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 the opportunity costs of electricity consumption depend on auction outcomes. Using data on bids, auction outcomes, and hourly electricity consumption from steel producers in Taiwan, this paper shows that failing to consider firms' strategic bidding behavior can lead to an overestimation of electricity reduction by at least 50%. We show that the overestimation works mainly through an adverse selection effect, in which firms bid low to win auctions when they anticipate low electricity consumption.

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1 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 opportunity costs of electricity 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 DR.

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.[3] Each auction collects bids (willingness to curtail usage) and reduction targets from participants and finds a market-clearing price (auction price) to balance the DR market. Participants

[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.

with bids lower than the auction price will win the auction, and each of them will receive a reward based on the amount of their 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 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. 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 test whether strategic bidding leads to an overestimation of load reduction in DR auctions, we exploit available data and features from an auction program to estimate the

[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.

treatment effect of winning auctions. Observing each participant's daily bids allows us to include a flexible function of the bid, to control for the strategic bidding effect. 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, conditional on the bids submitted for the auction day and market conditions, the treatment status cannot be directly manipulated by firms, and could therefore be viewed as effectively random.

Our results suggest that the effect of receiving a DR request from the program is associated with a 12% to 17% 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. In particular, estimates of load reduction from alternative specifications based on a regression-discontinuity design (RDD) are between 13% and 19%. 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 program's CBL-based price elasticity is also three to four times higher than our estimates that account for firms' strategic bidding behavior. 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.

To explore the channel of the strategic bidding effect, we show that it can be decomposed into an adverse selection effect and a moral hazard effect. The adverse selection effect captures the difference between a participant's counterfactual load on winning days and its business-as-usual (BAU) load, while the moral hazard effect is the difference between the BAU load and the CBL. In Appendix B, we outline conditions under which baseline inflation is profitable, assuming there is no uncertainty in auction outcomes or DR event windows. We propose tests for each type of effect. Our tests utilize data on days when participants *lose* auctions and thus have no direct monetary incentives to reduce consumption. Under the assumption that there is no strategic bidding behavior, there should be no correlation between electricity consumption on these days and bids placed, nor with these days' future baseline eligibility. We find evidence of the adverse selection effect, but we do not find evidence to support the moral hazard effect.

One possible explanation for the absence of baseline boosting is the associated risk of losses, as both auction outcomes and event windows are beyond firms' direct control. Another potential challenge in implementing baseline boosting is the need for coordination between a firm's energy management unit (responsible for bid submissions) and its production unit. In contrast, the adverse selection effect involves firms adjusting their bids to exploit their volatile consumption patterns without incurring additional production costs.

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.[6] Jessoe and Rapson (2015) study the first large-scale

[6]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.

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 decomposing the baseline problem stemming from the DR programs into an adverse selection and a moral hazard effect. In addition, we empirically test these two effects. We present evidence that industrial users adversely select themselves into the DR program, bidding lower to win auctions when they anticipate lower electricity consumption.

The paper proceeds as follows. Section 2 describes the DR program and the data. Section 3 introduces a model that reflects a participant's decision problem. Section 4 shows the empirical strategy and provides the estimation results. Section 5 decomposes the strategic bidding effect into an adverse selection and a moral hazard effect and tests the potential channels of the strategic bidding effect. Section 6 discusses implications of the strategic bidding effect. Section 7 concludes.

2 Program Overview and Data

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.[7] Although the utility company never publishes its demand in DR auctions in advance, it is safe to say that it is related to market conditions in the electricity industry. Figures 1(a) and 1(b) plot the daily requested DR and the electricity system's reserve margin (system operating reserve divided by the expected peak load) of the utility company from 2018 to 2019. During this period, the electricity system's reserve margin ranges between 2.89% and 26.86%, being below 6% on 29 days (all in 2018). 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%.

The primary goal of the DR program in our setting is load reduction. The load of a customer during a specified time window, such as from 13:00 to 17:00, is defined as their maximum consumption level during that period. To establish a participant's CBL for this time window, the program calculates the average electricity consumption based on the same time window across the preceding five workdays on which the participant did not succeed in the DR auctions. The program assigns a specific time window for each day-ahead DR request and calculates its load reduction by finding the difference between the CBL and the participant's actual load during that time window.

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

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 customers of the Taiwan Power Company in 2019 and found that, while 72.8% of managers in the energy management unit were aware of demand response 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.[8] An auction participant next specifies its rate plan in the program, including the default bid, target for load reduction, payment type (either *economy* or *reliable*, discussed in detail below), and number of hours committed to load reduction per winning day (i.e., a two-hour or four-hour reduction).[9] Participants selecting the two-hour reduction at the beginning of the month enter the two-hour day-ahead auctions and do not compete with those selecting the four-hour reduction (who are in the four-hour day-ahead auctions) throughout the month. Participants can submit bids up to two decimal digits, but the maximum bid is capped at 10 NTD.

The economy plan is designed to encourage C&I customers to participate in the DR program. The 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. The reliable plan pays more to winning participants who meet their targets (compared to the economy plan) but also penalizes those who fail to do so. Additional details on payment structures are provided in Appendix A.

For a day-ahead auction on day d, a participant is allowed to change its bid up until the auction closes at 11 am on day $d-1$. After that, the utility company collects all eligible

[8] 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.

[9] 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 (b per kW, its reservation price for curtailing its electricity consumption) to the system. When a participant fails to submit a bid for a particular day, the default bid will be used.

bids and runs a program to calculate the day-ahead market clearing price.[10] Participants with bids lower than the day-ahead market clearing price win the day-ahead auction and are notified before 6 pm on day $d-1$.[11] The winning notice (i.e., the DR request) includes a start time for load reduction for day d, which varies by day and by participant, and becomes known to a participant only after it wins an auction.[12] 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) 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.

Data Description

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. 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). 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

[10] 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.

[11] 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 d. 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.

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

a subset of participants (39 participants) in the steel industry and refer to them as 'the consumption sample' below.[13] 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.[14] We remove five auctions where this abnormality happened to make sure 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 4, we report on the robustness of our estimates when we relax these restrictions.

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 2(a) and 2(b) plot the distribution of bids and daily auction prices, respectively. While bids are allowed to have

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

[14]Conversations with the staff at the utility company indicate that, because the auction outcome is jointly determined with the company's test run system of the day-ahead energy market, there are thousands of constraints in the system to be met. 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.

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.

The auction prices at the 50th and 90th percentiles are 1.35 NTD and 3.25 NTD, respectively.[15] It is noteworthy that only 11 out of 735 auctions reached the maximum auction price of 10 NTD, and all of these instances occurred in May 2018. However, an interesting observation is that nearly 30% of bids were placed at 10 NTD, 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, 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.

Table 1 provides summary statistics of our main sample. Panel A presents firms' hourly load (kW). Panel B, focusing on firms' strategic bidding behavior, includes variables such as the winning probability and the bid-cutoff gap. This gap is defined as the absolute value of the difference between a firm's bid and the realized auction price. Panel C shows variables regarding firms' load reduction behavior, including the performance ratio (load reduction divided by target) and an indicator variable measuring whether a load reduction target is met or not on winning days. Given that large heterogeneity exists across firms, and that

[15] 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.

firms differ in their incentive plans (economy or reliable), Table 1 presents the results by load reduction target and by incentive plan. In the following, we refer to firms with 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 plan as the economy and reliable firms, respectively.

The average hourly load is 15,309 kW.[16] 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. 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 compared to 1.13 NTD for low-target firms), and a larger average gap between their losing bids and auction prices (6.14 NTD compared to 3.79 NTD 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 1 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 compared to 1.07 NTD for economy firms), and a larger average gap between their losing bids and the auction prices (6.93 NTD compared to 4.81 NTD for low-target firms). Unsurprisingly, reliable firms also meet their targets more often than economy firms (95% than 26%), and their average performance ratio is closer to one (1.1 compared to 1.28 for economy firms).

If some firms could use their bids to affect auction outcomes, such strategic bidding

[16] 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.

behavior might result in an overestimation of the program's impact in terms of reducing load during peak demand hours. Nevertheless, Figure 3 shows that, while many firms place their bids at the maximum to avoid winning, they do not have perfect control over their treatment status. Figure 3(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 3(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.

3 Theoretical Framework

This section provides a simple theoretical framework to illustrate how firms determine their bids and reduce their loads in the daily DR auction. Since the utility company does not reveal the bid distribution in the daily auction, each firm lacks sufficient information to compete against the others, so the firm's decision problem can be viewed as a single-agent problem. We also focus on one representative auction in one day; therefore, the profit maximization problem described in this section refers to a firm in an auction.

There are two periods on this day: the bidding and the reduction period. In the bidding period, the firm chooses its bid b with the winning probability $G(b)$, where $G(.)$ is assumed to be exogenous to the firms. Then the firm may win or lose the auction and get a notice from the utility company. In the reduction period, if the firm wins the auction, it determines its load reduction x. Since the opportunity costs of reducing electricity consumption may vary across firms, they choose their optimal load reduction x^* at which the marginal benefit of the savings equals the marginal cost. We assume that the optimal load reduction does not depend on the firm's bid in the previous period, and the cost incurred for the load reduction x^* is $c(x^*)$.

As we mentioned in the previous section, the utility company calculates the load reduction based on the firm's CBL and its actual load. Assume that the firm has a schedule, according to which it needs to consume a certain level of load, called its scheduled load, SchL. Then, the load reduction calculated by the utility company is CBL $-$ (SchL $- x$). In the bidding period, the firm chooses a bid b to maximize its expected profits:

$$G(b) \times \{b \times [\text{CBL} - \text{SchL} + x^*] - c(x^*)\}\,. \tag{1}$$

The first-order condition is

$$b + \frac{G(b)}{G'(b)} = \frac{c(x^*)}{\text{CBL} - \text{SchL} + x^*}. \tag{2}$$

If the CBL is the same as the scheduled load, SchL, then the optimal bid $\tilde{b}$ satisfies

$$\tilde{b} + \frac{G(\tilde{b})}{G'(\tilde{b})} = \frac{c(x^*)}{x^*}. \tag{3}$$

However, if the firm inflates its CBL or its scheduled load is very low, such as on a shutdown day, then we will have CBL $-$ SchL > 0. In this case, the optimal bid b^* based on equation (2) will be less than $\tilde{b}$ when $G(b)/G'(b)$ is a monotone function.

Therefore, we make the following prediction:

Prediction 1 *If the firm has a higher level of CBL or a lower level of scheduled load, then the firm is more likely to lower its bid in the DR auction.*

In conclusion, this simple theoretical framework points out that firms have incentives to lower their bids when they have a higher baseline or a lower scheduled load. Therefore, we need to consider the bid adjustment by firms to consistently estimate the effect of winning the auction.

4 Empirical Strategy and Results

Empirical Strategy

Our theoretical model suggests that a firm's scheduled load on winning days (unobserved by researchers) is correlated with its bid. Because firms can also affect their winning probabilities in DR auctions by adjusting their bids, the treatment assignment is not exogenous, so that simply regressing electricity consumption on auction outcomes will result in biased estimates. Fortunately, we observe bids submitted at the individual firm-by-auction level, allowing us to include a flexible function of the bid in our estimation to mitigate the selection problem. Some features of the DR program also aid our empirical strategy. First, bids are predetermined before both the treatment assignments and firms' load reduction efforts. Second, neither auction prices nor rival bids are ever observed by firms, so that variation in treatment status exists even when similar bids are placed by the same firm. We also include firm-by-month-of-sample fixed effects and firm-by-hour-of-day fixed effects to account for permanent differences in a firm's electricity consumption across months and hours.

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

$$\begin{aligned} Y_{i,hdm} =& \alpha_{i,m} + \alpha_{i,h} + \beta_1 WinInWindow_{i,hdm} + \beta_2 WinOutsideWindow_{i,hdm} \\ & + f(b_{i,dm}) + \mathbf{X}'_{dm}\beta_3 + \epsilon_{i,hdm}, \end{aligned} \tag{4}$$

where $Y_{i,hdm}$ is firm i's hourly load (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; $\mathbf{X}_{dm}$ are covariates for market conditions, including temperature, reserve margin, recent price, and auction price. The indicator variable $WinInWindow_{i,hdm}$ equals one if firm i wins the auction on day d, and hour h is within the DR window, and zero otherwise, while the indicator variable $WinOutsideWindow_{i,hdm}$

equals one if firm i wins the auction on day d but hour h is not within the DR window and zero otherwise. 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.

Empirical Results

Table 2 provides regression estimates for equation (4). All results include firm-by-month-of-sample fixed effects. Column (1) gives the estimates without covariates, while column (2) adds market-level covariates, and column (3) further includes firm-by-hour-of-day fixed effects. Columns (4) to (6) include control variables to account for firms' strategic bidding behavior.

Without controlling for bids, a DR request for treated hours is associated with a load reduction ranging from 0.465 log points (37%) to 0.588 log points (44%). Once we control for the bid, the estimated load reduction in column (4) declines to 0.173 log points (16%), and even to 0.129 log points (12%) in column (5) when we use a higher-degree polynomial (a cubic function) of the bid. In column (6), we use four bid segments (bids greater than 7.5 as the baseline group) to control the bid function, and the estimated load reduction is 0.182 log points (17 %). The coefficients of $WinOutsideWindow$ are insignificant after we control the bid function, which implies that there is no spillover effect outside of the DR window on winning days. After controlling for the bid, most coefficients of the market-level covariates are statistically insignificant, except for the coefficient of the reserve margin, which is negative and statistically significant, suggesting that firms tend to use less electricity when supply is not constrained. Overall, we find that it is important to control for the bid in estimating firms' electricity consumption behavior and that, after taking firms' strategic bidding behavior into account, receiving a DR request on average reduces a firm's electricity consumption by 12% to 17%.

Heterogeneous Effects

Next, we explore the heterogeneous effects among 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).[17] This allows us to investigate how these characteristics influence the effect of a DR request. We also provide estimates of the treatment effect at the individual firm level.

Panel A of Table 3 presents the results of equation (4) for each subgroup based on the same specification (with a cubic function of the bid) as was shown in column (5) of Table 2. Columns (1) and (2) in Table 3 show that high-target firms have a larger load reduction after receiving a DR request: high- and low-target firms reduce their electricity consumption by 0.16 log points (14.7%) and 0.088 log points (8.4%), respectively. In addition, based on the payment type, columns (3) and (4) show that reliable firms have a tremendous 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 results indicate that our main findings are not driven by days with extremely high auction prices, though we find that, for days with higher auction prices, the treatment effect is stronger, but cannot be estimated with precision.

We also estimate equation (4) by firm. 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. Because not every firm changes its bid frequently, we use a linear function of the bid in the regression. We present the estimated coefficient of the $WinInWindow$ variable for each firm in Figure 4 and separate

[17] We use 5 NTD because it is the midpoint of the price range.

the results by load reduction target. Figures 4(a) and 4(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 4(a)), we find 25% of firms (5 out of 20) have a negative and significant treatment effect. By contrast, for high-target firms (Figure 4(b)), about 37% of firms (7 out of 19) 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 DR. 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.

Robustness Analysis

Our preferred specification uses logged hourly load as the dependent variable, and adopts a third-order polynomial function of the bid to control for the effect of bids on electricity consumption. Columns (1) to (4) of Table 4 report results from alternative specifications. We first limit the sample to those observations with bids that are close to the auction price, so that our results are less affected by observations with extreme bids. Column (1) shows the results when we limit the gap between the bid and the auction price to be less than or equal to one. In addition, columns (2) and (3) report the results using second-order and fourth-order polynomial functions of the bid, respectively. Because using the log transformation drops observations with zero electricity consumption, column (4) reports results from the inverse hyperbolic sine (arcsinh) transformation of hourly load. We do not find these changes in specifications affect our results dramatically. Appendix Table E1 reports specifications using hourly load divided by a firm's load reduction target as the dependent variable. The results are qualitatively consistent with those reported in Table 2.

Next, we examine the effect on the estimation results of expanding our sample size. In our final main sample, we removed observations from auctions with a missing auction price, from auctions with any losing bid lower than the auction price, and observations outside the 10 am to 10 pm window.[18] Columns (5) to (7) of Table 4 report the results when we remove each of the above restrictions in turn, respectively. The estimated coefficients of the treatment effect during the DR window are all significant and are between -0.16 and -0.202 in these three columns, suggesting that our main results are robust to alternative ways of constructing the sample.

We also explore the robustness of our estimates using the RDD. Specifically, we use the distance between a bid and the auction's winning cutoff (i.e., the auction price) as the running variable and rely on the discontinuity of the winning cutoff to estimate the effect of receiving a DR request. Although firms can submit different bids to affect their likelihood of winning, they have no knowledge of the realized auction prices. Therefore, for observations close to the winning cutoff, treatment status is almost equivalent to a random assignment. The difference between the RDD and our preferred method (equation (4)) is that the RDD only uses observations around the cutoff and fits two separate functions of the bid, one above and one below the cutoff. In equation (4), we use all observations and fit a flexible bid function for all bids submitted.

Table 5 shows the results for the RDD. Column (1) presents the results without covariates. Columns (2) and (3) include variables for the market condition and firm-by-hour-of-day fixed effects. We find that the estimates of the treatment effect based on the RDD are between -0.137 and -0.206. These estimates are similar to those in columns (4), (5), and (6) of Table 2, suggesting that our main results are robust to the alternative specification. In addition, Panel B of Table 3 presents estimates for the subgroup analysis based on the RDD. These estimates are similar in magnitude to those in Panel A, except for the case of high auction

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

prices. For this subgroup, the treatment effect is not only stronger than that for low auction prices, but is also statistically significant.

5 Decomposing the Strategic Bidding Effect

In this section, we show that the load reduction based on the CBL data has two components: the treatment effect under the potential outcome framework and the bias component due to the strategic bidding effect. We then show that the strategic bidding effect can be decomposed into an adverse selection effect and a moral hazard effect. Finally, we discuss our strategies to test these effects and perform the empirical tests.

For firm i, let Y_i^1 and Y_i^0 denote the potential load when the firm is and is not given a monetary reward to save electricity, respectively. D_i equals one when the firm wins the auction and zero otherwise. To calculate the change in load q_i for firm i, the utility company uses the difference between the firm's actual load and its customer baseline load CBL_i. However, the estimate for the treatment effect in the previous section refers to the difference between Y_i^1 and Y_i^0. Based on this concept, the mean observed change in load can be decomposed into the treatment effect of winning the auction and the bias component:

$$\begin{aligned}
\mathrm{E}[q_i] &= \mathrm{E}[Y_i^1|D_i=1] - \mathrm{E}[Y_i^0|D_i=0, CBL_i] \\
&= \underbrace{\mathrm{E}[Y_i^1|D_i=1] - \mathrm{E}[Y_i^0|D_i=1]}_{\text{the treatment effect}} + \underbrace{\mathrm{E}[Y_i^0|D_i=1] - \mathrm{E}[Y_i^0|D_i=0, CBL_i]}_{\text{the bias component}}.
\end{aligned} \tag{5}$$

The bias component depends on how well $\mathrm{E}[Y_i^0|D_i=1]$ can be approximated by its counterpart, $\mathrm{E}[Y_i^0|D_i=0, CBL_i]$. Figure 5 also illustrates this gap. If the CBL truly reflects the counterfactual load under the treatment assignment, then our estimate should be the same as that calculated by the utility company. However, if the CBL is larger than the counterfactual load, which creates a negative bias term, then the utility company will overestimate the reduction in the program. Our estimate in the previous section implies that the CBL on average is much larger than the counterfactual load.

Let BAU_i denote each firm's business-as-usual (BAU) load. We can further decompose the bias component into the adverse selection effect and the moral hazard effect:

$$\begin{aligned} & \mathrm{E}[Y_i^0|D_i=1] - \mathrm{E}[Y_i^0|D_i=0, CBL_i] \\ = & \underbrace{\mathrm{E}[Y_i^0|D_i=1] - \mathrm{E}[Y_i^0|D_i=0, BAU_i]}_{\text{the adverse selection effect}} + \underbrace{\mathrm{E}[Y_i^0|D_i=0, BAU_i] - \mathrm{E}[Y_i^0|D_i=0, CBL_i]}_{\text{the moral hazard effect}}. \end{aligned} \tag{6}$$

The adverse selection effect captures the difference between the counterfactual load and the BAU load. Suppose a firm plans to shut down its plant on day d for scheduled maintenance. If it wins the auction on day d, the counterfactual load on that day will be lower than its BAU load, which will generate a negative adverse selection effect. In addition, the moral hazard effect expresses the difference between the BAU load and the CBL. If a firm inflates its CBL, then a negative moral hazard effect will be expected, which will also contribute to the bias component. Therefore, the utility company will overestimate the load reduction when the adverse selection effect, the moral hazard effect, or both exist in the market. Figure 5 presents these two effects.

Equation (6) suggests that, using the observed data when firms *lose* auctions, we can compare the load on baseline-eligible days (for future winning days' baseline) to the load on baseline-ineligible days to detect the moral hazard effect. By contrast, detecting the adverse selection effect is less straightforward because we never observe the counterfactual load Y_i^0 when $D_i = 1$. Instead, we use the load on losing days when bids are closer to the cutoff to serve as a proxy for the counterfactual load on winning days. We then test whether the load on losing days varies with the bid to examine the adverse selection effect. Note that we implement both tests, for the moral hazard and adverse selection effects, only using data from losing days.

Moral Hazard Effect

To verify the moral hazard effect, we calculate each firm's average load at the daily level (from 10 am to 10 pm) when they lose DR auctions. If the moral hazard effect exists, we expect to see a higher load on baseline-eligible days than ineligible days. We use a linear, a discrete, and a non-linear specification to estimate the following equation:

$$BaselineEligible_{i,dm} = \alpha_{i,m} + \mathbf{Z}'_{i,dm}\beta + \epsilon_{i,dm}, \tag{7}$$

where $BaselineEligible_{i,dm}$ equals one if firm i's load on day-of-sample d in month-of-sample m is baseline-eligible for future winning days and zero otherwise. For the linear specification, $\mathbf{Z}_{i,dm}$ is $\ln(DailyLoad)_{i,dm}$, which is the logarithm of a firm's average daily load. For the discrete specification, $\mathbf{Z}_{i,dm}$ is a dummy variable $HighLoad_{i,dm}$ indicating whether firm i's average daily load is above its average monthly load or not. For the non-linear specification, $\mathbf{Z}_{i,dm}$ includes a set of dummies indicating each of the load quartiles (the first quartile is the baseline group). In addition, we include the fixed effect $\alpha_{i,m}$ for firm i's baseline-eligibility in month m. We expect β to be positive in all specifications if the moral hazard effect exists.

Table 6 provides the results from equation (7). In column (1), the coefficient associated with $\ln(DailyLoad)_{i,dm}$ is negative and insignificant, which suggests that a day with higher load is not correlated with a higher probability of being baseline-eligible for future winning days. The coefficient associated with $HighLoad_{i,dm}$ in column (2) is also insignificant. Finally, the results in column (3) indicate that there is no correlation between daily load and baseline-eligibility, even under the non-linear specification. In conclusion, we do not find evidence of the moral hazard effect in any of the specifications.

Adverse Selection Effect

If the adverse selection effect exists, firms might strategically bid lower to win DR auctions on their idle days, although such bidding strategies do not assure auction success. To empirically test for the presence of adverse selection, we can examine whether lower daily bids are correlated with lower daily electricity consumption on the days firms do not win the auction, which would imply that firms are more likely to reduce their bids in anticipation of lower electricity consumption, and would be an indicator of adverse selection in DR auctions.

We test the adverse selection effect by estimating the following equation:

$$Y_{i,dm} = \alpha_{i,m} + \gamma b_{i,dm} + \mathbf{X}'_{dm}\delta + \epsilon_{i,dm}, \tag{8}$$

where $Y_{i,dm}$ is the logarithm of firm i's daily load, and $b_{i,dm}$ is firm i's bid on day-of-sample d in month-of-sample m; $\mathbf{X}_{dm}$ are covariates for market conditions, including daily temperature, reserve margin, recent marginal price, and auction price; $\alpha_{i,m}$ is the fixed effect for firm i's logged consumption in month m. In this linear specification, we expect γ to be positive if the adverse selection effect exists. In another specification, we allow the effect of the bid on logged consumption to be non-linear and include a set of indicator variables for different bid segments, including $b_{i,dm} \leq 2.5$, $2.5 < b_{i,dm} \leq 5$, and $5 < b_{i,dm} \leq 7.5$. In this specification, the base group includes bids greater than 7.5 and less than or equal to 10. We expect the coefficients associated with the bid segments to be negative if the adverse selection effect exists.

Table 7 presents the results for both linear and non-linear specifications. Columns (1) and (2) show that higher daily bids are associated with a higher daily load, suggesting an adverse selection effect for firms. In addition, columns (3) and (4) provide estimates of the regression model that explores the effect on load of bids in different segments. The estimates suggest that lower bid segments are associated with lower electricity consumption. In particular, the lowest bid segment ($b_{i,dm} \leq 2.5$) is associated with the largest decrease in log consumption among the three bid segments. This pattern implies that firms tend to submit their bids in the lowest bid segment when their electricity consumption is the lowest, implying that, if these lower bids lead to winning auctions, the associated counterfactual load (without a DR request) will be lower than their BAU load.

To sum up, we find that using the CBL-based data overestimates the load reduction from

DR requests, and the bias component is driven by the adverse selection effect that comes from firms' strategic bidding behavior.

6 Estimated Demand Elasticity and Policy Implications

We have shown that failing to account for firms' strategic behavior can lead to an overestimation of DR. In this section, we compare the total paid load reduction—calculated based on the CBL—over the entire sample period, and its implied price elasticity, to our estimates.

We compare the paid and estimated load reduction for each auction day. We use estimates at the individual firm level to calculate the estimated load reduction. Figure 6 plots the paid and estimated average daily reduction by month. The estimated monthly reduction ranges from 0.35 MW (July 2019) to 87.71 MW (May 2018), while the paid reduction is at least 2.03 times the estimated reduction, suggesting that, throughout the sample period, at least 50.8% of the paid reduction is due to the strategic bidding effect.

We also compare the implied price elasticity based on the paid load reduction to our estimates. Under the DR program, firm i's cost of electricity consumption on day d, denoted by p_d, depends on its auction outcome. Without a DR incentive, p_d is equal to its marginal retail price p^r_d. When a DR incentive is provided, p_d is equal to $p^r_d + b_{i,d}$, where $b_{i,d}$ is the winning bid of firm i on day d. We use publicly available tariff schedules from the utility company and observed winning bids to find p^r_d and $b_{i,d}$, respectively. We discuss how we construct p^r_d in detail in Appendix C.

To estimate the price elasticity based on CBL data, we use the winners' load reduction in the data to back out each winner's CBL on each winning day.[19] By doing so, we construct load data for each DR request under two treatment outcomes: with or without the DR treatment. We then stack the observed load and CBL for all DR requests in the data to create a single load variable $kw^{CBL}_{i,d}$ that has different treatment outcomes on the same DR request day. We regress $\ln(kw_{i,d})$ on the treatment variable $WinInWindow_{i,d}$ to get the

[19]We can do so because we have data for the observed load on winning days.

estimated load reduction, and regress $\ln(kw_{i,d}^{CBL})$ on $\ln(p_d)$ to estimate the price elasticity based on the CBL data. Similarly, to estimate the price elasticity based on our estimates, we predict each firm's load with or without a DR request using our estimates from Table 2 and apply the procedures described above to create a load variable $kw_{i,d}^{pred}$. We regress $\ln(kw_{i,d}^{pred})$ on $\ln(p_d)$ to find the price elasticity based on the predicted results.

Table 8 reports two sets of results. The first set (columns (1) and (2)) and the second set (columns (3) to (5)) are obtained when the counterfactual load is constructed based on the CBL and the predicted load, respectively. Specifically, columns (3) to (5) report estimates of the price elasticity based on the estimated coefficients from columns (4) to (6) of Table 2, respectively.[20]

The results based on the CBL data show that receiving a DR request is associated with a reduction of 0.684 log points (50%) in electricity consumption, and the associated price elasticity is -0.893. Previous studies of C&I users' price elasticity of electricity typically put their estimates between zero (unresponsive) and -0.119 (Patrick and Wolak, 2001; Jessoe and Rapson, 2015; Blonz, 2022). By contrast, the second set of results show that, after controlling for firms' strategic bidding behavior, the price elasticity of firms is between -0.192 and -0.271. It is important to recognize the large difference between the above two sets of estimates. Industrial users' electricity consumption accounts for at least 50% of total electricity consumption in Taiwan, and the extent to which power producers can exercise their market power depends on the market's demand elasticity. Thus, energy policies based on the incorrect CBL-driven price elasticity will result in a large underestimation of power producers' market power.

[20] We do not report the corresponding coefficients on the $WinInWindow$ variable for the second set of results because they are identical to those reported in Table 2.

7 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, to implement a DR program, a baseline must be constructed, which requires private information that is only available from firms, leading to an asymmetric information problem.

This paper shows that firms adversely select themselves into DR auctions by bidding lower when their electricity consumption is low, resulting in an overestimation of the program's effectiveness. Our estimates suggest that about 50% of the paid load reduction is inframarginal. After adjusting for the strategic bidding effect, our analysis reveals that winning a DR auction reduces firms' electricity consumption by an average of 12% to 17%. We do not find evidence of baseline inflation in our study. However, we note that our sample is drawn from manufacturers in the steel industry, and our results may not apply to industries that have the technologies to boost load in a short period of time.

Dynamic inefficiency could emerge from firms' strategic bidding behavior in DR auctions. Firms with volatile electricity consumption could bid strategically and undercut other firms in auctions, even when they have higher reduction costs. A natural extension of our study would be to estimate the reduction costs for industry users. These estimates could be used to further quantify dynamic inefficiency and to explore the benefits that could be gained from mechanisms facilitating the truthful revelation of firms' baseline consumption.

References

Aigner, D. J. and J. G. Hirschberg (1985). Commercial/industrial customer response to time-of-use electricity prices: Some experimental results. *The RAND Journal of Economics 16*(3), 341–355.

Aigner, D. J., J. Newman, and A. Tishler (1994). The response of small and medium-size business customers to time-of-use (TOU) electricity rates in Israel. *Journal of Applied Econometrics 9*(3), 283–304.

Allcott, H. (2011). Rethinking real-time electricity pricing. *Resource and Energy Economics 33*(4), 820–842. Special Section: Sustainable Resource Use and Economic Dynamics.

Blonz, J. A. (2022). Making the best of the second-best: Welfare consequences of time-varying electricity prices. *Journal of the Association of Environmental and Resource Economists 9*(6), 1087–1126.

Bollinger, B. K. and W. R. Hartmann (2020). Information vs. automation and implications for dynamic pricing. *Management Science 66*(1), 290–314.

Borenstein, S. (2013). Effective and equitable adoption of opt-in residential dynamic electricity pricing. *Review of Industrial Organization 42*(2), 127–160.

Burkhardt, J., K. Gillingham, and P. K. Kopalle (2019). Experimental evidence on the effect of information and pricing on residential electricity consumption. Working Paper 25576, National Bureau of Economic Research.

Bushnell, J., B. F. Hobbs, and F. A. Wolak (2009). When it comes to demand response, is FERC its own worst enemy? *Electricity Journal 22*(8), 9–18.

Fabra, N., D. Rapson, M. Reguant, and J. Wang (2021). Estimating the elasticity to real-time pricing: Evidence from the Spanish electricity market. *AEA Papers and Proceedings 111*, 425–29.

Harding, M. and S. Sexton (2017). Household response to time-varying electricity prices. *Annual Review of Resource Economics 9*(1), 337–359.

Herriges, J. A., S. M. Baladi, D. W. Caves, and B. F. Neenan (1993). The response of industrial customers to electric rates based upon dynamic marginal costs. *The Review of Economics and Statistics 75*(3), 446–454.

Hortaçsu, A. and S. L. Puller (2008). Understanding strategic bidding in multi-unit auctions: a case study of the Texas electricity spot market. *The RAND Journal of Economics 39*(1), 86–114.

Isogawa, D., H. Ohashi, and T. Anai (2022). Role of advance notice on high-priced hours: Critical peak pricing on industrial demand. Working Paper 22-E-068, The Research Institute of Economy, Trade and Industry.

Ito, K. (2015). Asymmetric incentives in subsidies: Evidence from a large-scale electricity rebate program. *American Economic Journal: Economic Policy 7*(3), 209–237.

Jessoe, K. and D. Rapson (2014). Knowledge is (less) power: Experimental evidence from residential energy use. *American Economic Review 104*(4), 1417–38.

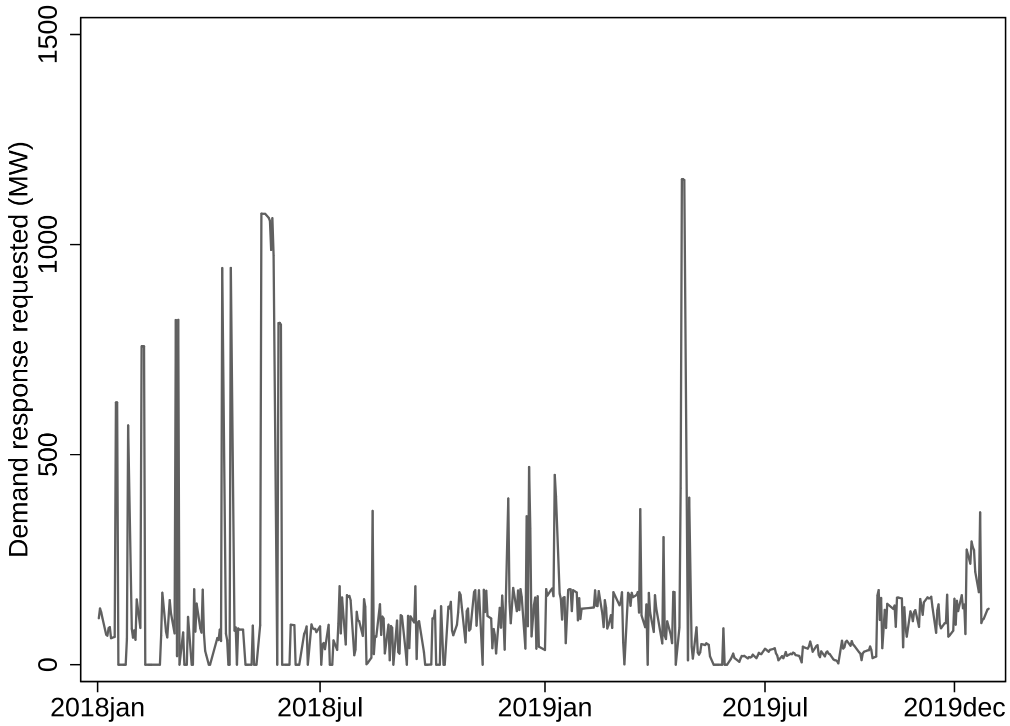
Jessoe, K. and D. Rapson (2015). Commercial and industrial demand response under mandatory time-of-use electricity pricing. *The Journal of Industrial Economics 63*(3), 397–421.

Patrick, R. H. and F. A. Wolak (2001). Estimating the customer-level demand for electricity under real-time market prices. Working Paper 8213, National Bureau of Economic Research.

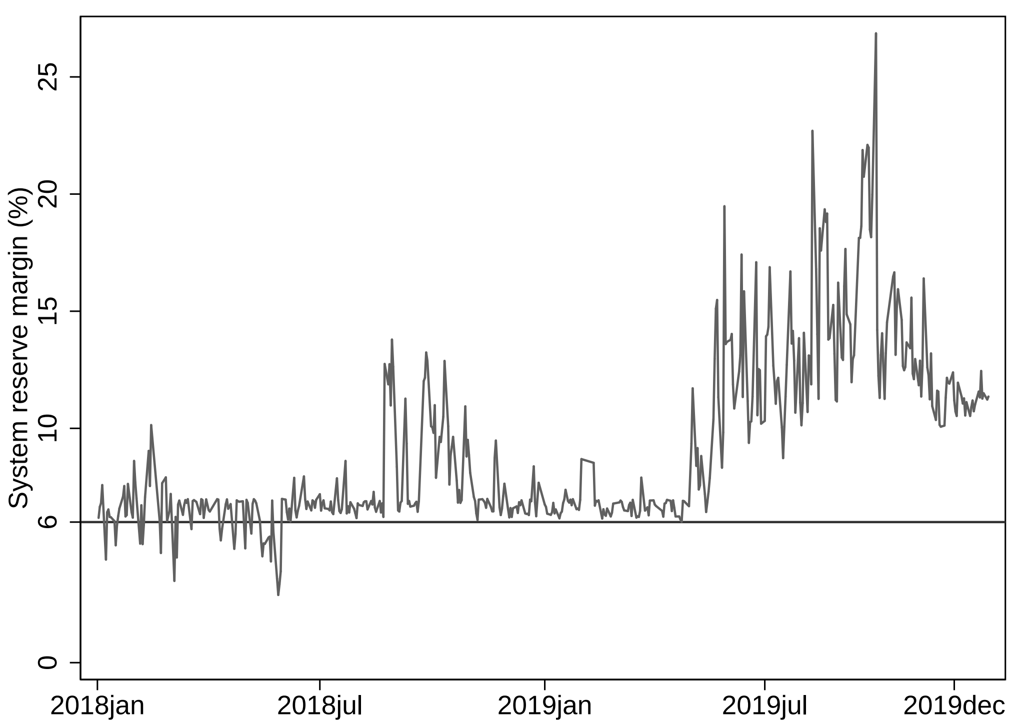
Schwenen, S. (2015). Strategic bidding in multi-unit auctions with capacity constrained bidders: the New York capacity market. *The RAND Journal of Economics 46*(4), 730–750.

Wolfram, C. D. (1998). Strategic bidding in a multiunit auction: An empirical analysis of bids to supply electricity in England and Wales. *The RAND Journal of Economics 29*(4), 703–725.

Yang, S.-C., C.-C. Hsieh, M.-F. Hung, H.-H. Liu, C.-W. Tsai, and C.-L. Peng (2019). Estimating demand response potential with AMI data. *Monthly Journal of Taipower's Engineering 855*, 73–95.

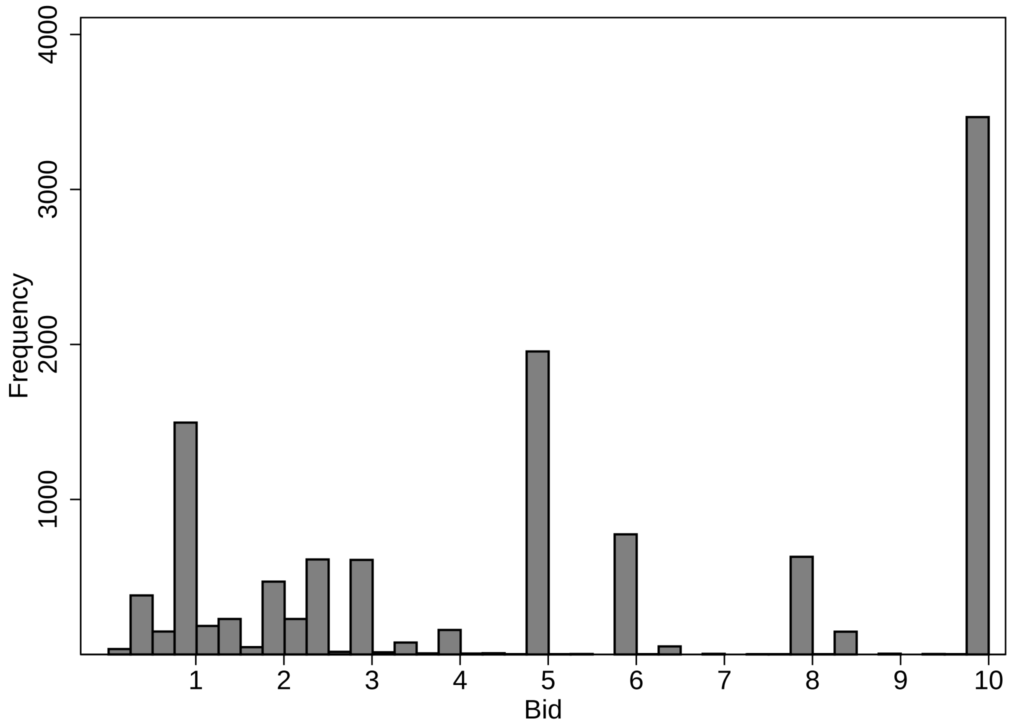


(a) DR Requested

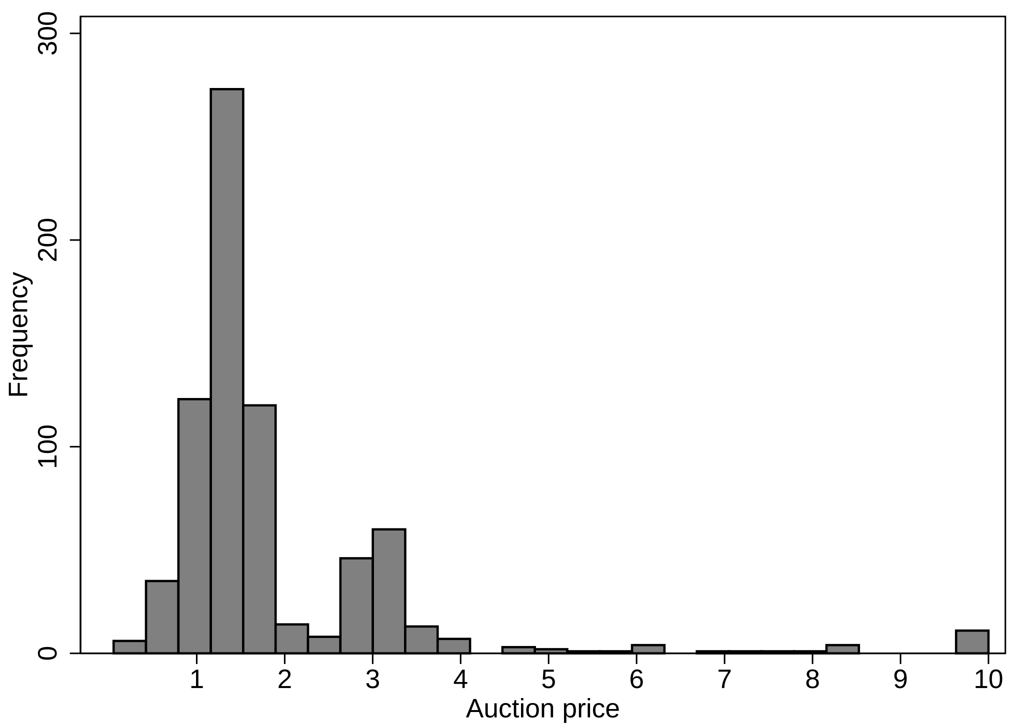


(b) Reserve Margin

Figure 1: DR Requested and Reserve Margin

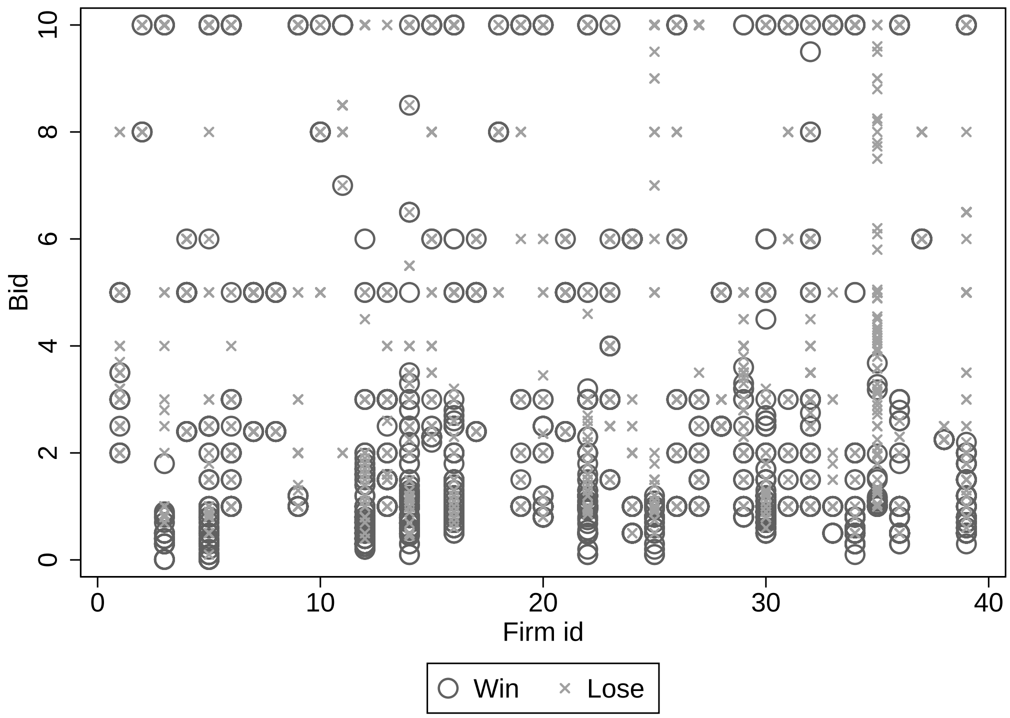


(a) Bid

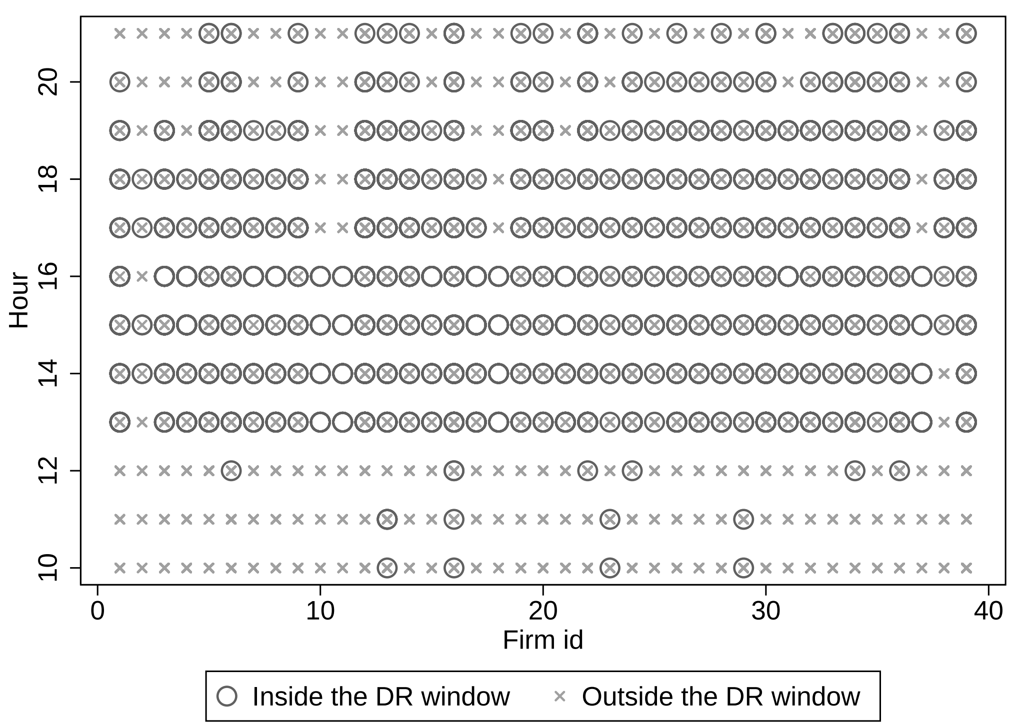


(b) Auction Price

Figure 2: Distribution of Bids and Auction Prices

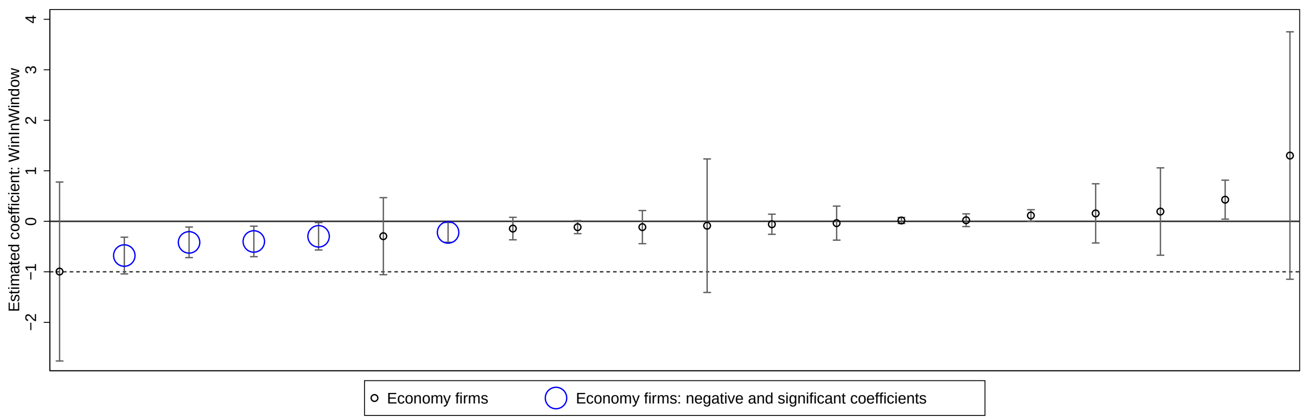


(a) Bids Submitted by Firm

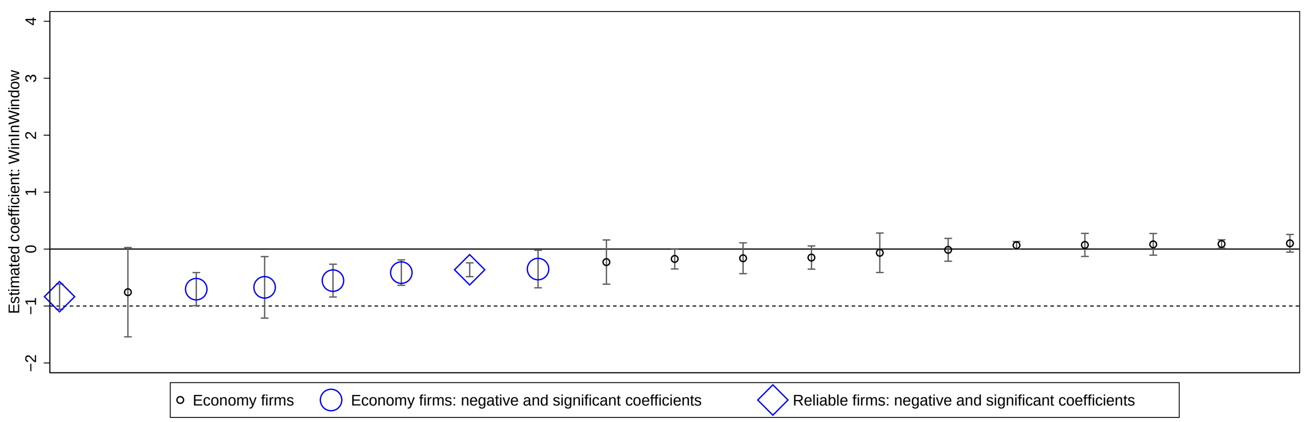


(b) DR Window by Firm

Figure 3: Treatment Status by Firm



(a) Firms with Load Reduction Target Below the Median



(b) Firms with Load Reduction Target Above the Median

Figure 4: The Effect of DR Request on Performance Ratio

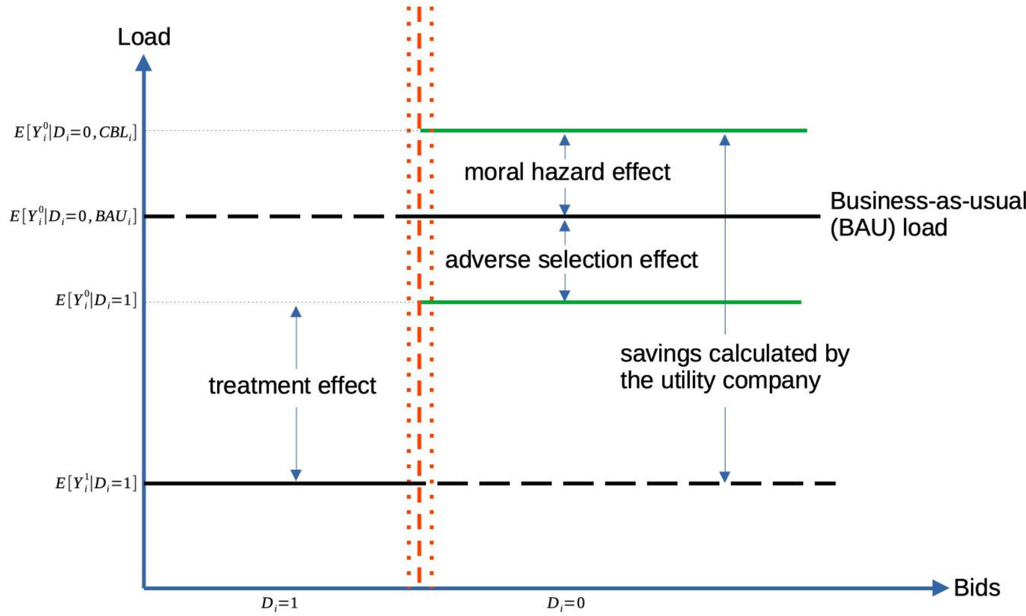


Figure 5: Decomposition of the Strategic Bidding Effect

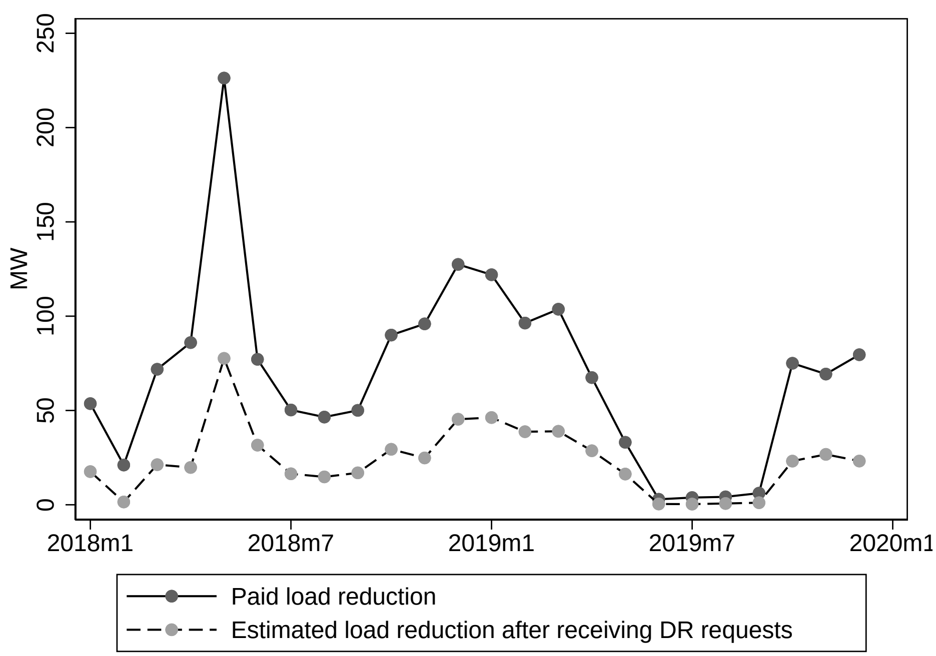


Figure 6: Estimated Average Monthly Load Reduction

Table 1: 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)
Observations	11780	6158	5622	11240	540
Bid-cutoff gap (winning days)	1.05	1.13	0.97	1.07	0.77
	(1.44)	(1.55)	(1.31)	(1.46)	(0.99)
Observations	2661	1325	1336	2467	194
Bid-cutoff gap (losing days)	4.89	3.79	6.14	4.81	6.93
	(3.11)	(2.65)	(3.12)	(3.09)	(2.82)
Observations	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. 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 2: The Effect of Receiving a DR Request on Electricity Consumption

	(1)	(2)	(3)	(4)	(5)	(6)
Win in window	-0.465**	-0.524**	-0.588**	-0.173**	-0.129**	-0.182**
	(0.039)	(0.040)	(0.039)	(0.038)	(0.040)	(0.039)
Win outside window	-0.406**	-0.467**	-0.441**	-0.037	0.008	-0.045
	(0.033)	(0.035)	(0.034)	(0.035)	(0.038)	(0.037)
Temperature		0.002	0.001	0.002	0.002	0.002
		(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Reserve margin		-0.017**	-0.017**	-0.016**	-0.016**	-0.016**
		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Recent price		0.009	0.009	-0.001	0.001	0.002
		(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Auction price		0.056**	0.056**	0.009	0.004	0.010
		(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Bid				0.078**	0.096	
				(0.006)	(0.097)	
Bid^2					0.012	
					(0.023)	
Bid^3					-0.001	
					(0.001)	
$\text{Bid} \leq 2.5$						-0.685**
						(0.056)
$2.5 < \text{Bid} \leq 5$						-0.437**
						(0.064)
$5 < \text{Bid} \leq 7.5$						-0.134
						(0.102)
Constant	7.497**	7.484**	7.083**	6.656**	6.551**	7.422**
	(0.007)	(0.144)	(0.145)	(0.144)	(0.168)	(0.148)
Firm-by-hour-of-day fixed effects?	No	No	Yes	Yes	Yes	Yes
Order of polynomial function of bid	0	0	0	1	3	0
Observations	138652	138652	138652	138652	138652	138652

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 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 3: Heterogeneous Effects

	(1) Target: low	(2) Target: high	(3) Economy	(4) Reliable	(5) Price: low	(6) Price: high
Panel A: Regressions with bid controls						
Win in window	-0.088^{+}	-0.160*	-0.071^{+}	-1.003**	-0.111**	-0.395
	(0.047)	(0.065)	(0.040)	(0.153)	(0.043)	(0.243)
Panel B: RDD						
Win in window	-0.166**	-0.207**	-0.126**	-1.069**	-0.155**	-1.329**
	(0.055)	(0.035)	(0.034)	(0.081)	(0.042)	(0.159)
P-value	0.003	0.000	0.000	0.000	0.001	0.000
Bandwidth	0.978	1.466	1.042	3.770	0.962	2.391
Effected observations	20038	20374	36668	2753	35242	2725
Observations	72535	66117	132333	6319	132450	6202

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 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 4: Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Win in window	-0.126*	-0.119**	-0.128**	-0.111**	-0.160**	-0.138**	-0.202**
	(0.063)	(0.041)	(0.040)	(0.043)	(0.029)	(0.040)	(0.036)
Win outside window	-0.006	0.017	0.008	0.027	-0.011	0.007	0.010
	(0.061)	(0.038)	(0.037)	(0.042)	(0.023)	(0.038)	(0.031)
Temperature	0.003	0.002	0.002	-0.000	-0.003	0.001	0.002
	(0.006)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Reserve margin	-0.008	-0.016**	-0.016**	-0.018**	-0.011**	-0.016**	-0.016**
	(0.007)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
Recent price	-0.028	0.000	-0.001	-0.009	-0.018	-0.001	0.010
	(0.031)	(0.017)	(0.017)	(0.020)	(0.014)	(0.017)	(0.017)
Auction price	-0.029	0.003	0.004	-0.002		0.006	0.009
	(0.059)	(0.007)	(0.007)	(0.009)		(0.007)	(0.007)
Bid	0.507**	0.179**	0.547**	0.187+	0.081	0.088	0.077
	(0.189)	(0.034)	(0.142)	(0.107)	(0.078)	(0.096)	(0.084)
Bid^2	-0.067	-0.009**	-0.206**	-0.009	0.012	0.013	0.006
	(0.059)	(0.003)	(0.062)	(0.025)	(0.019)	(0.022)	(0.020)
Bid^3	0.004		0.035**	-0.000	-0.001	-0.001	-0.001
	(0.004)		(0.010)	(0.002)	(0.001)	(0.001)	(0.001)
Bid^4			-0.002**				
			(0.001)				
Constant	6.488**	6.485**	6.302**	7.263**	6.766**	6.598**	6.661**
	(0.278)	(0.154)	(0.175)	(0.190)	(0.138)	(0.168)	(0.157)
Bandwidth	1	N	N	N	N	N	N
Order of polynomial function of bid	3	2	4	3	3	3	3
arcsinh transformation	N	N	N	Y	N	N	N
Auctions without an auction price	N	N	N	N	Y	N	N
Auctions when losers have lower bids	N	N	N	N	N	Y	N
Data outside the 10 am to 10 pm window	N	N	N	N	N	N	Y
Observations	37957	138652	138652	139138	169901	140502	279759

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 whose auction price cannot be constructed are excluded except in column (5). Data from auctions with any losing bid lower than the auction price are excluded except in column (6). Data before 10:00 and after 22:00 are excluded except in column (7). All regressions include firm-by-month-of-sample 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 5: Regression-Discontinuity Design Estimates

	(1)	(2)	(3)
Win in window	-0.137**	-0.149**	-0.206**
	(0.033)	(0.032)	(0.032)
P-value	0.000	0.000	0.000
Bandwidth	1.000	1.002	1.023
Control for market conditions?	No	Yes	Yes
Firm-by-hour-of-day fixed effects?	No	No	Yes
Effective observations	37525	37957	38689
Observations	138652	138652	138652

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 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 6: Testing the Moral Hazard Effect

	(1)	(2)	(3)
ln(daily load)	-0.003		
	(0.007)		
High load		0.014	
		(0.009)	
Load in the second quartile			-0.013
			(0.012)
Load in the third quartile			0.010
			(0.012)
Load in the fourth quartile			0.000
			(0.013)
Constant	0.421**	0.389**	0.398**
	(0.052)	(0.005)	(0.007)
Observations	9114	9119	9119

Notes: This estimation uses daily data from days when firms lose auctions. The dependent variable is a day's eligibility to serve as the baseline (for future reward days). All regressions include firm-by-month-of-sample 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 7: Testing the Adverse Selection Effect

	(1)	(2)	(3)	(4)
Bid	0.074**	0.074**		
	(0.007)	(0.007)		
Bid $\leq$ 2.5			-0.646**	-0.639**
			(0.064)	(0.064)
2.5 $<$ Bid $\leq$ 5			-0.438**	-0.433**
			(0.082)	(0.082)
5 $<$ Bid $\leq$ 7.5			-0.117	-0.104
			(0.122)	(0.122)
Temperature		-0.002		-0.002
		(0.004)		(0.004)
Reserve margin		-0.020**		-0.021**
		(0.006)		(0.006)
Recent price		0.017		0.020
		(0.020)		(0.020)
Auction price		0.003		0.002
		(0.010)		(0.010)
Constant	7.477**	7.664**	8.208**	8.387**
	(0.047)	(0.170)	(0.034)	(0.170)
Observations	9114	9114	9114	9114

Notes: This estimation uses daily data from days when firms lose auctions. The dependent variable is a firm's logged daily load between 10:00 and 22:00. All regressions include firm-by-month-of-sample 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 8: Estimated Price Elasticity

	Load based on CBL		Predicted load		
	(1)	(2)	(3)	(4)	(5)
Win in window	-0.684**				
	(0.017)				
ln(price)		-0.893**	-0.259**	-0.192**	-0.271**
		(0.038)	(0.004)	(0.003)	(0.004)
Constant	8.236**	9.106**	7.443**	7.301**	7.459**
	(0.012)	(0.052)	(0.006)	(0.004)	(0.006)
Observations	5316	5316	5316	5316	5316

Notes: The dependent variable is the logged load (observed and counterfactual) on DR request days. In columns (1) and (2), the counterfactual load is constructed based on a firm's CBL. In columns (3)-(5), the counterfactual load is constructed based on the results in columns (4) to (6) of Table 2, respectively. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

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.[21]

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

[21] Denote an economy participant's performance ratio by x. During summer time (June to September), the deduction ratio is 1.1 when $80\% \leq x \leq 120\%$, 1.05 when $60\% \leq x < 80\%$ or $120\% < x \leq 150\%$, and 1 when $x < 60\%$ or $x > 150\%$. All else being equal, the deduction ratios are higher during summer time.

$\bar{q}$. 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:

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

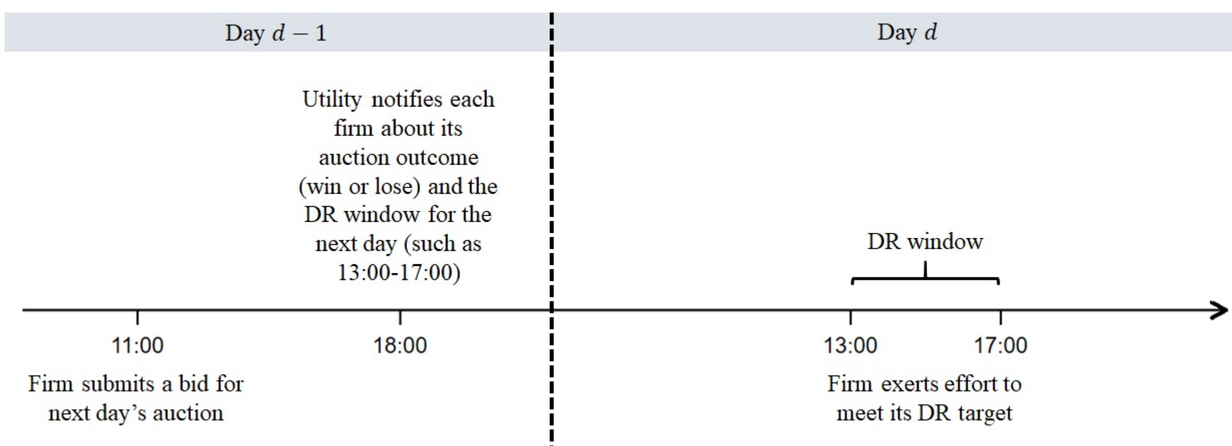


Figure A1: The Timeline of a Demand Response Auction

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, NTD/kWh), a firm can deliberately boost its electricity 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.

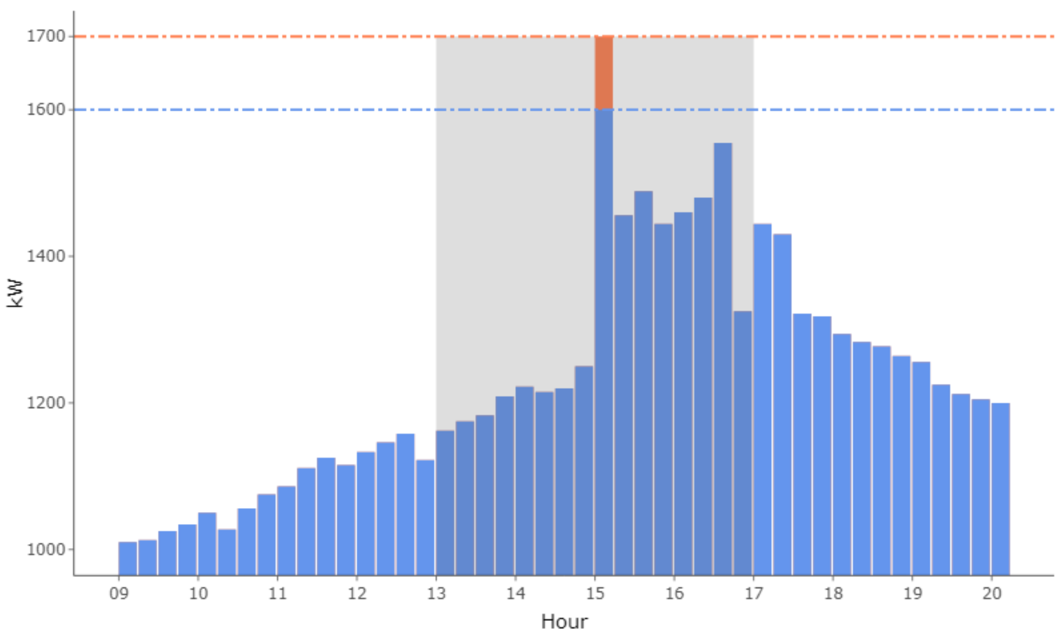


Figure B1: Baseline Boosting

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 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-period tariff, p^r is equal to 3.29 from 7:30 to 22:30 in the summer, and so when b is greater than 1.03—a threshold quite moderate compared to the median auction price of 1.35—there exists a moral hazard problem.

C Data Construction

Our dataset does not include the auction price (i.e., the cutoff) for each auction or the precise retail tariff schedules chosen by each firm. In the following section, we will discuss our method for constructing the auction price and provide additional details about the retail tariff schedules available to industrial users.

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.

Retail Price

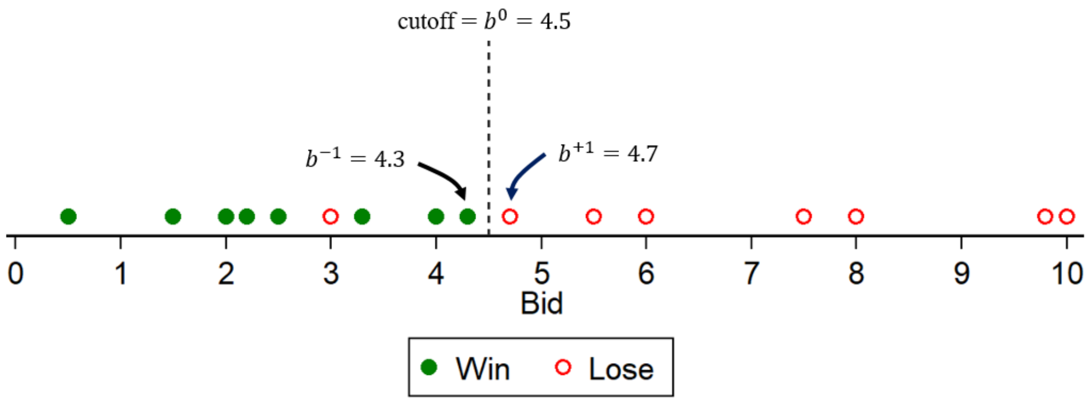


Figure C1: Construction of the Auction Price

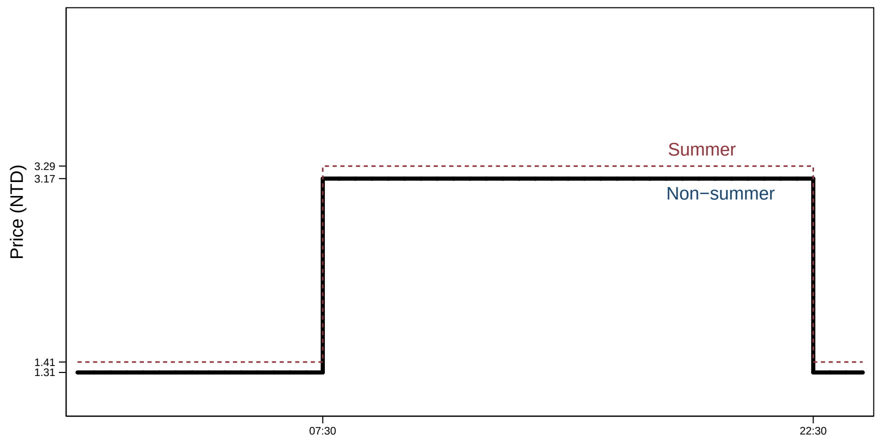
A firm's cost of electricity consumption in a given hour h on day d without a DR incentive is its marginal retail price p^r_{hd}. We use publicly available tariff schedules from the utility company to calculate p^r_{hd}. Given that the load reduction based on the CBL data is only available at the daily level, we use p^r_{hd} to calculate an average price p^r_d for each DR window.

All industrial users are subject to time-of-use pricing. However, each firm could choose to enroll in a two-period schedule (peak and off-peak) or a three-period schedule (peak, semi-peak, and off-peak). We could find out p^r_d for each firm if we know whether it enrolled in a two-period or a three-period schedule. Unfortunately, we do not have access to such information. Figure C2 plots the two types of tariff schedules. Our price elasticity estimates in the main text are based on the two-period schedule. We present the estimates using the three-period schedule in Table C1. The results are qualitatively similar to those based on the two-period pricing schedule.

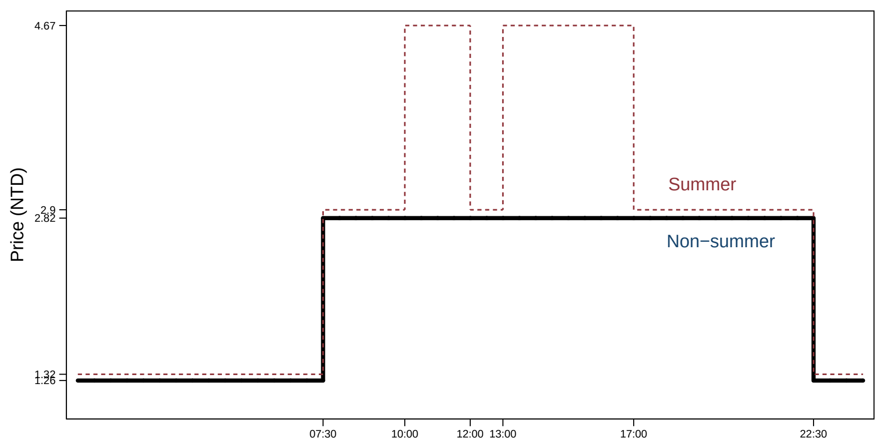
D Sample Representativeness

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

Figure C2: Retail Price



(a) Two-period Pricing Schedule



(b) Three-period Pricing Schedule

Table C1: Estimated Price Elasticity Based on Three-part Pricing Schedule

	Load based on CBL		Predicted load		
	(1)	(2)	(3)	(4)	(5)
Win in window	-0.684**				
	(0.017)				
ln(price)		-0.858**	-0.245**	-0.181**	-0.256**
		(0.036)	(0.004)	(0.003)	(0.004)
Constant	8.236**	9.053**	7.422**	7.286**	7.437**
	(0.012)	(0.050)	(0.006)	(0.004)	(0.006)
Observations	5316	5316	5316	5316	5316

Notes: The dependent variable is the logged load (observed and counterfactual) on DR request days. In columns (1) and (2), the counterfactual load is constructed based on a firm's CBL. In columns (3)-(5), the counterfactual load is constructed based on the results from columns (4) to (6) of Table 2, respectively. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

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.

E Additional Results

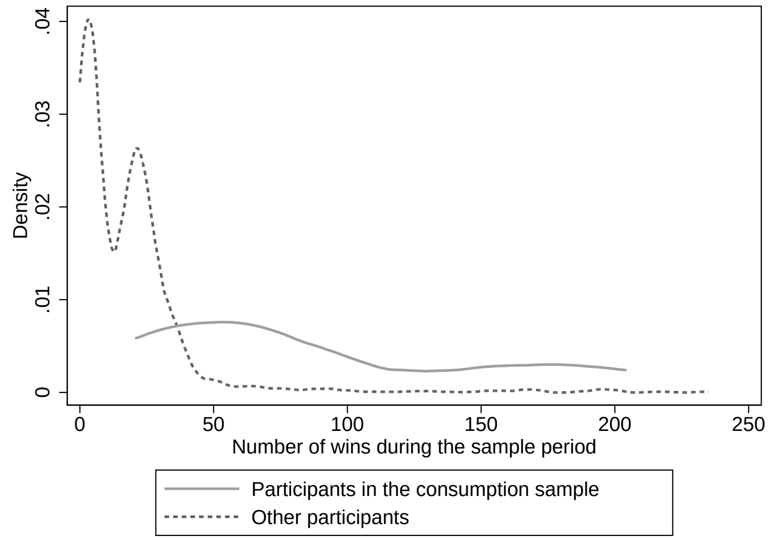


Figure D1: Number of Wins During the Sample Period

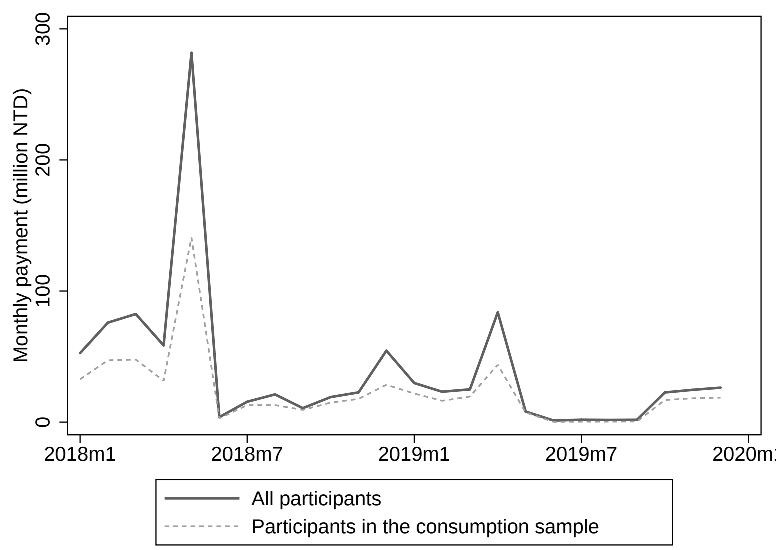


Figure D2: Monthly Payment

Table E1: The Effect of Receiving a DR Request on Consumption Relative to Target

	(1)	(2)	(3)	(4)	(5)	(6)
Win in window	-1.187**	-1.324**	-1.407**	-0.209*	-0.280*	-0.289*
	(0.212)	(0.227)	(0.239)	(0.104)	(0.115)	(0.113)
Win outside window	-1.105**	-1.248**	-1.208**	-0.038	-0.109	-0.118
	(0.201)	(0.219)	(0.212)	(0.097)	(0.110)	(0.102)
Temperature		0.001	0.001	0.003	0.003	0.004
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Reserve margin		-0.014	-0.013	-0.009	-0.008	-0.008
		(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Recent price		-0.001	-0.001	-0.028	-0.031	-0.028
		(0.047)	(0.047)	(0.046)	(0.047)	(0.047)
Auction price		0.138**	0.138**	0.001	0.008	0.008
		(0.033)	(0.033)	(0.025)	(0.027)	(0.025)
Bid				0.225**	0.202	
				(0.042)	(0.363)	
Bid^2					-0.021	
					(0.077)	
Bid^3					0.002	
					(0.005)	
Bid ≤ 2.5						-1.977**
						(0.365)
$2.5 <$ Bid ≤ 5						-1.347**
						(0.296)
$5 <$ Bid ≤ 7.5						-1.393**
						(0.386)
Constant	2.782**	2.634**	2.216**	0.982**	1.149*	3.253**
	(0.043)	(0.297)	(0.305)	(0.344)	(0.452)	(0.384)
Firm-by-hour-of-day fixed effects?	No	No	Yes	Yes	Yes	Yes
Order of polynomial function of bid	0	0	0	1	3	0
Observations	139138	139138	139138	139138	139138	139138

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