms) in hour h on day d in month m; $\alpha_{i,m}$ and $\alpha_{i,h}$ are firm-by-month-of-sample and firm-by-hour-of-day fixed effects, respectively; $f(b_{i,dm})$ is a flexible function of the bid-cutoff gap and $\mathbf{X}_{dm}$ are covariates for market conditions, including temperature, reserve margin, recent price, and auction price. The indicator variable $WinInWindow_{i,hdm}$ takes the value of one if firm i wins the auction on day d, and hour h is within the DR window, and zero otherwise. Similarly, the indicator variable $WinOutsideWindow_{i,hdm}$ takes the value of one if firm i wins the auction on day d but hour h is not within the DR window and zero otherwise.

In our preferred specification, $f(b_{i,dm})$ includes a linear function of the bid-cutoff gap and its interaction with the indicator for winning events ($Win_{i,dm}$) to account for the strategic bidding effect. In addition, we restrict the sample to observations with small absolute bid-cutoff gaps (i.e., the bandwidth). This approach exploits the sharp treatment assignment rule at the auction cutoff and the estimated treatment effect can therefore be interpreted as coming from a regression discontinuity design using a uniform kernel. We conduct several robustness checks to show that our results are not driven by the choice of bandwidth, kernel, or polynomial order used in estimation. For completeness, we also show results from a specification that includes a linear control for bid in the full sample.

We expect β_1 to be negative if firms reduce electricity consumption during hours inside the DR window. Such a reduction would be a direct response to the DR requests. On the other hand, we use β_2 to capture the spillover effect outside of the DR window on winning days. This effect captures any extended impact of DR requests on firm behavior beyond the designated hours. Standard errors are clustered at the firm-by-month-of-sample level.

V(ii) Empirical Results

Table II provides regression estimates from equation (2). The row labeled "Proximity" indicates the absolute distance between a firm's bid and the auction price (in NTD/kWh). All results include market-level covariates, firm-by-month-of-sample, and firm-by-hour-of-day fixed effects. Column (1) presents naive estimates without accounting for the strategic bidding effect, while columns (2)-(5) give estimates addressing firms' strategic bidding behavior. Column (2) reports estimates when a linear function of bid is included in the estimating equation, and columns (3) to (5) report estimates based on the RD design when the absolute of bid-cutoff gaps are limited to 3, 2, and 1, respectively.

[Place Table II about here.]

Without controlling for the strategic bidding effect, the estimated coefficient of β_1 in column (1) is -0.588 and is statistically significant, suggesting that a DR request is associated with a load reduction of 0.588 log points (44%) during the DR window. After controlling for the bid, the estimated load reduction in column (2) remains statistically significant but declines to 0.173 log points (16%). Estimates of β_1 from the RD design are -0.190, -0.230, and -0.149, when we restrict the bandwidth to 3, 2, and 1, respectively, and all remain statistically significant. More importantly, coefficients that explicitly account for the strategic bidding effect (columns (2)-(5))

differ significantly from the naive estimate reported in column (1). The coefficients of $WinOutsideWindow$ are negative across all columns. Nevertheless, the magnitude of the estimated coefficient is small (3%) compared to the main effect and cannot be precisely estimated when we control for the bid in the estimation (column (2)) or when we restrict the bandwidth to one (column (5)), which implies that there is not much spillover effect outside the DR window on winning days.

To sum up, we find that it is important to account for firms' strategic bidding behavior in estimating firms' electricity consumption behavior. In our preferred specification (RD design with a bandwidth of one), we show that after accounting for firms' strategic bidding behavior, a DR request on average reduces a firm's electricity consumption by 14%.

V(iii) Heterogeneous Effects

Next, we explore the heterogeneous effects across firms. We split the sample into subgroups based on firms' load reduction target (low or high), payment type (economy or reliable), and auction price (lower or higher than 5 NTD/kWh).[29] This allows us to investigate how these characteristics influence the effect of a DR request.

[Place Table III about here.]

Table III presents the results for the subgroups based on our preferred specification (RD design with a bandwidth of one). All estimated coefficients associated with $WinInWindow_{i,dm}$ are negative across all subgroups, but due to a smaller sample size used in the RD design, the effect of a DR request in some subgroups cannot be estimated with precision. Columns (1) and (2) in Table III show that high-target firms have a larger load reduction after receiving a DR request: low- and high-target firms reduce their electricity consumption by 0.102 log points (9.7%) and 0.175 log points (16%), respectively. In addition, based on the payment type, columns (3) and (4) show that reliable firms have a substantially greater load reduction compared to economy firms, suggesting that including a punishment device in the payment structure matters. Lastly, columns (5) and (6) display the results by high or low auction price. The treatment effect is much stronger on days with higher auction prices, suggesting that firms exert additional efforts to reduce their electricity consumption in response to larger DR incentives.

We also estimate equation (2) at the firm level. To better explain the coefficient, we replace logged hourly load with hourly load divided by a firm's load reduction target as our outcome variable. In this way, if a firm meets its load reduction target perfectly, we expect the firm's coefficient of the $WinInWindow$ variable to be exactly negative one.[30] Following our preferred specification, we limit samples to those within the bandwidth of one. Because not every firm changes its bid frequently and has observations within this narrow bandwidth, we can only estimate RD coefficients at the firm level for 29 firms.

[Place Figure 7 about here.]

We present the estimated coefficient of the $WinInWindow$ variable for each firm in Figure 7, separating the results into two subfigures by load reduction target. Figures 7(a) and 7(b) give the results for firms below and above the median load reduction target, respectively. In each sub-figure, we arrange the firms in order of the magnitude of their estimated coefficients. We present the coefficients associated with economy and reliable firms using circle and diamond symbols, respectively, and upgrade firms with a negative and significant coefficient of the $WinInWindow$ variable to larger symbols.

For low-target firms (Figure 7(a)), we find none of firms (0 out of 13) have a negative and significant treatment effect. By contrast, for high-target firms (Figure 7(b)), about 19% of firms (3 out of 16) are estimated to have a negative and significant treatment effect. This pattern suggests that there may exist fixed costs of installing the measures needed to provide the demand response. We also find that both reliable firms have a negative and significant treatment effect, even though only one of them has an estimated confidence interval of performance ratio that covers negative one.

V(iv) Robustness Analysis

Our preferred specification uses logged hourly load as the dependent variable and adopts the RD design that limits the bandwidth to one with a uniform kernel and includes a linear function of the bid-cutoff gap for both sides of the cutoff. Table IV explores alternative specifications and the effect on the estimation results of expanding our sample size.

[Place Table IV about here.]

First, we consider the effect of bandwidth and kernel selection on our results. Column (1) of Table IV presents the estimate following Cattaneo, Idrobo and Titiunik [2020]'s recommendation, using a linear function of the bid-cutoff gap for both sides of the cutoff but incorporates bias correction with optimal bandwidth selection and the triangular kernel. Columns (2) and (3) report the results using alternative specifications, including a uniform kernel and a second order function of the bid-cutoff gap, respectively. The estimates from columns (1) to (3) are between -0.192 and -0.207, which are not statistically different from our preferred specifications shown in Table II, suggesting that our main results are robust to these alternative specifications. Figure 8 plots the estimated coefficients of $WinInWindow_{i,dm}$ along with their

95% confidence intervals using our preferred specifications by bandwidth. We note that as we move to narrower bandwidths, the treatment effects are identified from a smaller set of firms who were able to bid within these narrow bandwidths, because some firms do not have observations on both sides of the cutoff when we use narrower bandwidths. Nevertheless, all of the coefficients are negative and significantly different from zero and reject the naive coefficients reported in column (1) of Table II.

[Place Figure 8 about here.]

Because using the log transformation drops observations with zero electricity consumption, column (4) of Table IV reports results from the inverse hyperbolic sine (arcsinh) transformation of hourly load. We also examine the effect on the estimation results of expanding our sample size. In our final main sample, we removed observations from auctions with any losing bid lower than the auction price, and observations outside the 10 am to 10 pm window.[31] Columns (5) and (6) of Table IV report the results when we remove the above restrictions, respectively. The results are also consistent with those reported in Table II.

VI Estimated Load Reduction and Effective Price of Electricity

We have shown that failing to account for firms' strategic behavior can lead to an overestimation of the effect of receiving a DR request. In this section, we compare our estimated total load reduction and average effective price of electricity with their CBL-based counterparts, with both calculated over the entire sample period.

For each firm on each auction day, we observe its CBL-based load reduction (in kW), which allows us to calculate the total monthly load reduction in electricity (in kWh) by first multiplying each firm's load reduction by the number of hours in its DR window, and then summing over auction-winning days and firms within the month.[32] CBL-based total monthly payments can also be directly calculated from the data.[33] We then calculate CBL-based average effective price of electricity (in NTD/kWh) by dividing the total monthly payment by the total monthly load reduction in electricity.

We use firm-level estimates to calculate the estimated load reduction, the total monthly load reduction in electricity, and the average effective price of electricity. As a result, the rest of the comparisons are based on 29 firms for which we have sufficient observations to implement the RD empirical strategy. Given that the utility company always sets load reduction to zero whenever a firm's actual load is higher than its CBL on an auction day, for firms with negative estimated load reduction, we also set their load reduction to zero over the entire period of our study.

[Place Figure 9 about here.]

[Place Figure 10 about here.]

Figure 9 plots the paid and estimated average load reduction by month. Similarly, Figure 10 shows the average effective price of electricity based on both paid and estimated load reduction. The estimated load reduction ranges from 0 MW (June 2019 to September 2019) to 64.85 MW (May 2018), while the paid load reduction is at least twice the estimated load reduction, suggesting that, throughout the sample period, at least 50% of the paid load reduction is due to the strategic bidding effect. As a result, the estimated average effective price of electricity in Figure 10 reaches 28.9 NTD/kWh, compared to the maximum observed value of 9.46 NTD/kWh based on CBL-based calculations.

VII Conclusion

Both dynamic pricing and DR programs are important tools for maintaining the stability and reliability of electricity systems, especially in cases where a substantial portion of the energy supply depends on renewable sources. Nevertheless, implementing a DR program requires constructing a baseline, which in turn relies on private information available only to firms, leading to an asymmetric information problem.

This paper shows that firms strategically select into DR auctions, leading to an overestimation of the program's effectiveness. Our estimates suggest that about 50% of the paid load reduction is inframarginal. After accounting for the strategic bidding effect, our analysis reveals that winning a DR auction reduces firms' electricity consumption by an average of 14%.

Dynamic inefficiency could emerge from firms' strategic bidding in DR auctions. Firms with volatile electricity consumption could bid strategically and undercut other firms in auctions, even when they have higher curtailment costs. A natural extension of this study would be to estimate the curtailment costs of industrial users. Such estimates could help quantify dynamic inefficiency and explore the benefits of mechanisms that facilitate the truthful revelation of firms' baseline consumption.

FOOTNOTES

[1]For example, the New York Independent System Operator (NYISO) allows eligible customers to bid in the Day-Ahead Demand Response Program (DADRP) and several Californian utility companies also offer day-ahead capacity bidding programs (CBP) to customers.

[2]Each firm's electricity bill includes a fixed charge and an energy charge.

[3]Workdays refer to weekdays that are not national holidays. We discuss the features of the DR auctions studied in this paper in detail and compare them with typical multi-unit auctions in Sections II and IV, respectively.

[4]To be precise, the payment is structured so that the better a participant meets its load reduction target, the higher the final payment is. We discuss the payment structure in detail in Appendix A.

[5]An empirical instance of a moral hazard problem within a DR program occurred at the Baltimore Orioles baseball stadium in 2010. On a day without an Orioles game, the stadium increased its electricity consumption by turning on its lighting. This action was in response to an emergency event declared by the grid operator PJM, scheduled to start two hours later. See the Federal Energy Regulatory Commission's investigation report (Docket No. IN12-15-000), which can be found at `https://www.ferc.gov/sites/default/files/enforcement/civil-penalties/actions/143FERC61218.pdf`.

[6]In Appendix B, we outline conditions under which baseline inflation is profitable, assuming there is no uncertainty in auction outcomes or DR event windows.

[7]For recent studies that also exploit close cutoffs to compare winners and losers in procurement auctions and awards, see Kroft, Luo, Mogstad and Setzler [2025], Hvide and Meling [2022], and Lagios and Méon [2024]. These papers examine imperfect competition in labor and product markets, startup profitability, and book sales, respectively, and are therefore set in contexts different from ours.

[8]In earlier studies, Aigner, Newman and Tishler [1994] and Aigner and Hirschberg [1985] provide early experimental evidence on TOU pricing and find small shifts in usage from peak to off-peak periods. Herriges, Baladi, Caves and Neenan [1993] look at the effect of RTP on industrial customers and conclude that firms were able to shift their usage in response to RTP, but the effect was not

uniform across firms.

[9]The rest of the generation is covered by nine major independent power producers (IPPs), independent renewable units, and co-generation units.

[10]According to an article written by staff at the utility company [Tang, Chang, Lin and Chang, 2016], in order to balance the grid, the day-ahead market auctioneer aggregates supply curves from all virtual and actual generating units and calculates (1) the cost-minimizing dispatch solutions for each time period subject to various ramping conditions based on unit characteristics, and (2) the day-ahead market price, which is the bid from the last (i.e., highest-bidding) generating unit dispatched. The DR auctioneer sends DR requests to participants within each virtual unit in order, starting with the participant with the lowest bid, until their aggregate load reduction target exceeds the quantity demanded by the day-ahead auctioneer. If a virtual unit is not dispatched, participants within the unit still receive a DR request as long as their bid is below the day-ahead market price.

[11]System operating reserve is the difference between system capacity and load.

[12]System capacity increased after mid-2019 due to the addition of new generating units.

[13]The program requires a participant to commit to a selected plan for the entire month, during which the participant can submit daily day-ahead bids to the system.

[14]The utility company offers other DR options such as the 8-days-per-month (P1) or 6-hours-per-day (P2) programs, in which participants are allowed to select a time period for load reduction. Unlike DR auctions, a participant's rewards per kWh under P1 and P2 are fixed (not subject to daily market conditions). Our data are limited to participants who select DR auctions.

[15]When a participant fails to submit a bid for a particular day, the default bid will be used.

[16]During our study period, the total number of hours that could be won by any participant in a month was capped at either 36, 60, or 72, depending on the electricity supply conditions. A participant's bid would therefore be removed from an auction if it reached the month's hour limit.

[17]During days when the electricity grid's condition is critical, a participant losing the day-ahead market may receive a DR request two hours before the start time on day t. Such DR requests are rare and the response time is different from that in the day-ahead market; therefore, we exclude data from these requests.

[18] To illustrate, suppose a participant selects a four-hour reduction plan and wins the auction on July 9. If the start time in the winning notice is 13:00, then the designated time period for load reduction is from 13:00 to 17:00 on July 9.

[19] We observe monthly fixed payments, penalty terms, and daily variable payments (in NTD) to each firm in the data.

[20] Steel producers are defined as producers with the industry code 241 in Taiwan's standard industrial classification system.

[21] Conversations with staff at the utility company indicate that, because participants are grouped into only a few virtual generating units and because the auction outcome is jointly determined with the company's day-ahead market—requiring the system to satisfy thousands of constraints—there can be considerable complexity in determining winners. Therefore, in rare cases, this may result in winners who do not necessarily align with the lowest bidders. This anomaly could lead to complaints about the utility company. Hence, this also explains the utility company's hesitancy to make the daily auction prices public information.

[22] All auction prices are positive. During this period, generation from renewable sources represented only 4.59% and 5.56% of the total generation in 2018 and 2019, respectively.

[23] Of the 39 firms, 35 maintain no more than two levels of targets, and 16 never adjust their targets at all. In addition, 35 firms never switch to a different incentive plan.

[24] The maximum hourly load is 286,400 kW. Out of 139,138 hours in the data (at the firm-by-hour level), 486 hours have zero electricity consumption.

[25] As noted in Section III, firms do not appear to adjust their targets frequently. In practice, firms under the economic plan receive slightly higher payments when their load reduction is close to the target, while those under the reliable plan are penalized if their load reduction falls short of their target. For simplicity, the theoretical framework assumes that payments depend only on load reduction and bids, abstracting from the role of the target.

[26] We provide a formal proof of this result in Appendix E.

[27] In this example, the auction price is set to the median of simulated bids.

[28] We thank the reviewer for encouraging us to explore this possibility.

[29]We use 5 NTD/kWh because it is the midpoint of the price range.

[30]The results using hourly load divided by the firm's load reduction target as the dependent variable (in a pooled regression including all 39 firms) are qualitatively consistent with those reported in Table 2. However, due to the large variation in targets across firms, it is more appropriate to examine performance rates at the individual firm level.

[31]Recall that we cannot construct the auction price if there is no winner or no loser at all in an auction.

[32]Recall that load during a DR window is defined as the maximum consumption level during the window.

[33]We follow the utility's payment formula to calculate monthly payments to each firm.

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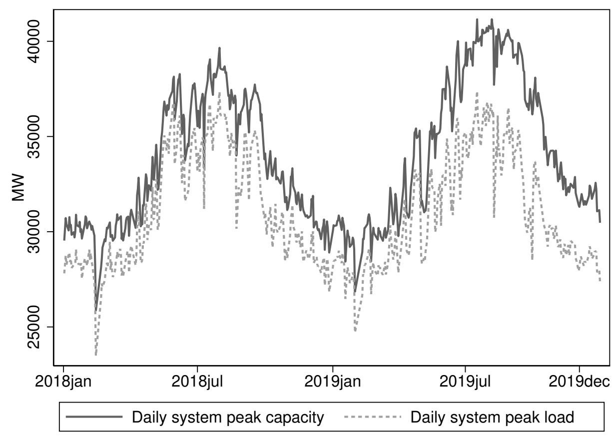
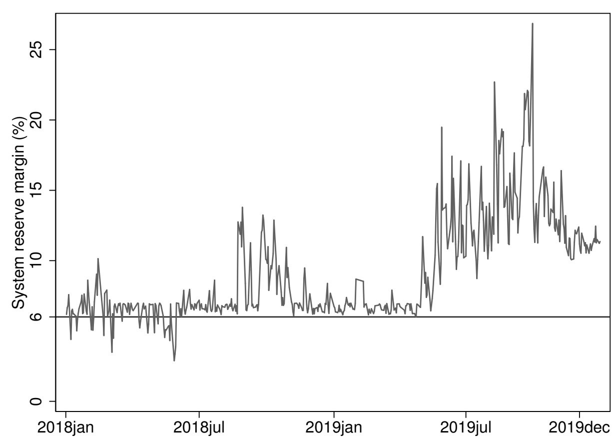
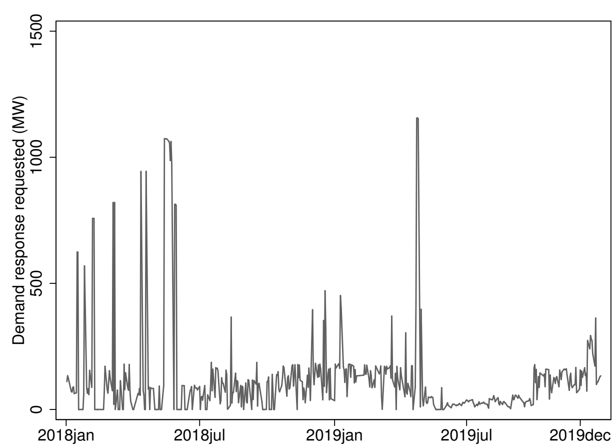


(a) System Capacity and Load



(b) Reserve Margin



(c) DR Requested

Figure 1: DR Requested and Grid Conditions

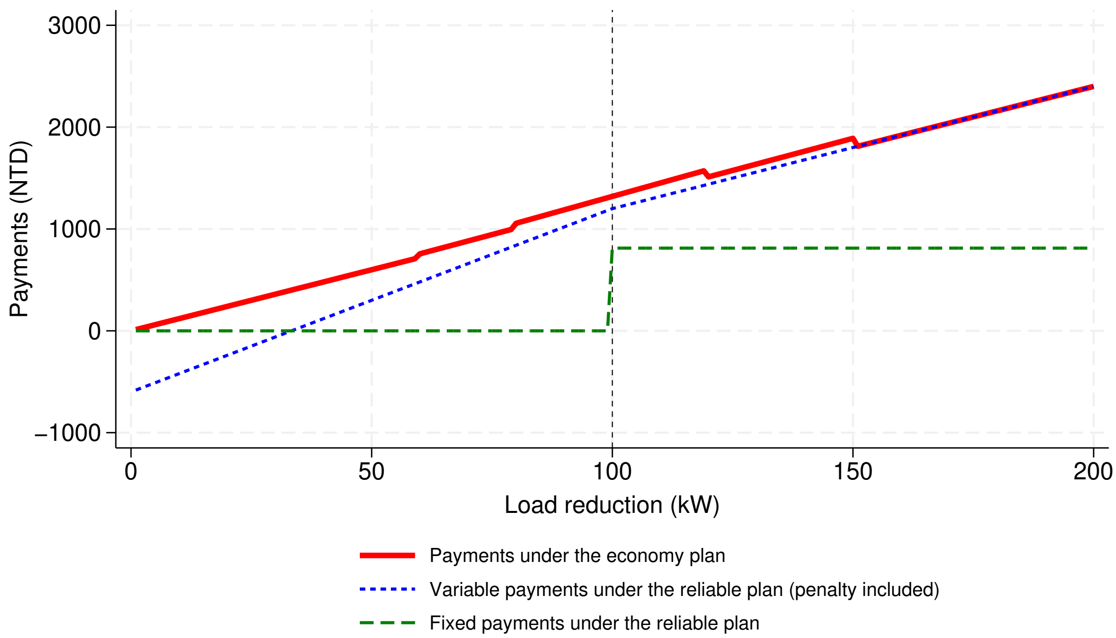
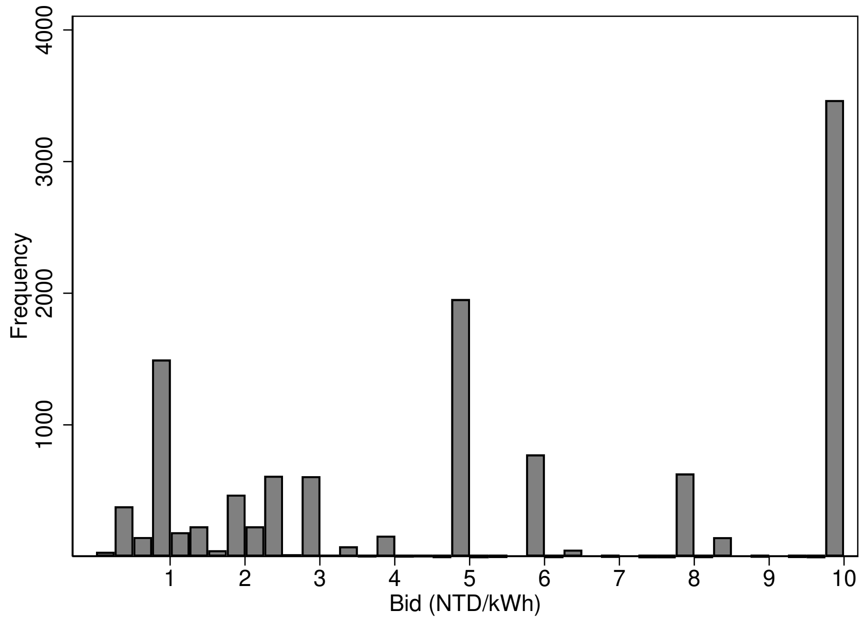
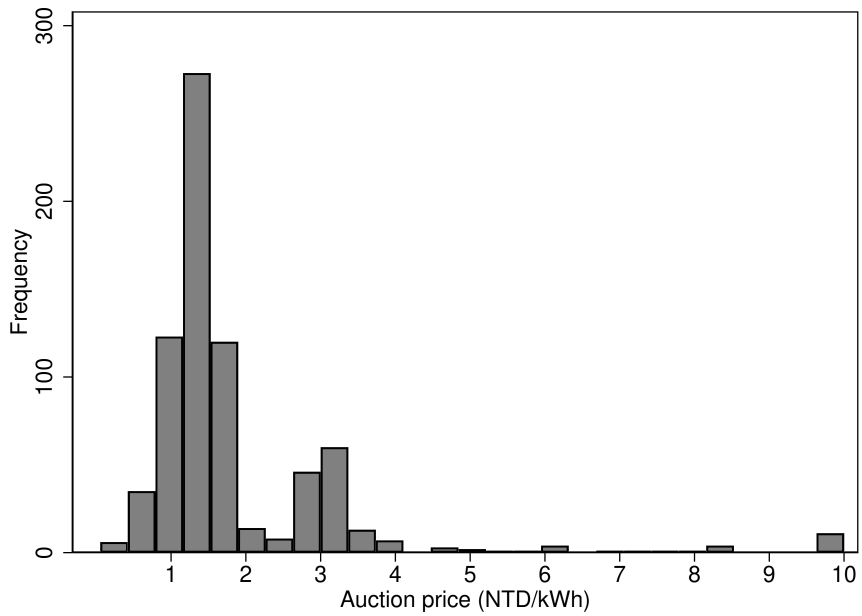


Figure 2: Load Reduction and Payments

Note: This figure illustrates the relationship between load reduction and payments under different payment plans for a given auction day. In the example, the load reduction target is 100 kW, the bid is 3 NTD/kWh, and the length of the DR window is 4 hours.

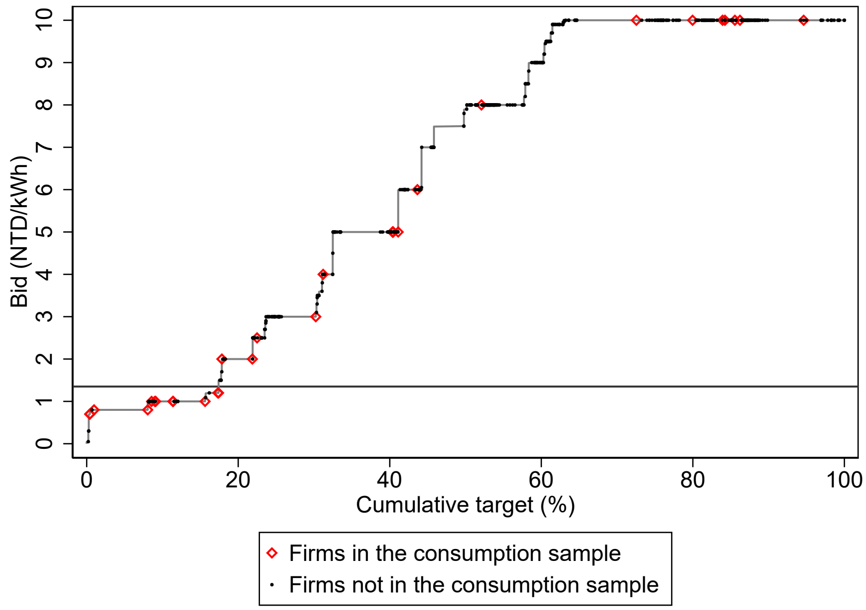


(a) Bid

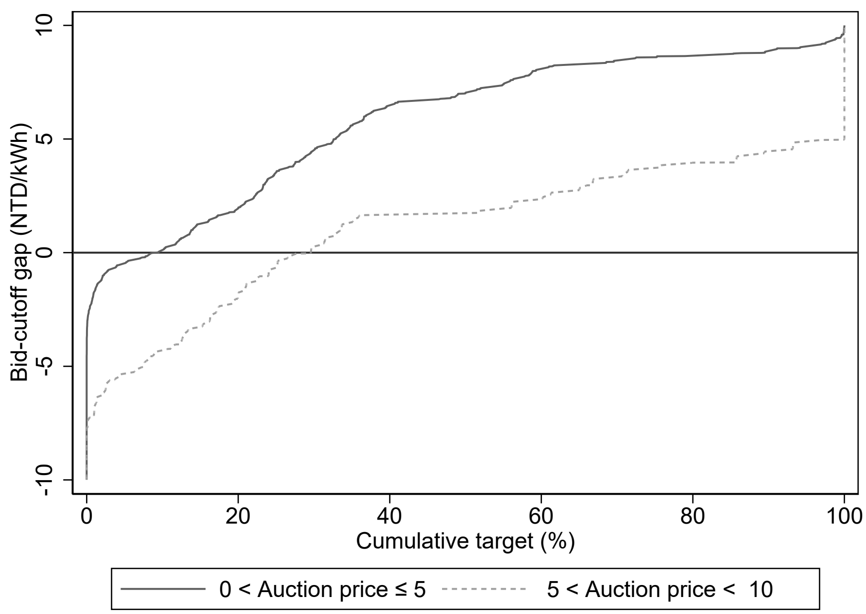


(b) Auction Price

Figure 3: Distribution of Bids and Auction Prices

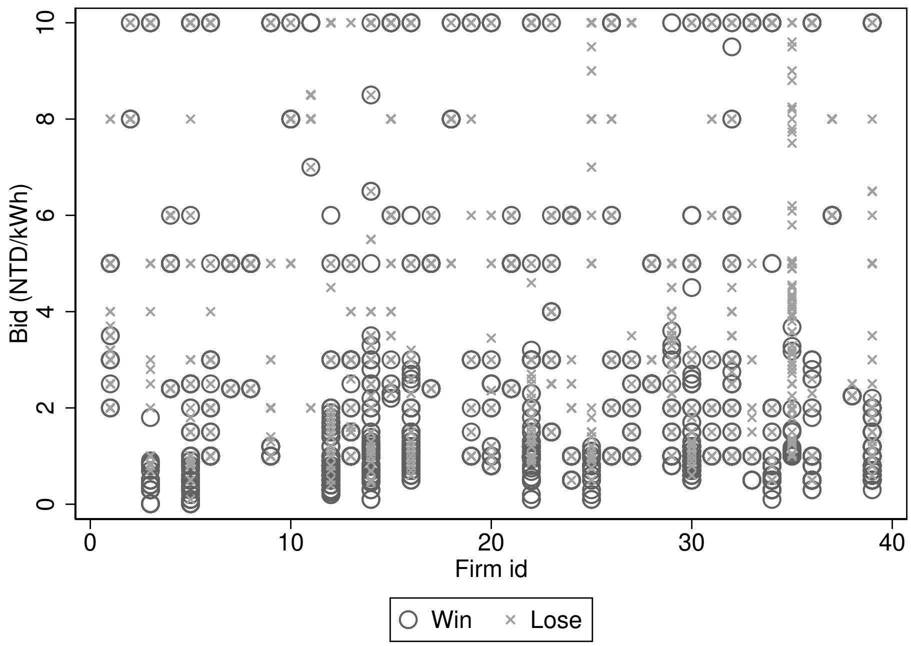


(a) Supply Curve of a Single Auction

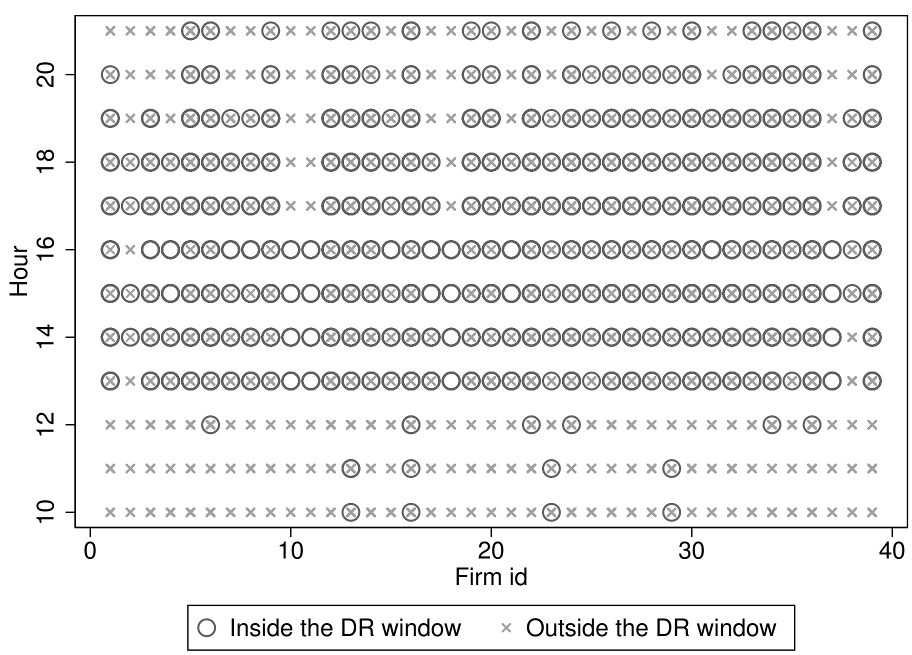


(b) The Average Supply Curve

Figure 4: Supply Curve



(a) Bids Submitted by Firm



(b) DR Window by Firm

Figure 5: Treatment Status by Firm

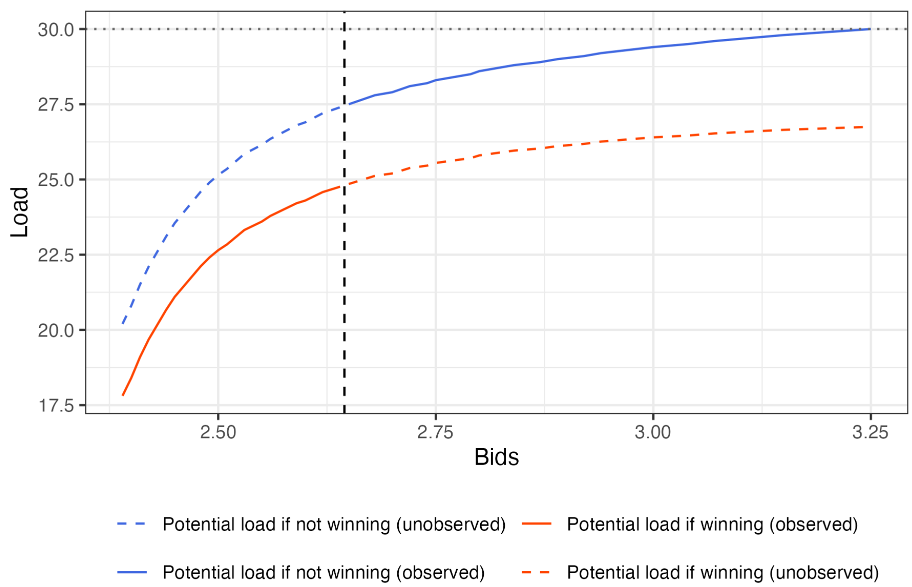
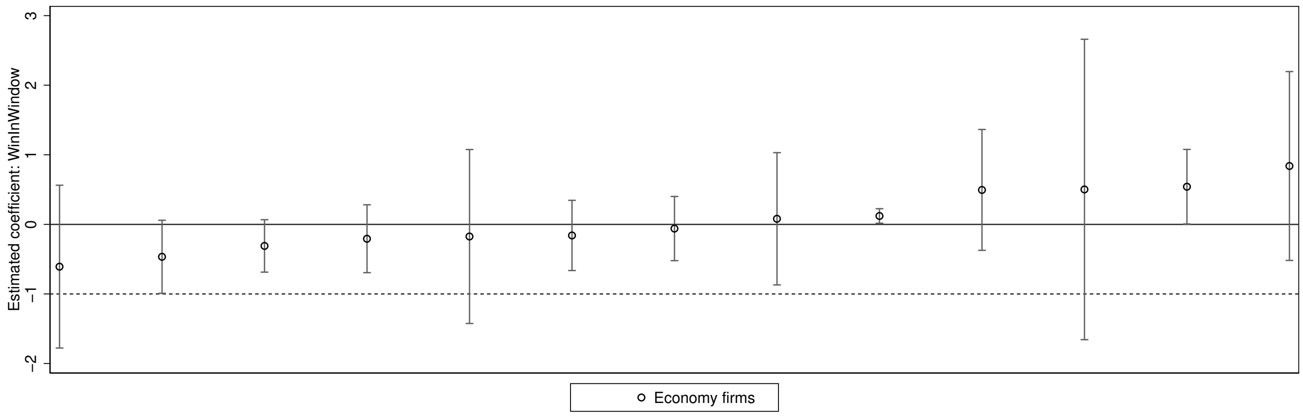
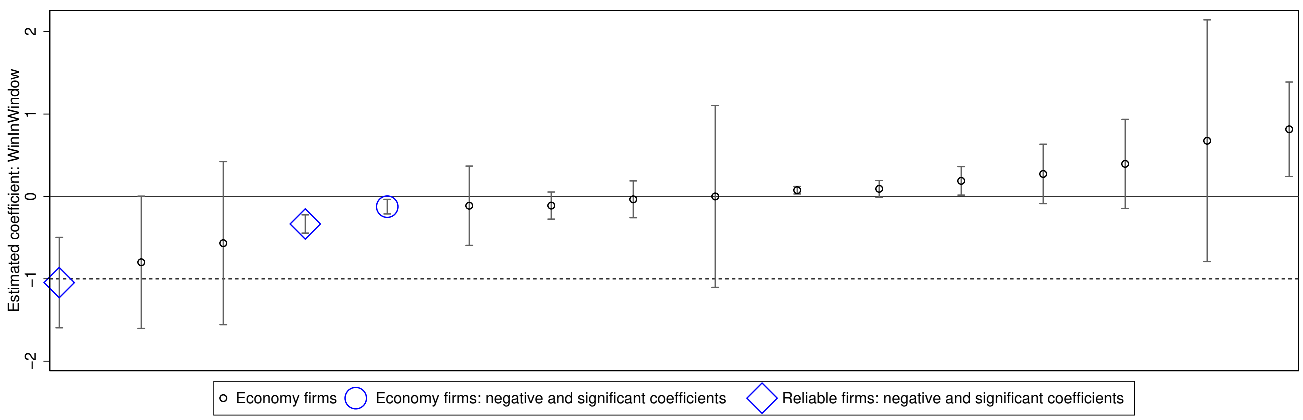


Figure 6: Simulated Bids and Curtailment by Scheduled Load



(a) Firms with Load Reduction Target Below the Median



(b) Firms with Load Reduction Target Above the Median

Figure 7: The Effect of DR Request on Performance Ratio

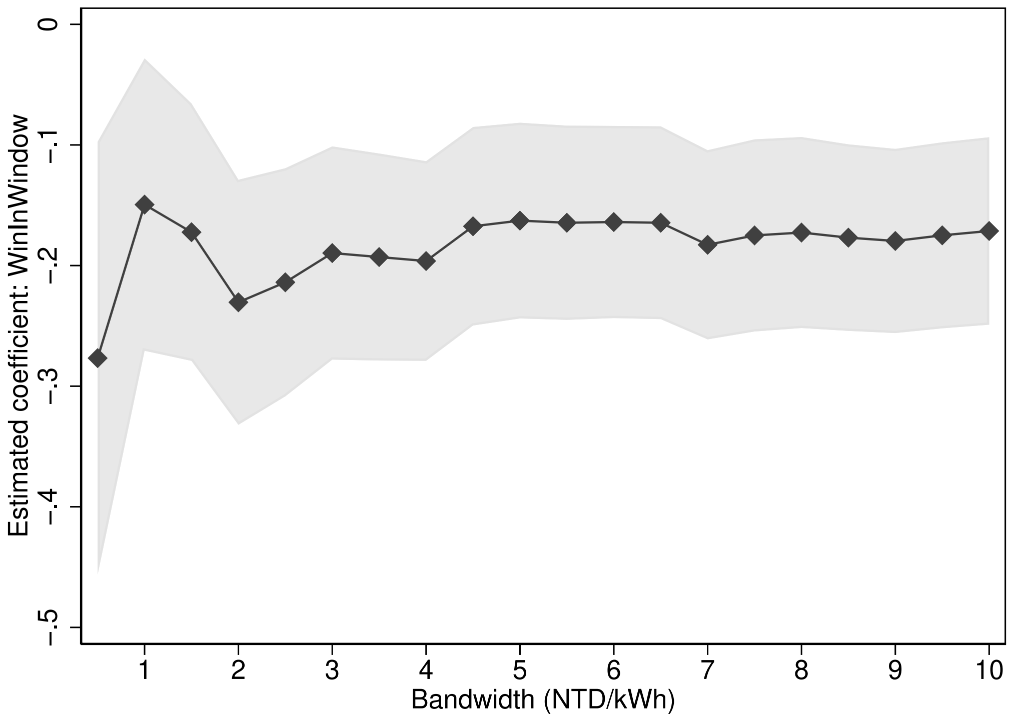


Figure 8: Robustness of Bandwidth Selection

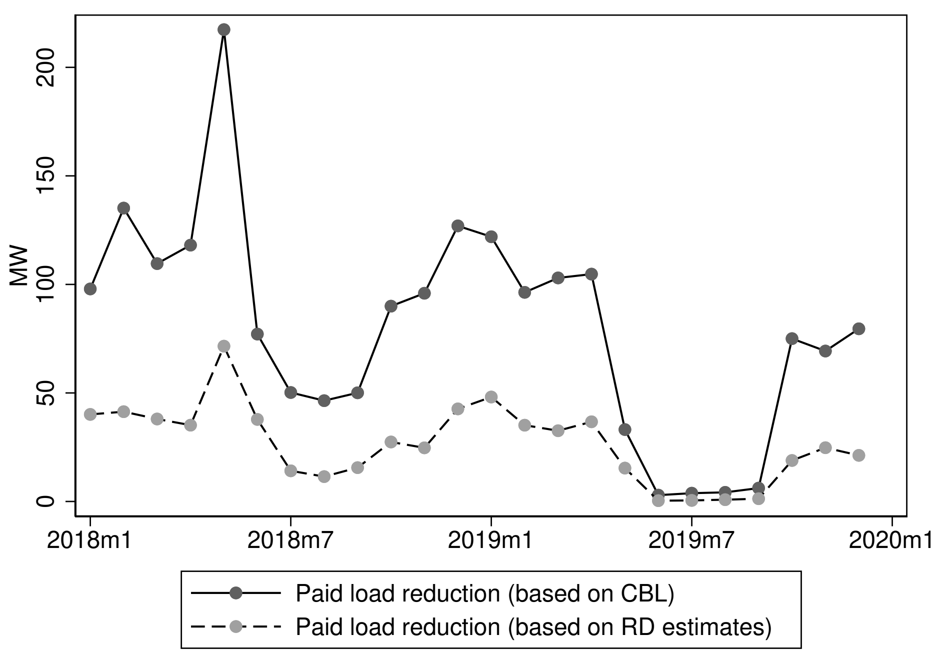


Figure 9: Estimated Average Monthly Load Reduction

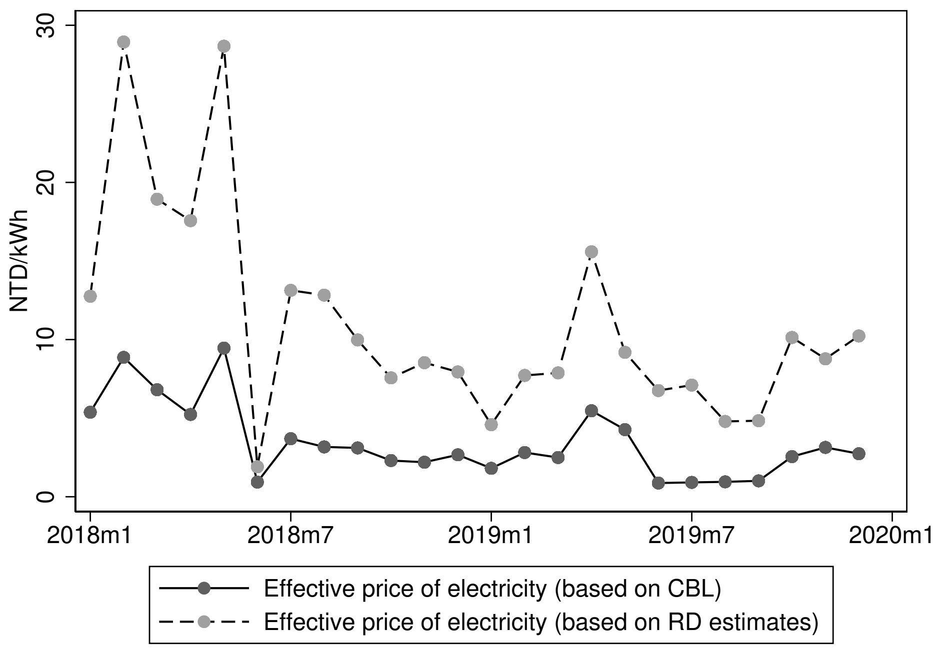


Figure 10: Effective Price of Electricity

Table I: Summary Statistics

	(1) All	(2) Low target	(3) High target	(4) Economy	(5) Reliable
Panel A: Hourly consumption					
Load (kW)	15309	1021	30972	13065	62292
	(37114)	(1183)	(49162)	(35170)	(44804)
Observations	139138	72764	66374	132796	6342
Panel B: Bidding behavior (daily outcomes)					
Winning rate	0.23	0.22	0.24	0.22	0.36
	(0.42)	(0.41)	(0.43)	(0.41)	(0.48)
Winning bid	1.92	1.92	1.91	1.97	1.23
	(2.27)	(1.87)	(2.61)	(2.27)	(2.25)
Winning bid-cutoff gap	-1.05	-1.13	-0.97	-1.07	-0.77
	(1.44)	(1.55)	(1.31)	(1.46)	(0.99)
Losing bid	6.47	5.31	7.79	6.38	8.83
	(3.17)	(2.64)	(3.19)	(3.14)	(2.85)
Losing bid-cutoff gap	4.89	3.79	6.14	4.81	6.93
	(3.11)	(2.65)	(3.12)	(3.09)	(2.82)
Observations	11780	6158	5622	11240	540
Winning outcomes	2661	1325	1336	2467	194
Losing outcomes	9119	4833	4286	8773	346
Panel C: Load reduction behavior (daily outcomes on winning days)					
Performance ratio	1.27	1.82	0.72	1.28	1.10
	(4.06)	(5.66)	(0.76)	(4.22)	(0.13)
Meeting target	0.31	0.29	0.33	0.26	0.95
	(0.46)	(0.45)	(0.47)	(0.44)	(0.21)
Number of firms	39	20	19	37	2

Notes: Means are shown without parentheses. Standard deviations are shown in parentheses. Bid-cutoff gap: bid minus the auction price. Performance ratio: a firm's load reduction on winning days divided by its load reduction target. Meeting target: an indicator variable that equals one when a firm's load reduction is greater than or equal to its target on a winning day and zero otherwise. Low-target (high-target) firms: firms whose load reduction target is below (above) the median load reduction target (1500 kW). Economy (reliable) firms: firms that select the economy (reliable) plan.

Table II: The Effect of Receiving a DR Request on Electricity Consumption

	(1)	(2)	(3)	(4)	(5)
Design	NA	Control for bid		RD	
Proximity	Any	Any	3	2	1
Win in window	-0.588**	-0.173**	-0.190**	-0.230**	-0.149*
	(0.039)	(0.038)	(0.045)	(0.052)	(0.062)
Win outside window	-0.441**	-0.037	-0.077+	-0.117*	-0.029
	(0.034)	(0.035)	(0.043)	(0.050)	(0.060)
Temperature	0.001	0.002	-0.001	0.000	0.004
	(0.004)	(0.003)	(0.005)	(0.005)	(0.006)
Reserve margin	-0.017**	-0.016**	-0.019**	-0.018**	-0.009
	(0.005)	(0.005)	(0.006)	(0.007)	(0.006)
Recent price	0.009	-0.001	-0.027	-0.023	-0.028
	(0.017)	(0.017)	(0.025)	(0.031)	(0.032)
Auction price	0.056**	0.009	0.120**	0.125**	0.186**
	(0.008)	(0.007)	(0.021)	(0.026)	(0.043)
Bid		0.078**			
		(0.006)			
Bid-cutoff gap			0.120**	0.085*	0.298**
			(0.028)	(0.037)	(0.086)
Bid-cutoff gap × Win			-0.052	-0.039	-0.115
			(0.041)	(0.067)	(0.111)
Constant	7.083**	6.656**	6.812**	6.838**	6.713**
	(0.145)	(0.144)	(0.193)	(0.217)	(0.251)
Observations	138652	138652	60855	52837	37957

Notes: The dependent variable is a firm's logged hourly load. Data before 10:00 and after 22:00 are excluded. Proximity refers to the absolute distance between a firm's bid and the auction price. Bid-cutoff gap: bid minus the auction price. All regressions include firm-by-month-of-sample and firm-by-hour-of-day fixed effects. Standard errors, shown in parentheses, are clustered at the firm-by-month-of-sample level. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table III: Heterogeneous Effects

	(1) Target: low	(2) Target: high	(3) Economy	(4) Reliable	(5) Price: low	(6) Price: high
Win in window	-0.102	-0.175^{+}	-0.077	-1.036**	-0.102	-1.193**
	(0.086)	(0.090)	(0.064)	(0.178)	(0.063)	(0.343)
Observations	20486	17471	35730	2227	35942	2015

Notes: The dependent variable is a firm's logged hourly load. Data before 10:00 and after 22:00 are excluded. All regressions include firm-by-month-of-sample and firm-by-hour-of-day fixed effects. Standard errors, shown in parentheses, are clustered at the firm-by-month-of-sample level. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table IV: Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)
Win in window	-0.207**	-0.192**	-0.192**	-0.130^{+}	-0.174**	-0.189**
	(0.032)	(0.036)	(0.037)	(0.069)	(0.066)	(0.056)
Bias correction	Y	Y	Y	N	N	N
Kernel	triangular	uniform	triangular	uniform	uniform	uniform
Order of polynomial function of bid	1	1	2	1	1	1
Bandwidth	1.023	0.691	1.688	1	1	1
Arcsinh transformation	N	N	N	Y	N	N
Auctions when losers have lower bids	N	N	N	N	Y	N
Data outside the 10 am to 10 pm window	N	N	N	N	N	Y
Observations	38689	28617	47959	38050	38775	77666

Notes: The dependent variable is a firm's logged hourly load, except in column (4), which uses the inverse hyperbolic sine (arcsinh) transformation of the hourly load. Data from auctions with any losing bid lower than the auction price are excluded except in column (5). Data before 10:00 and after 22:00 are excluded except in column (6). All regressions include firm-by-month-of-sample and firm-by-hour-of-day fixed effects. Standard errors, shown in parentheses, are clustered at the firm-by-month-of-sample level. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Appendix

A Timeline and Payment Structure of DR Auctions

In this section, we provide details of the timeline and payment structure of DR auctions. Figure A1 shows the timeline of a DR auction on day d. When a firm submits a winning bid and receives a DR window assignment from the utility company on day $d-1$, the payment it receives depends on its actual load reduction inside the DR window on the winning day d, and the DR plan it has chosen for that month.

Suppose an economy participant has won K auctions in month m. Denote each won auction by $k = 1, 2, ..., K$. The total payment for month m under the economy plan is as follows:

$$\text{economy payment}_m = \Big(\sum_{k=1}^{K} b_k d_k \max(q_k, 0)\Big)H.$$

where b_k is the bid, q_k is the load reduction, d_k is the deduction ratio, and H is the selected number of hours for load reduction per day (either two hours or four hours). The deduction ratio is a function of the participant's performance ratio (realized reduction divided by the target), and the rate structure is publicly known. The better a participant meets its target, the higher the deduction ratio is.[34]

By contrast, the *reliable* plan asks for a participant's commitment. Specifically, the payment structure of a typical reliable plan includes (1) a monthly fixed payment (FP), (2) a variable payment (VP, depending on whether a bid is accepted or not), and (3) a penalty term (PN). The monthly fixed payment depends on whether the participant successfully reaches its target every time it wins an auction. Let $\bar{q}$ denote the target selected by the participant for month m, p^f the payment factor (a parameter determined by the utility company, either 60 or 65), and n the number of days when the participant meets its target $\bar{q}$. The fixed payment is as follows:

$$FP = \begin{cases} \bar{q} \times p^f \times 1.2, & \text{if } n = K \\ \bar{q} \times p^f \times (n/K), & \text{if } n < K. \end{cases}$$

The variable payment is as follows:

$$VP = \Big(\sum_{k=1}^{K} b_k \max(q_k^r, 0) \Big) H.$$

The penalty arises when the participant falls short of the target for some won auction k (i.e., $\bar{q} > q_k$), and is as follows:

$$PN = \Big(\sum_{k=1}^{K} 0.5 b_k \max(\bar{q} - q_k, 0) \Big) H.$$

In Section II, we illustrate how payments from a single winning event vary with the incentive plan and realized load reduction, as shown in Figure 2. In the example, the load reduction target is 100 kW, the bid is 3 NTD/kWh, the DR window is 4 hours, the number of auctions won per month is 8, and the payment factor is 65 NTD. We assume that the participant has already failed to meet its target in one of the previous winning events. Therefore, the monthly fixed payment for meeting the target in this single winning event is 812.5 NTD.

B An Example of Baseline Inflation

In this section, we show that, when the winning bid (b) is high enough compared to the current electricity retail price (p^r), a firm can deliberately boost its electricity

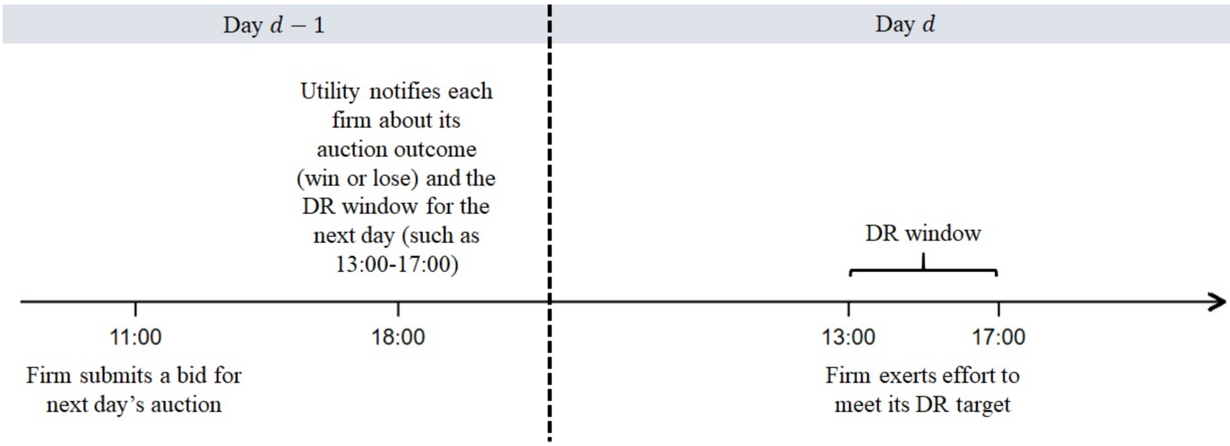


Figure A1: The Timeline of a Demand Response Auction

consumption on a non-winning day $t-1$ to earn a positive return from the DR auction on the winning day t. First, recall that load is defined as the maximum consumption during a time window, and notice that, even though our data come at the hourly level, the raw data transmitted from each firm to the utility company are at a finer level, i.e., at the 15-min interval level. These features result in a firm being able to boost the load by x kW in a four-hour window without raising its consumption by x kW throughout the entire four-hour window. Figure B1 provides a hypothetical electricity consumption pattern on day $t-1$ to illustrate this idea. In the figure, the scheduled load for the four-hour window 13:00 to 17:00 is 1,600 kW. However, if the firm raises its consumption from 1,600 kW to 1,700 kW, even only for the 15:00-15:15 window, its load for the four-hour window will be increased by 100 kW. Because the CBL for a given time window is defined as the average load over the previous five non-winning days, it follows that, by boosting its load by 100 kW on day $t-1$, the firm can increase its CBL for day t by 20 kW.

More generally, boosting the electricity consumption for a 15-min interval within a time window with length h on day $t-1$ by 1 kW raises day t's CBL by $1/5$ kW. The cost of doing so is $p^r/4$, while the benefit of doing so is $bh/5$ (a $1/5$ kW load reduction

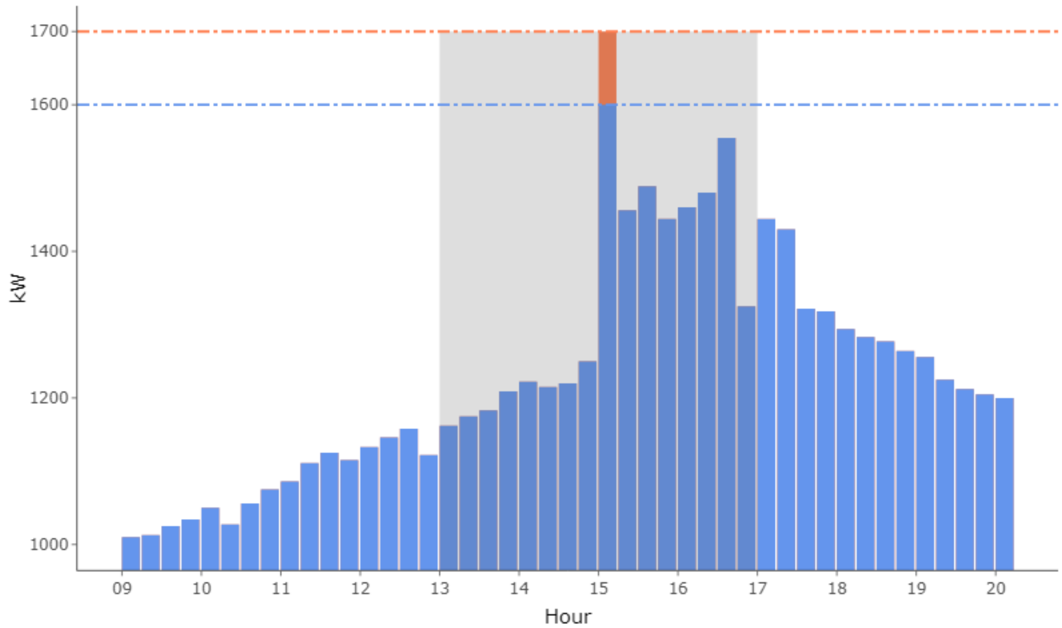


Figure B1: Baseline Boosting

from the boosted baseline for a total of h hours, with each hour rewarded by the winning bid b). If there is no uncertainty in the auction outcomes and no uncertainty in the DR event windows, it is profitable for a firm with a four-hour plan to boost its baseline as long as $b > 0.3125p^r$. Particularly, for firms selecting a two-part tariff retail rate, p^r is equal to 3.29 NTD/kWh from 7:30 to 22:30 in the summer, and so when b is greater than 1.03 NTD/kWh—a threshold quite moderate compared to the median auction price of 1.35 NTD/kWh—there exists a moral hazard problem.

C Auction Price Construction

Our dataset does not include the auction price (i.e., the cutoff) for each auction. In the following section, we discuss our method for constructing the auction price.

Figure C1 illustrates how we construct the auction price. For each auction, we first sort bids to find the maximum winning bid, b^{-1}. Then, for all losing bids no less than b^{-1}, we find their minimum, b^{+1}. The auction price b^0 is defined as the average of b^{-1} and b^{+1}. By construction, all winning bids are below the cutoff. However, we observe cases where a firm's losing bid is below the maximum winning bid from another firm (such as $b = 3$ in Figure C1). For firms in the consumption sample, there were five auctions when the auction outcomes were not completely consistent with the bids. We remove these auctions from the sample. We also exclude auctions where there was no winner or no loser at all. In these cases, b^{-1} and b^{+1} cannot be defined, and so the auction price cannot be determined. In this way, we find that the minimum gap (in absolute value) between a bid and the auction price is 0.005. For rare cases where $b^{-1} = b^{+1} = b^0$, we subtract the minimum gap from b^{-1} and add the minimum gap to b^{+1} to make sure that b^0 separates b^{-1} and b^{+1} in each auction.

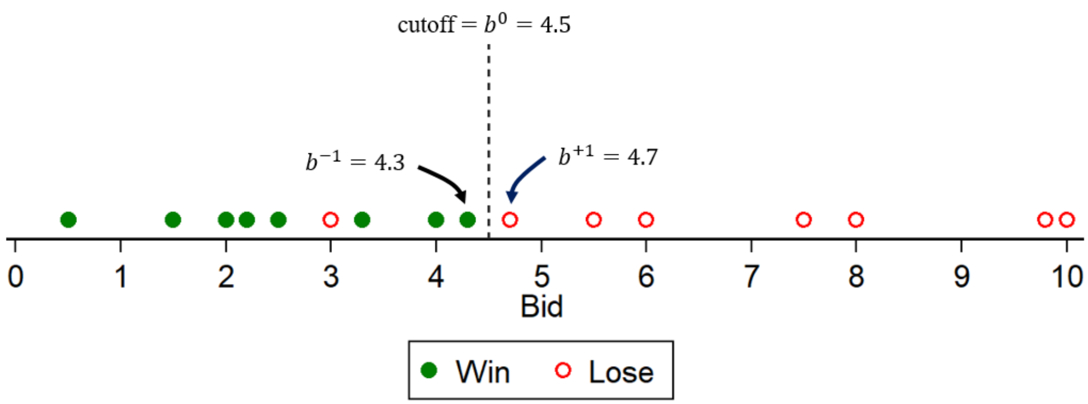


Figure C1: Construction of the Auction Price

D Sample Representativeness

The consumption sample has a good coverage of the participants that won the most auctions. Figure D1 shows the coverage of the consumption sample in terms of the number of wins by each participant during the sample period. Over the sample period, the average number of wins by each participant inside and outside of the consumption sample is 88.1 and 17.6, respectively. Firms in the consumption sample are also important in terms of the payments they received from the program. Overall, participants in the consumption sample account for 59% of the total payments from the program. Figure D2 plots the monthly payments of the program. For 20 out of the total 24 months during the sample period, participants in the consumption sample account for at least 50% of the program's monthly payments.

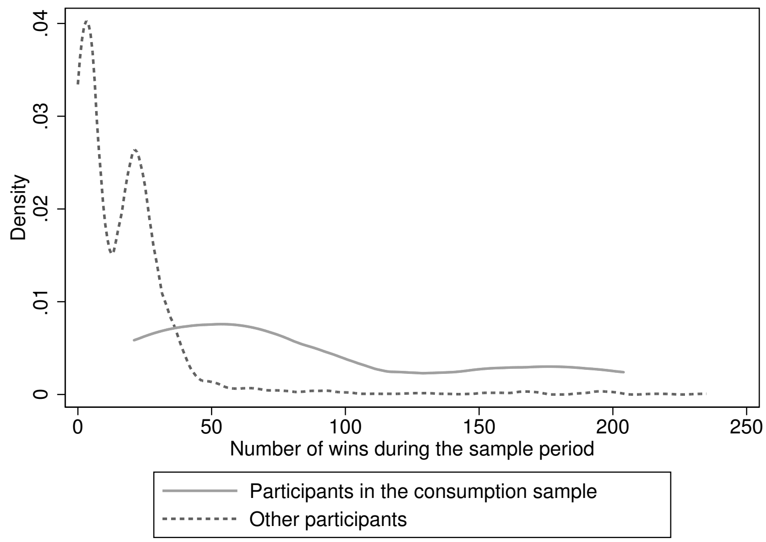


Figure D1: Number of Wins During the Sample Period

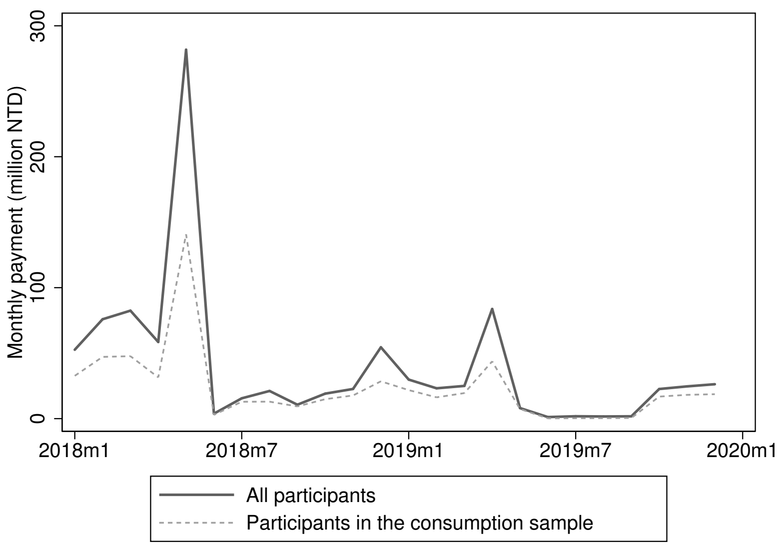


Figure D2: Monthly Payment

E Comparative Statics of the Optimal Bid

This appendix provides a formal proof that a firm's optimal bid in the DR auction decreases when the difference between its customer baseline load (CBL) and its scheduled load (SchL) increases. Let this difference be denoted by $\Delta \equiv \text{CBL} - \text{SchL}$. We aim to show that the firm's optimal bid $b^*(\Delta)$ is decreasing in Δ.

Recall that the first-order condition for the firm's problem is given by

$$G'(b) \cdot [b \cdot (\Delta + x^*(b)) - c(x^*(b))] + G(b) \cdot (\Delta + x^*(b)) = 0,$$

where $G(b)$ is the probability of winning the auction, $x^*(b)$ is the optimal second-stage load reduction, and $c(x)$ is the firm's cost function.

To simplify notation, define

$$\Phi(b, \Delta) \equiv G'(b) \cdot [b \cdot (\Delta + x^*(b)) - c(x^*(b))] + G(b) \cdot (\Delta + x^*(b)).$$

Let $b^*(\Delta)$ denote the optimal bid that satisfies $\Phi(b, \Delta) = 0$. By the implicit function theorem, the derivative of the optimal bid with respect to Δ is given by

$$\frac{\partial b^*(\Delta)}{\partial \Delta} = -\frac{\frac{\partial \Phi(b^*(\Delta), \Delta)}{\partial \Delta}}{\frac{\partial \Phi(b^*(\Delta), \Delta)}{\partial b}}.$$

To evaluate the numerator, we differentiate $\Phi(b, \Delta)$ with respect to Δ, treating b as fixed. Applying the first-order condition to simplify the expression, we obtain

$$\frac{\partial \Phi(b^*, \Delta)}{\partial \Delta} = \frac{G'(b^*) \cdot c(x^*(b^*))}{\Delta + x^*(b^*)}.$$

We now examine the sign of this expression. The probability function satisfies $G'(b) < 0$, the cost function satisfies $c(x) > 0$, and the optimal load reduction satisfies $x^*(b) > 0$. In addition, we consider the case where $\Delta > 0$. These conditions imply that the denominator $\Delta + x^*(b^*)$ is strictly positive, while the numerator is strictly negative. Therefore, it follows that

$$\frac{\partial \Phi(b^*, \Delta)}{\partial \Delta} < 0.$$

Because $b^*(\Delta)$ is the solution to a concave maximization problem, the second-order condition implies that

$$\frac{\partial \Phi(b^*, \Delta)}{\partial b} < 0.$$

Therefore,

$$\frac{\partial b^*(\Delta)}{\partial \Delta} = -\frac{\frac{\partial \Phi(b^*(\Delta), \Delta)}{\partial \Delta}}{\frac{\partial \Phi(b^*(\Delta), \Delta)}{\partial b}} < 0.$$

This result confirms that the optimal bid is decreasing in Δ, indicating that a firm with a higher baseline or a lower scheduled load is more likely to submit a lower bid in the auction.

F Curtailment Costs Dependent on Scheduled Load

In this section, we extend the theoretical framework presented in Section IV by allowing the curtailment cost to depend on the scheduled load, denoted by $c(x; \text{SchL})$. This specification captures the realistic possibility that reducing load becomes more expensive as scheduled load increases, implying $\frac{\partial c}{\partial \text{SchL}} > 0$.

Under this assumption, the first-order condition becomes:

$$b + \frac{G(b)}{G'(b)} = \frac{c(x^*(b; \text{SchL}), \text{SchL})}{\text{CBL} - \text{SchL} + x^*(b; \text{SchL})}. \tag{F.1}$$

Given a constant CBL, SchL influences the right-hand side (RHS) of the condition through multiple channels. From Appendix E, we know that if the RHS of equation (F.1) increases with SchL, then the optimal bid must also increase with SchL. We thus study the comparative statics by focusing solely on the RHS of equation (F.1). First, a higher SchL reduces the term CBL − SchL, which lowers the denominator. Second, as SchL increases, the marginal cost of curtailment typically rises, prompting the firm to choose a smaller load reduction x^*, which further decreases the denominator. Third, SchL also enters the numerator through the cost function $c(x^*, \text{SchL})$. While a smaller x^* tends to lower the cost, the direct effect of a higher SchL may increase it, rendering the total impact on the numerator ambiguous. Nevertheless, if $\frac{\partial c(x^*(b;\text{SchL}),\text{SchL})}{\partial \text{SchL}} > 0$, then a higher SchL always leads to a higher optimal bid.

For example, when the curtailment cost is specified as $c(x) = \frac{x^2}{2} + \text{SchL}$, the first-order condition becomes:

$$b + \frac{G(b)}{G'(b)} = \frac{b^2/2 + \text{SchL}}{\text{CBL} - \text{SchL} + b}.$$

Here, the RHS is clearly an increasing function of SchL, indicating that a higher scheduled load leads to a higher optimal bid.