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 the selection effect resulting from firms' strategic bidding behavior can lead to an over-estimation of electricity reduction by at least 50%. We show that the selection effect works mainly through a free-rider effect, in which firms bid low to win auctions when they anticipate low electricity consumption.

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1 Introduction

Time-varying electricity pricing programs and peak-time rebate programs inform users about market conditions and give them incentives to reduce electricity consumption when it is in short supply. In this paper, we study the effect of incentivizing demand response (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. For example, New York Independent System Operator (NYISO) allows eligible customers to bid in the Day-Ahead Demand Response Program (DADRP) and several California utilities companies also offer day-ahead capacity bidding programs (CBP) to customers.

We empirically examine how steel producers in Taiwan react to DR auctions. Large firms have a significant incentive to participate actively in DR auctions. During our study period, the maximum monthly payout to a single participant was almost 40 million NTD (around 1.33 million USD), and many firms received over 10% deductions in their energy charge from participating DR auctions in the same month. While previous work in the electricity market has shown that strategic behavior exists in the supply side, and such behavior can lead to market inefficiencies (Wolfram, 1998; Hortaçsu and Puller, 2008; Schwenen, 2015), there has been little empirical exploring whether strategic behavior exists in the demand side. In this paper, we explore whether users' strategic bidding behavior results in an over-estimation of their demand response.

The DR auction studied in this paper operates daily. 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 with bids lower than the auction price will win the auction, and they will receive a reward based on the amount of their electricity reduction.[1] The auction employs discriminatory pricing, where the higher the

[1] To be precise, the payment is structured so that the better a participant meets its load reduction target,

winning bid, the greater the payment to the participant. On a winning day, a participant's electricity consumption on the previous five losing days is used to establish their 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 poses concerns about whether participants may exploit it to construct 'event days' favorable to their existing load profiles or even manipulate their baseline consumption in order to boost their performance.[2] 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.

Under the presence of the potential selection effect stemming from strategic bidding, we exploit available data and features from DR auctions to estimate the treatment effect of winning auctions. Observing each participant's daily bids allows us to use a flexible function of bids to control for the selection effect. Features of the DR program also help 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 both auction prices and rival bids are never observed by firms, making auction prices difficult to be predicted exactly. Therefore, conditional on bids submitted for the auction day and market conditions, the treatment status cannot be directly manipulated by firms, and so could be viewed as good as 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

the higher the final payment is. We discuss the payment structure in detail in Appendix A.

[2]For example, Baltimore Orioles baseball stadium turned on stadium lighting on a non-Orioles game day in 2010 to inflate its consumption in response to the grid operator PJM's declaration of an emergency event scheduled to start two hours later. See 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.

stronger for firms selecting larger load reduction targets or for those who 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% to 19%. In contrast, the official average load reduction (which is based on the difference between CBL and observed load) is 50%, suggesting that the program is too optimistic about participants' ability to provide load reduction.

To explore the channel of the selection effect, we decompose the selection effect into a free-rider effect and a baseline effect. On the one hand, the free-rider effect captures the difference between a participant's counterfactual load on winning days and its business-as-usual (BAU) load. An example of the free-rider effect is when a firm wins auctions on a day with scheduled maintenance. On the other hand, the baseline effect is the difference between the BAU load and the CBL. An example of the baseline effect is when a firm wins an auction after it consumes a large amount of electricity during its five previous losing days. We propose two tests for each type of the selection effect using bids and electricity consumption data when participants *lose* auctions. We find strong (statistically and economically) evidence for the free-rider effect, but the baseline effect cannot be estimated with precision.

Our estimates show that failing to account for the selection effect leads the program to overestimate the program's 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 selection effect in demand auctions is costly in two ways: not only does the utility company overpay for load reduction, but inefficient participants with volatile load profiles and high marginal costs of load reduction can outbid efficient ones. We propose using adjusted bids to determine the merit order of the auction. Our counterfactual analysis suggests that, with the same load reduction target, the merit order obtained using adjusted bids is more cost-effective than that obtained using actual bids. Furthermore, the alternative merit order generates more load reduction and increases revenue for firms providing significant demand response, given the same budget constraint.

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, or real-time pricing (RTP) (Harding and Sexton, 2017). Households' demand elasticities of electricity implied in these studies tend to vary by program design and technologies to inform households about their consumption or to automate their response (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.[3] 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) find that peak pricing reduced usage of C&I customers by 13.5 percent 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 of 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 peak-time rebate programs.

[3]For eariler 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 pricing, but the effect was not uniform across firms. Patrick and Wolak (2001) study how UK C&I users react to real-time pricing.

Bushnell, Hobbs, and Wolak (2009) argues that due to the difficulty in accurately determining the baseline consumption level in the absence of a DR program, focusing too much on DR programs may crowd out true price response from other price-based mechanisms. Borenstein (2013) points out that these 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 but 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 the literature by decomposing the selection effect from a peak-time rebate program and providing empirical tests for the free-rider and the baseline effect. We present evidence that industrial users deliberately take advantage of the structure of the peak-time rebate program, bidding lower to win auctions when they anticipating lower electricity consumption.

The paper proceeds as follows. Section 2 describes the DR program and the data in Taiwan. 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 selection effect into a free-rider and a baseline effect and tests the potential channels of the selection effect. Section 6 discusses implications from the selection effect, describes an alternative way to construct the merit order, and conducts two counterfactual exercises based on the alternative merit order. 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.[4] Although the utility company never publishes its demand in DR auctions in advance,

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

it is safe to say that it is related to market conditions in the electricity industry. Figures 1(a) and 1(b) plot daily DR requested and the electricity system's reserve margin (system operating reserve divided by the expected peak load) by the utility company from 2018 to 2019. During this period, the electricity system's reserve margin ranges between 2.89% and 26.86%, with 29 days below 6% (all in 2018). Overall, 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%, DR requested by the utility company tends to be extremely high whenever the reserve margins are below 6%.

The object of the DR program in our setting is load reduction. A customer's load during a certain time window, say 13:00-17:00, is its peak consumption during this time. At the beginning of each month, each firm chooses whether or not to participate in DR auctions.[5] An auction participant next specifies its rate plan in the program, including 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., 2-hour reduction or 4-hour reduction).[6] Participants selecting the 2-hour reduction at the beginning of the month enter the 2-hour day-ahead auctions and do not compete with those selecting the 4-hour reduction (and in the 4-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 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

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

[6] 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.

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 in the Appendix A.

For a day-ahead auction on day d, a participant is allowed to change its bid before the auction closes at 11 am on day $d-1$. After that, the utility company collects all eligible bids and runs a program to calculate the day-ahead market clearing price.[7] Participants with bids lower than the day-ahead market clearing price win the day-ahead auction and are notified before 6 pm on day $d-1$.[8] 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 is known to a participant only after it wins an auction.[9] The utility company shows the previous 5-day 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.

Data Description

The program data from 2018 to 2019 were provided by the utility company. 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. To measure daily market conditions, we collect publicly available data, including maximum temperature, reserve margin, and previous 5-day average marginal price (henceforth, recent price). We also construct a variable to measure each auction's price. Appendix B provides additional details regarding how auction prices are constructed.

[7] During our study period, the number of total hours won by any participant in a month was capped at either 36, 60, or 72, depending on the supply condition of electricity. A participant's bid is removed from an auction if it reaches the month's hour limit.

[8] 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, and so we exclude data from these requests.

[9] To illustrate, suppose a participant selects a 4-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.

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.[10] 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 C. Our analysis is conducted on the consumption sample. The identity of all participants is kept anonymous.

We make some restrictions to our sample. First, we exclude auctions in which there was no winner or no loser at all. This removes extreme cases when 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. We remove five auctions when such abnormity happened to make sure that auction outcomes are consistent with bids. Sometimes a load reduction notice begins 15, 30, or 45 minutes after an hour. In such cases, the first and the last hour in the notice window are 'partially treated'. We cannot determine whether the maximum consumption of an hour occurs in the notice window for these partially treated hours, and so our final sample excludes them. Finally, all of the DR requests are between 10 a.m. and 10 p.m., and so our main analysis is conducted during these hours. In section 4, we report 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 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 information to do so, because

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

auction prices are not public information. The auction prices at the 50th and 90th percentiles are 1.35 and 3.25, respectively. However, nearly 30% of bids are placed at 10 NTD, suggesting that some firms submit the maximum bid to avoid winning.

Table 1 provides summary statistics of our main sample. Panel A presents firms' hourly load (kW). Panel B displays variables regarding firms' strategic bidding behavior, including the winning probability and the absolute value of the gap 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 the 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 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 or below the median load reduction target (1500 kW) as high-target or low-target firms, respectively, and firms selecting the economy or reliable plan as the economy or reliable firms, respectively.

The average hourly load is 15,309 kW.[11] The average load of high-target firms is higher than that of 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 large 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 further present the results for economy and reliable firms, respectively. We find that reliable firms consume more electricity and submit more sophis-

[11] 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.

ticated 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 large 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 behavior may result in an over-estimation of the program's effect on load reduction during peak demand hours. Nevertheless, Figure 3 shows that while many firms place their bids at the maximum bid 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 notice window on winning days by firm. With only a few exceptions, variation in treatment status (inside or outside the notification window) exists conditional on the same hour of 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 does not have enough information to compete against 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 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^* when the marginal benefit of 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 incurred cost 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 customer baseline load, CBL, and its actual load. Assume that the firm may have its schedule, which needs to consume a certain level of load, called a scheduled load, SchL. Then the load reduction calculated by the utility company is $\text{CBL} - (\text{SchL} - x)$. 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 customer baseline load, 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 consumer baseline load or the scheduled load is very low, such as the shutdown day, then we will have $\text{CBL} - \text{SchL} > 0$. Under this case, the optimal bid b^* based on equation (2) will be less than $\tilde{b}$ when when $G(b)/G'(b)$ is a monotone function.

Therefore, we will have the following prediction:

Prediction 1 *If the firm has a higher level of customer baseline load 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 adjust their bids when they have a higher baseline or 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 bids, the treatment assignment is not exogenous, and so 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 bids in our estimation to mitigate the selection problem. Features of the DR program also help our empirical strategy. First, bids are predetermined before both treatment assignments and firms' load reduction effort. Second, both auction prices and rival bids are never observed by firms, and so variation in treatment status exists even conditional on similar bids 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:

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

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 bids; $\mathbf{X}_{dm}$ are covariates for market conditions, including temperature, reserve margin, recent marginal price, and auction price. The indicator variable $Treated_{i,hdm}$ equals one if firm i wins the auction on day d, and hour h is within the notice window and zero otherwise, while the indicator variable $WinButNotTreated_{i,hdm}$ equals one if firm i wins the auction on day d but hour h is not within the notice window and zero otherwise. We expect β_1 to be negative if firms reduce electricity consumption after receiving DR requests, and we use β_2 to capture the spillover effect outside the the notice window on winning days. 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 percent) to 0.588 log points (44 percent). Once we control for bids, the estimated load reduction in column (4) declines to 0.173 log points (16 percent), and even to 0.129 log points (12 percent) in column (5) when we use higher-degree polynomials (a cubic function) of bids. 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 percent). The coefficients of $WinButNotTreated$ are insignificant after we control the bid function, which implies that there is no spillover effect outside the notice window on winning days. After controlling for bids, most coefficients of 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 bids 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).[12] 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 bids) as 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 percent) and 0.088 log points (8.4 percent), 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.

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

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 $Treated$ variable will be exactly negative one. Because not every firm changes its bid frequently, we use a linear function of bid in the regression. We present the estimated coefficient of the $Treated$ variable for each firm in Figure 4 and separate 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. We randomly sort firms in each sub-figure to protect the identity of firms. We present coefficients associated with economy and reliable firms using circle and diamond symbols, respectively and upgrade firms with a negative and significant coefficient of the $Treated$ 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 with a negative and significant treatment effect. This pattern suggests that there may exist fixed costs to install measures to provide 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.

Robustness Analysis

Our preferred specification uses logged hourly load as the dependent variable, and adopts the third-order of polynomial in 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 consider limiting the sample to those 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 the second-order and the fourth-order of polynomial of bids, 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 changes in specifications affect our results dramatically.

We also examine the effect of expanding our sample size on estimation results. Our final sample removes observations with a missing auction price, with an unreasonable gap price, and outside the 10 a.m. to 10 p.m window. Columns (5) to (7) of Table 4 report results when we remove each of the above restrictions, respectively. The estimated coefficients of the treatment effect during the notification window are all significant and are between -0.16 to -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 regression discontinuity (RD) design. 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 about realized auction prices. Therefore, for observations close to the winning cutoff, treatment status is almost equivalent to a random assignment. The difference between the RD design and our preferred method (equation (4)) is that the RD design only uses observations around the cutoff and fits two separate functions of bids, 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 RD design. 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 estimates of the treatment effect based on the RD design are between -0.137 to -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 subgroup analysis based on the RD design. These estimates are similar in magnitude to those in panel A, except for the case under high auction prices. For this subgroup, the treatment effect is not only stronger than that under low auction prices, but is also statistically significant.

5 Decomposing the Selection 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 selection effect. We then show that the selection effect can be decomposed into a free-rider effect and a baseline 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 1 when the firm wins the auction and 0 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 customer baseline load can truly reflect the counterfactual load under the treatment assignment, then our estimate should be the same as that calculated by the utility company. However, if the customer baseline load 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 customer baseline load 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 free-rider effect and the baseline effect:

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

The free-rider 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 generates a negative free-rider effect. In addition, the baseline effect expresses the difference between the BAU load and the customer baseline load. If a firm inflates its customer baseline load, then a negative baseline effect will be expected, which also contributes to the bias component. Figure 5 also presents these two effects. Therefore, the utility company would over-estimate the load reduction when the free-rider effect, the baseline effect, or both, exist in the market.

Equation (6) suggests that using the observed data when firms *lose* auctions, we can compare load on baseline eligible days (for future winning days' baseline) to load on baseline ineligible days to detect the baseline effect. By contrast, detecting the free-rider effect is less straightforward because we never observe the counterfactual load Y_i^0 when $D_i = 1$. Instead, we use 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 load on losing days varies with bids to examine the free-rider effect. Note that we implement both tests for the baseline and the free-rider effects using only data on losing days.

Baseline Effect

To verify the baseline effect, we calculate each firm's average load at the daily level (from 10 a.m. to 10 p.m.) when they lose DR auctions. If the baseline effect exists, we expect to see 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 to indicate 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 baseline effect exists.

Table 6 provides the results for equation (7). In column (1), the coefficient associated with $\ln(DailyLoad)_{i,dm}$ is 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 the baseline-eligibility even under the non-linear specification. In conclusion, we do not find evidence for the baseline effect across all specifications.

Free-Rider Effect

If the free-rider effect exists, firms may bid lower to win the auction on their shutdown days, but this does not guarantee their success. To test for the free-rider effect, we can analyze whether lower daily bids are correlated with lower daily loads on the days the firms lose the auction. We test the free-rider 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 same-day 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 free-rider effect exists. In another specification, we allow the effect of 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 coefficients associated with bid segments to be negative if the free-rider 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 higher daily load, suggesting a free-rider effect for firms. In addition, columns (3) and (4) provide estimates of the regression model that explores the effect on load for 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 three bid segments. This pattern implies that firms tend to submit their bids at the lowest bid segment when their electricity consumption is the lowest, and so 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 over-estimates the load reduction from DR requests, and the bias component is driven by the free-rider effect from firms' strategic bidding behavior.

6 Policy Implications and Counterfactual Analysis

We have shown that without accounting for firms' strategic behavior, the current program overestimates their DR response. In this section, we compare paid load reduction over the entire sample period and its implied price elasticity to our estimates. Note that paid load reduction is calculated by CBL minus the observed load. To improve the program, we also consider an alternative way to determine winners in DR auctions. We provide two counterfactual exercises by the alternative merit order.

Total Load Reduction and Implied Price Elasticity

To quantify the extent to which the program overestimates its procured load reduction from DR requests over the sample period, we compare paid and estimated load reduction for each auction day. We use estimates at the individual firm level to calculate estimated load reduction. Figure 6 plots paid and estimated average daily reduction by month. Estimated monthly reduction ranges from 0.35 MW (July 2019) to 87.71 MW (May 2018), while 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 selection effect.

We also compare the implied price elasticity based on paid load reduction (i.e., CBL-based) to our estimates. Under the DR program, firm i's cost of electricity consumption on day d, denoted as 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 B.

To estimate the price elasticity based on CBL data, we use winners' load reduction in the data to back out each winner's CBL on each winning day.[13] By doing so, we construct load data for each DR request under two treatment outcomes: with or without the DR treatment.

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

We then stack the observed load and CBL for all DR requests in the data to create a single load variable $kw_{i,d}^{CBL}$ that has different treatment outcomes on the same DR request day. We regress $\ln(kw_{i,d})$ on the treatment variable $Treat_{i,d}$ to get the estimated load reduction; and regress $\ln(kw_{i,d}^{CBL})$ on $\ln(p_d)$ to estimate the price elasticity based on 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 in Table 2 and apply the procedures describe 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 predicted results.

Table 8 reports two sets of results. The first set (columns (1) and (2)) and the second set (columns (3) to (5)) of the results are obtained when the counterfactual load is constructed based on CBL and based on the predicted load, respectively. Specifically, columns (3) to (5) report estimates of the price elasticity based on estimated coefficients in columns (4) to (6) of Table 2, respectively.[14]

Results based on CBL data show that receiving a DR request is associated with a reduction of 0.684 log points (50 percent) of electricity consumption, and the associated price elasticity is -0.893. Previous studies of commercial and industrial 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 the 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 under-estimation of power producers' market power.

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

Counterfactual Analysis

The current program constructs its merit order of DR requests using bids as the only sorting criterion. Given that a large amount of paid but inframarginal load reduction is due to the selection effect from firms' strategic bidding behavior, we next consider using adjusted bids to construct an alternative merit order of DR requests. The idea behind the adjusted bids is to move firms without a significant estimated treatment effect (henceforth, nonsavers) down to the end in the merit order, and adjust the merit order of firms with a significant estimated treatment effect (henceforth, savers) based on their estimated coefficients and official performance ratios.

Specifically, for firm i without a significant estimated treatment effect, we multiply its bid by a large number (i.e., 10000); for firm i with a significant estimated treatment effect, its adjusted bid (b_i^a) is constructed as follows:

$$b_i^a = \frac{\bar{r}_i}{|\hat{\beta}_i|} b_i,$$

where $\bar{r}_i$, $\hat{\beta}_i$, and b_i, are firm i's official performance ratio, estimated performance ratio, and actual bid, respectively. To illustrate, consider two firms (firm 1 and firm 2) with their bids, official and estimated performance ratios equal to $b = (1.99, 2)$, $\bar{r} = (1, 1)$, and $\hat{\beta} = (0.1, 1)$, respectively. Firm 1's demand response is overrated because its treatment effect is only one-tenth of its official performance ratio. However, firm 1 is more likely to win DR an auction because its bid undercuts firm 2's. By contrast, their adjusted bids are 19.9 and 2, respectively, and so under the alternative merit order, firm 2 is more likely to win the auction than firm 1. We also note that the adjusted bids only affect the merit order without affecting the actual payment scheme after a firm wins an auction.

We perform two counterfactual exercises to examine the effect of using alternative bids to determine auction winners. In each exercise, we ask each auction to meet a target that it has already achieved in the data. The difference is that this time the auction needs to find winners based on alternative bids to meet the same target. In the first exercise, the target is the auction's total estimated load reduction.[15] In the second exercise, the target is the auction's total payout (a total budget target). Given a target, the auction then procures load reduction in the DR market based on alternative bids until it meets its target. We provide a hypothetical example to illustrate the idea of the counterfactual analysis in Appendix D. After winners are determined, we calculate the total payment and the total load reduction generated in the first and the second counterfactual exercise, respectively, and present the results in Figure 7.

Figure 7(a) plots the results from the load reduction target. Each dot represents the results from an auction. The horizontal and the vertical axes represent hourly payments under the actual bid and the alternative bids, respectively. Therefore, points below the 45-degree line represent cases when the alternative merit order (compared to the existing merit order) generates lower payment to participants. The results suggest that using the alternative merit order to determine winners can either maintain the total payment or result in a reduction in the total payment for the utility company in each auction of the sample. The results in Table 9 show that during the sample period, the total payments from adjusted bids are about 67% of those from actual bids. We also note that even though all of the payments go to savers under the alternative merit order, their total payments are still less than those from the current merit order.

Next, Figure 7(b) plots the results from the total budget target. The horizontal and the vertical axes are the procured load reductions under the actual bid and the alternative bids, respectively. We find that for each auction in the sample, using adjusted bids provides more load reduction than using actual bids. Table 9 shows that even though the total payments are the same in the both merit orders by construction, the total payment to nonsavers decreases

[15] For example, consider the case with two firms in an auction, where firm 1 and firm 2 have load reduction targets of 500 kW and 100 kW, respectively, and estimated performance ratios of 0.1 and 1, respectively. If both firms win the auction, the total estimated load reduction from the auction will be $500\times0.1+100\times1 = 150$ kW.

and is transferred to savers. Therefore, both the utility company and the savers benefit from the alternative merit order under the total budget target. Finally, the average cost per unit of load reduction is lowest (3.08 NTD/kW) in the case with adjusted bids and a load reduction target, followed by the case with adjusted bids and a total payment target (3.83 NTD/kW), and highest in the case with actual bids (4.59 NTD/kW).

7 Conclusion

This paper shows that firms bid strategically in DR auctions by bidding lower when their electricity consumption is low, resulting in an overestimation of the program's effectiveness. After adjusting for this selection effect, our analysis reveals that winning a DR auction reduces firms' electricity consumption by an average of 12% to 17%.

Several sources of inefficiency could emerge from firms' strategic bidding behavior in DR auctions. First, the program overpays for load reduction that would have occurred anyway without the program's monetary incentives. Our estimates suggest that about 50% of paid load reduction is inframarginal. Moreover, firms with volatile electricity consumption could bid strategically and undercut other firms in auctions, even when they have higher reduction costs. We show that incorporating estimates of the program's treatment effect on electricity consumption into the winner determination process could help to restore the efficient merit order. Last, an over-optimistic estimate of demand response from end-users could lead regulators to underestimate the market power in the supply side, which will give rise to even more welfare loss in the power industry.

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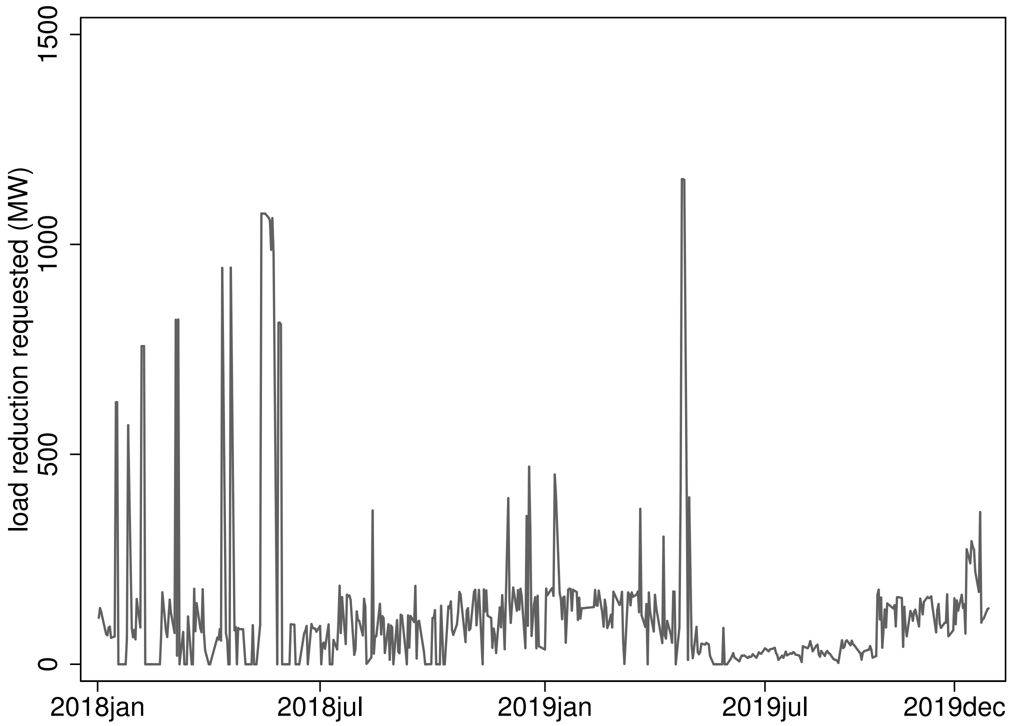
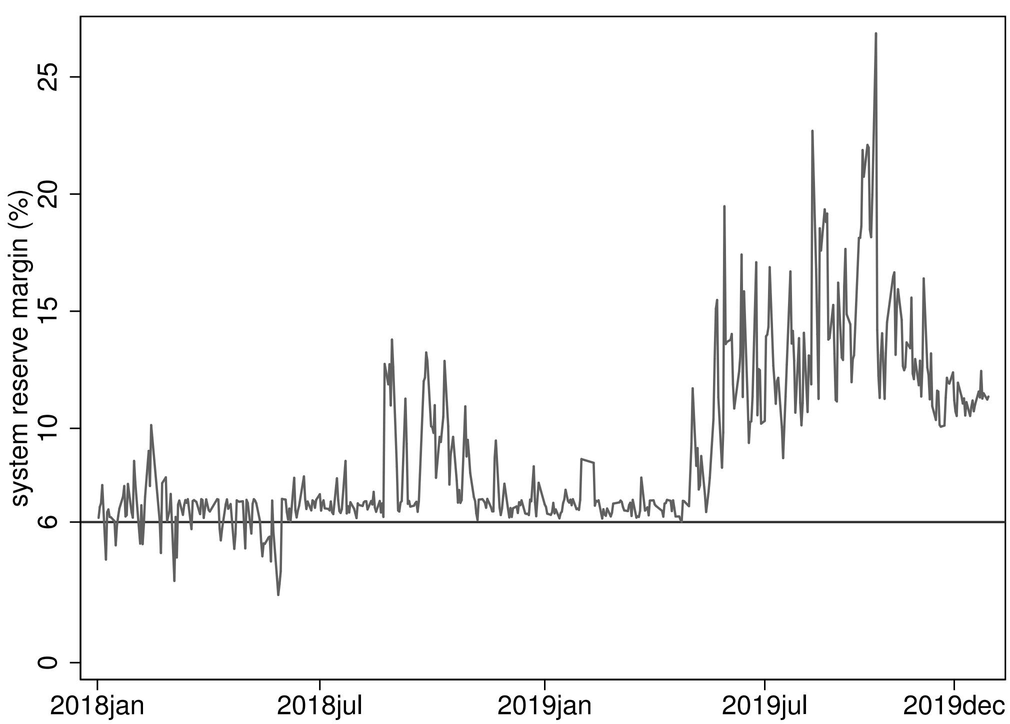
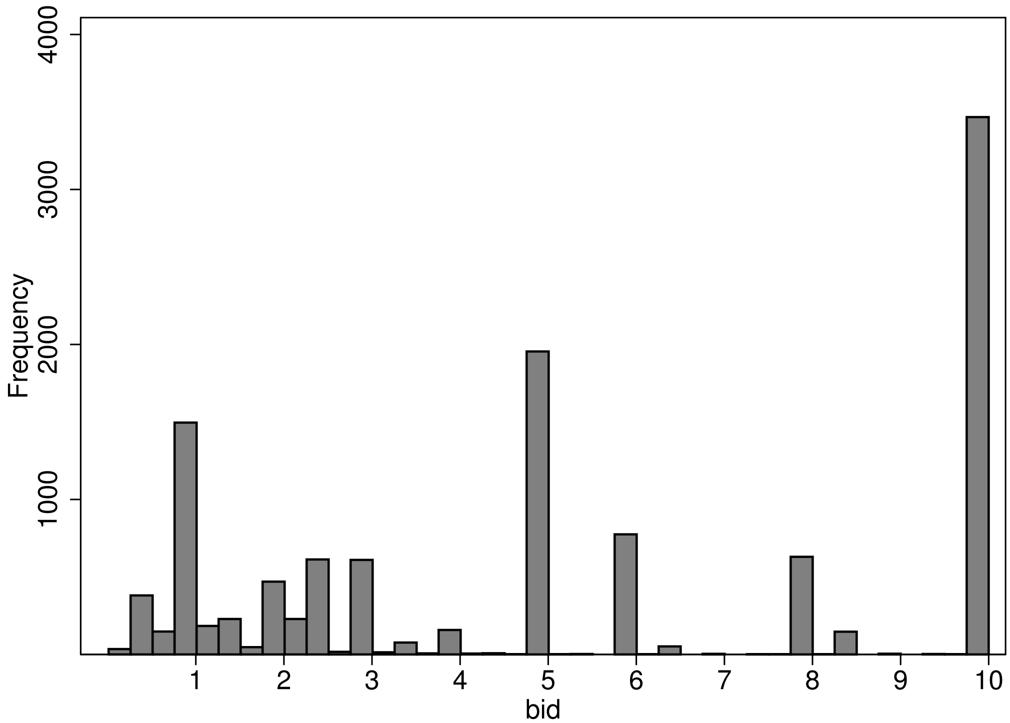


(a) DR requested

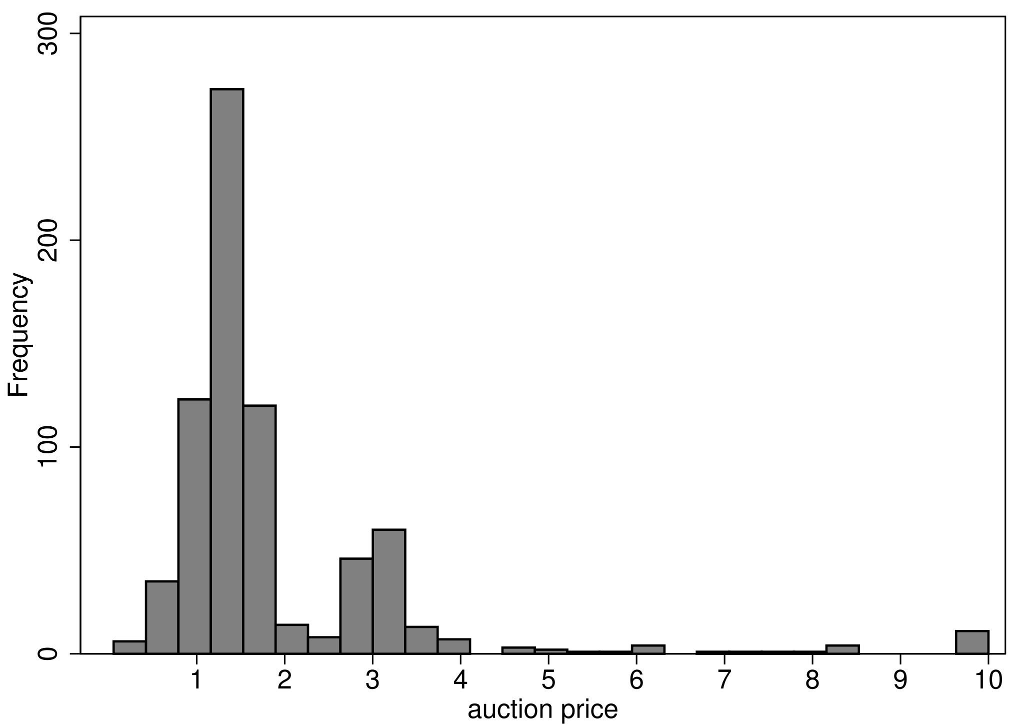


(b) Reserve margin

Figure 1: Load Reduction Requested and Reserve Margin

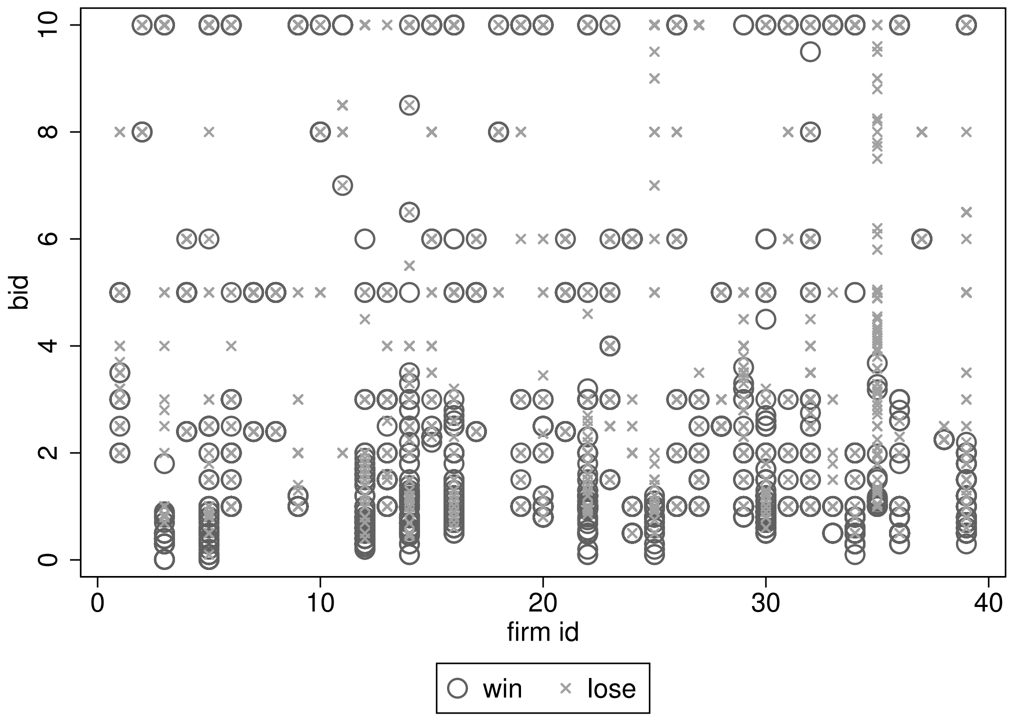


(a) Bid

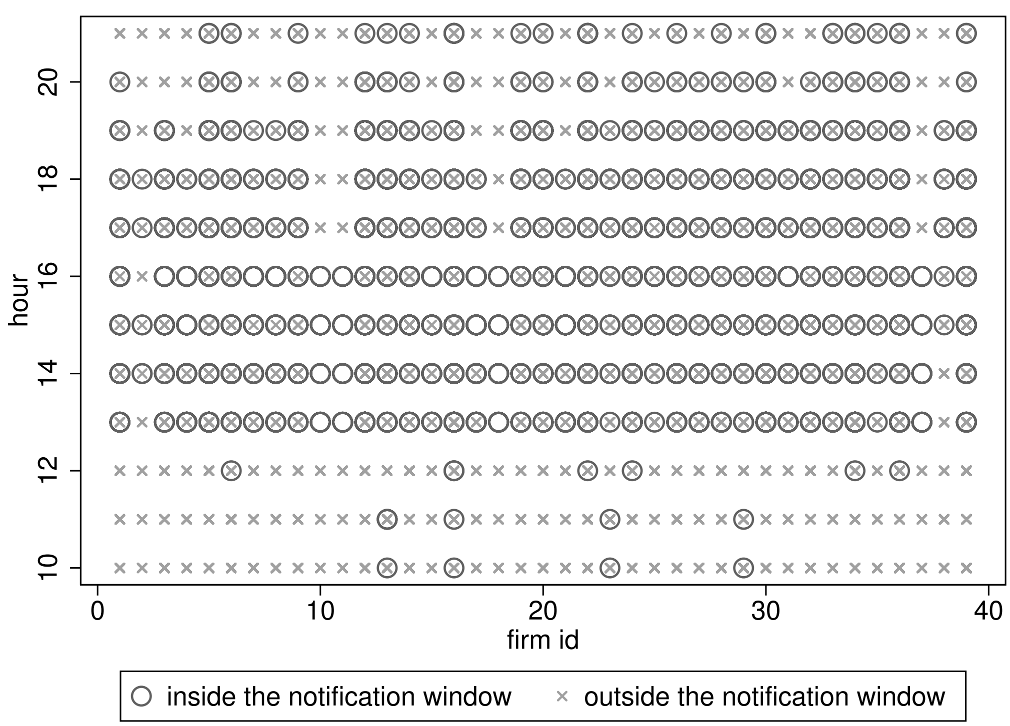


(b) Auction price

Figure 2: Distribution of Bids and Auction Prices

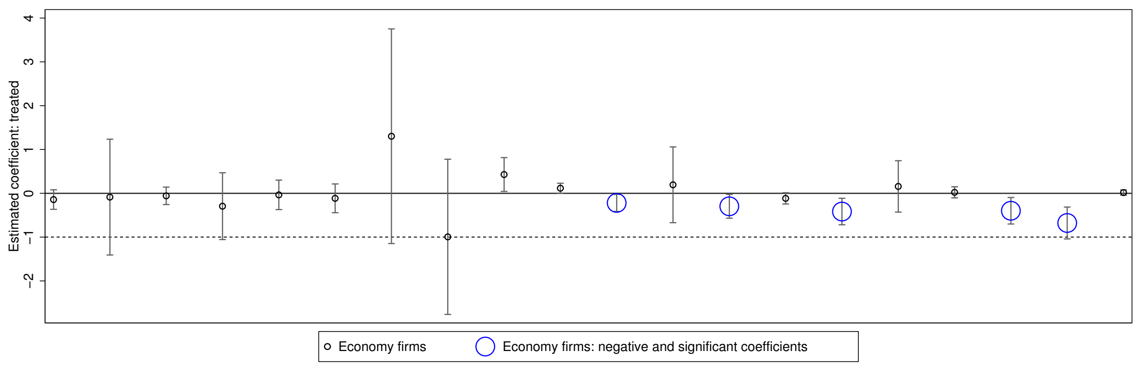


(a) Bids Submitted by Firm

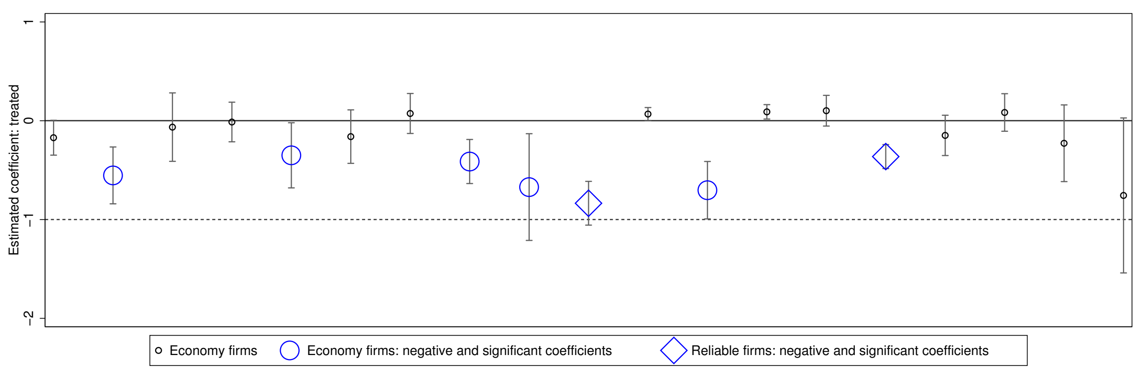


(b) Winning Notification by Firm

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: Heterogeneous Effects

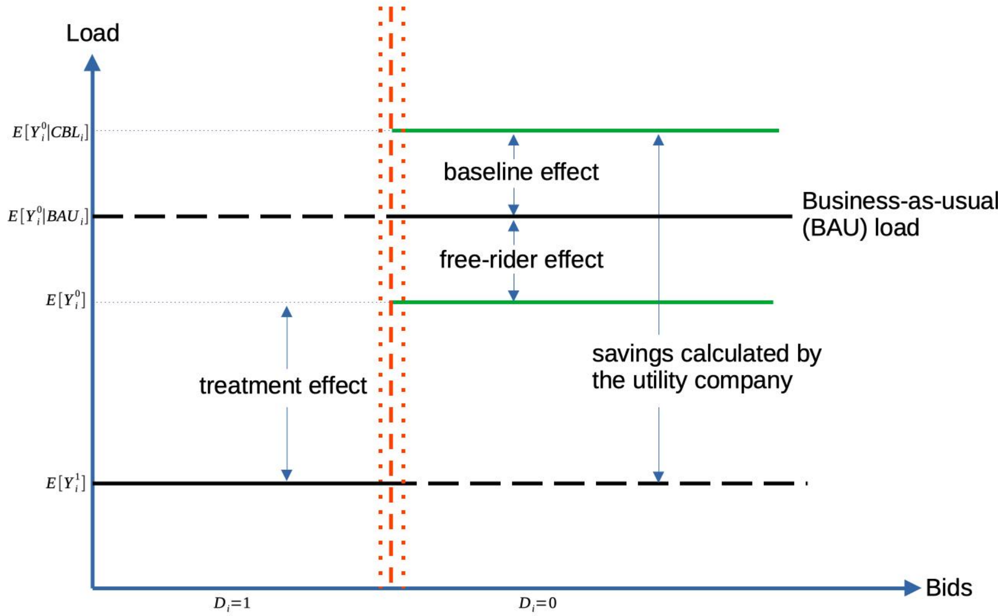


Figure 5: Decomposition of the Selection Effect

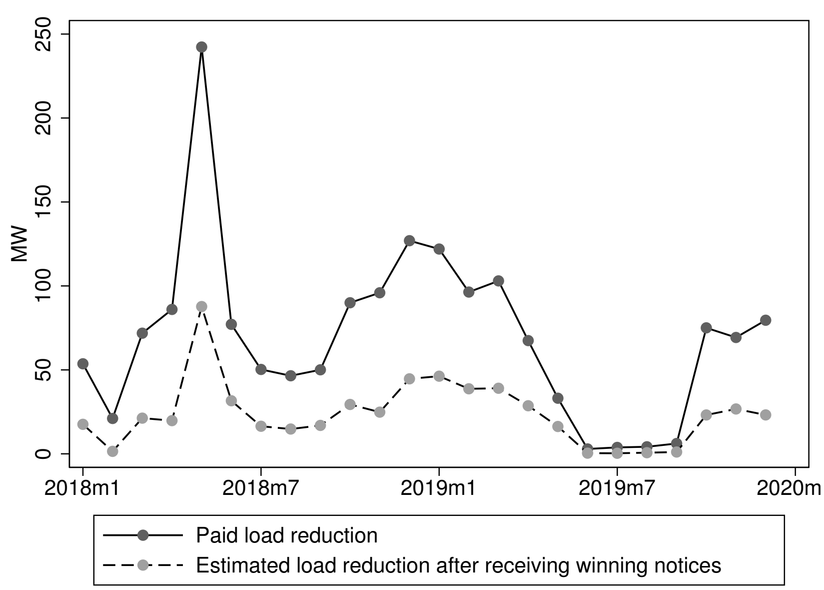
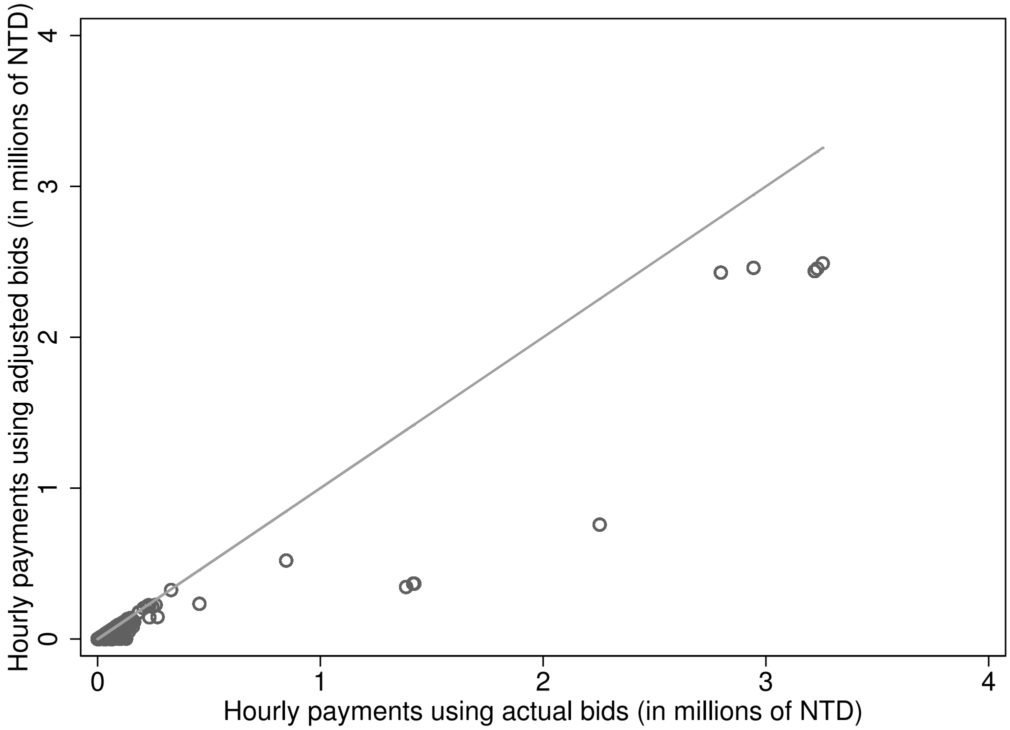
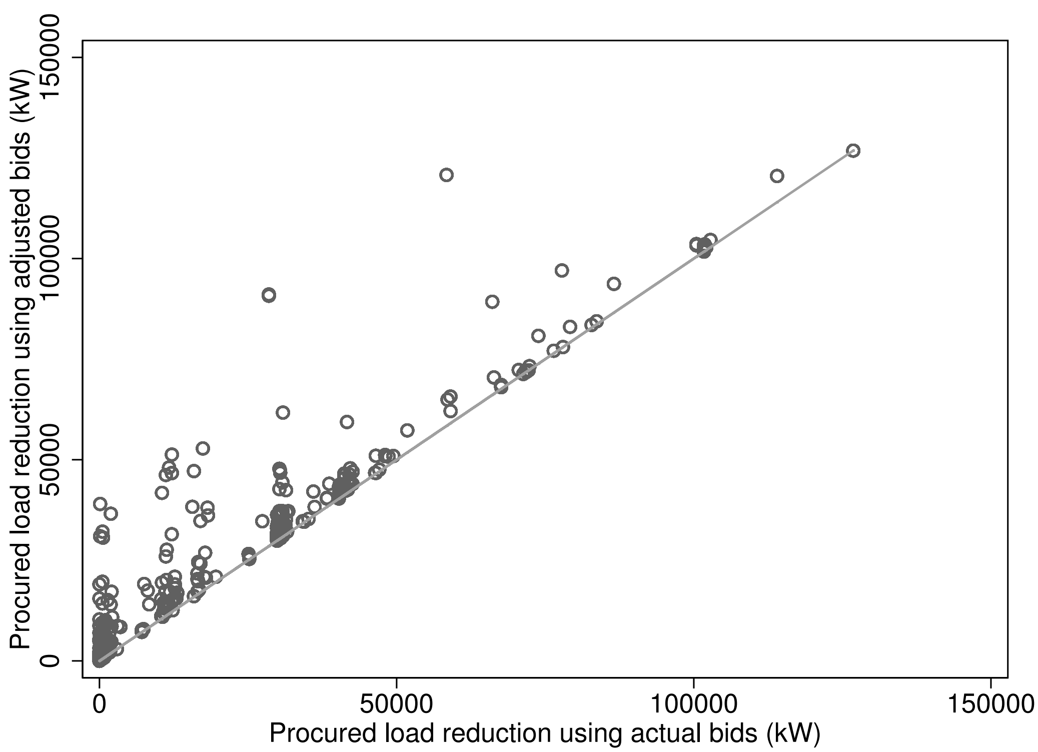


Figure 6: Estimated Average Monthly Load Reduction



(a) Load reduction target



(b) Total budget target

Figure 7: Alternative Merit Order: Results by Auction

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
Distance to the cutoff (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
Distance to the cutoff (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 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 with their load reduction target below (above) the median load reduction target (1500 kW). Economy (reliable) firms: firms select an economy (reliable) plan.

Table 2: The Effect of Receiving a DR Request on Electricity Consumption

	(1)	(2)	(3)	(4)	(5)	(6)
Treated	-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 but not treated	-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)	
Bid ≤ 2.5						-0.685**
						(0.056)
$2.5 <$ Bid ≤ 5						-0.437**
						(0.064)
$5 <$ Bid ≤ 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 in 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) Economic	(4) Reliable	(5) Price: low	(6) Price: high
Panel A: Regressions with bid controls						
Treated	-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: RD design						
Treated	-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)
Treated	-0.126*	-0.119**	-0.128**	-0.111**	-0.160**	-0.129**	-0.202**
	(0.063)	(0.041)	(0.040)	(0.043)	(0.029)	(0.040)	(0.036)
Win but not treated	-0.006	0.017	0.008	0.027	-0.011	0.008	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	0.002	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		0.004	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	0.096	0.077
	(0.189)	(0.034)	(0.142)	(0.107)	(0.078)	(0.097)	(0.084)
Bid^2	-0.067	-0.009**	-0.206**	-0.009	0.012	0.012	0.006
	(0.059)	(0.003)	(0.062)	(0.025)	(0.019)	(0.023)	(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**	6.551**	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 in bid	3	2	4	3	3	3	3
arcsinh transformation	N	N	N	Y	N	N	N
Drop missing auction price	Y	Y	Y	Y	N	Y	Y
Drop unreasonable gap price	Y	Y	Y	Y	Y	N	Y
10 am to 10 pm only	Y	Y	Y	Y	Y	Y	N
Observations	37957	138652	138652	139138	169901	138652	279759

Notes: The dependent variable is a firm's logged hourly load except for column (4), which uses the inverse hyperbolic sine (arcsinh) transformation of the hourly load. Data before 10:00 and after 22:00 are excluded except for 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)
Treated	-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
Effected 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 Baseline 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 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 Free-rider Effect

	(1)	(2)	(3)	(4)
Bid	0.074^{**}	0.074^{**}		
	(0.007)	(0.007)		
Bid ≤ 2.5			-0.646^{**}	-0.639^{**}
			(0.064)	(0.064)
$2.5 <$ Bid ≤ 5			-0.438^{**}	-0.433^{**}
			(0.082)	(0.082)
$5 <$ Bid ≤ 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 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)
Treated	-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 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 results in columns (4) to (6) of Table 2, respectively. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table 9: Counterfactuals

			Adjusted bids			
	Actual bids		Target: load reduction		Target: total payment	
	DR	Payment	DR	Payment	DR	Payment
	(1)	(2)	(3)	(4)	(5)	(6)
Nonsavers	0	47.08	0	0	0	12.90
Savers	37.73	125.92	37.73	116.38	45.22	160.10
Total	37.73	173.00	37.73	116.38	45.22	173.00
Avg. cost		4.59		3.08		3.83

Notes: This table reports total reductions in electricity (in gigawatt hours) and total payments (in millions of NTD) to firms for 735 auctions in our study. Columns (1) and (2) report the results when winner determination is based on actual bids, while columns (3)-(6) show the counterfactual results when winner determination is based on adjusted bids.

Appendix

A Payment Structure

Suppose an economy participant has won K auctions in month m. Denote each won auction as k, $k = 1, 2, ..., K$. 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 2 hours or 4 hours). The deduction ratio is a function of a 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.[16]

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:

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

[16] Denote an economy participant's performance ratio as 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.

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:

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

B Data Construction

Auction Price

The data do not include the auction price (i.e., the cutoff) for each auction. Figure B1 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 when a firm's losing bid is below the maximum winning bid from another firm (such as $b = 3$ in Figure B1). For firms in the consumption data, there were five auctions when auction outcomes were not completely consistent with their bids. We remove these auctions from the sample. We also exclude auctions when 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 when $b^{-1} = b^{+1} = b^0$, 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.

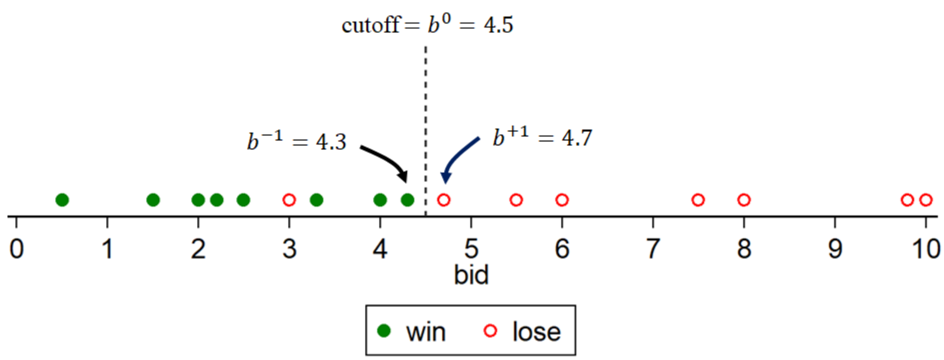


Figure B1: Construction of the Auction Price

Retail 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 load reduction based on the CBL data is only available for the daily level, we use p^r_{hd} to calculate an average price p^r_d for each notice window.

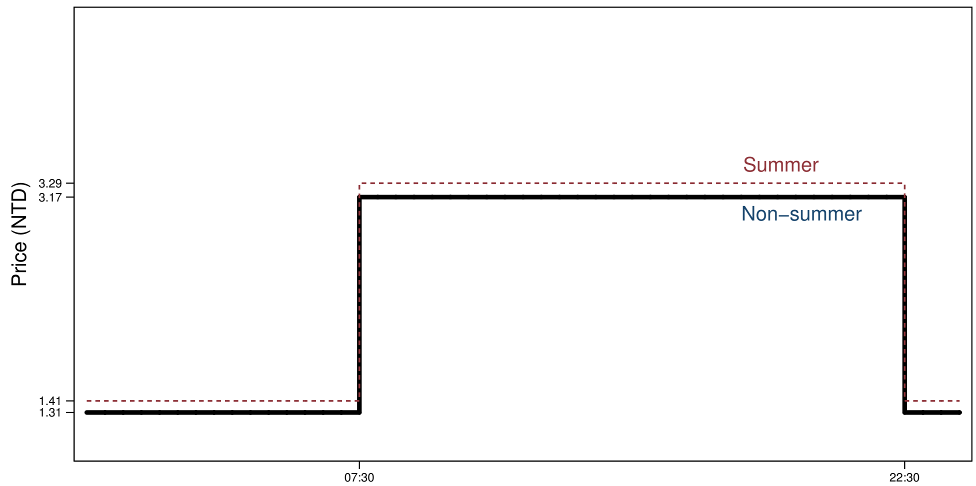
All industrial users are subject to time-of-use pricing. However, each firm could choose to enroll in a two-period schedule (peak and off-peak) or a three-period schedule (peak, semi-peak, and off-peak). We can find out p^r_d for each firm as long as we know whether it enrolls in a two-period or a three-period schedule. Unfortunately, we do not have access to such information. Figure B2 plots 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 B1. The results are qualitatively similar to those based on the two-period pricing schedule.

Table B1: Estimated Price Elasticity Based on Three-part Pricing Schedule

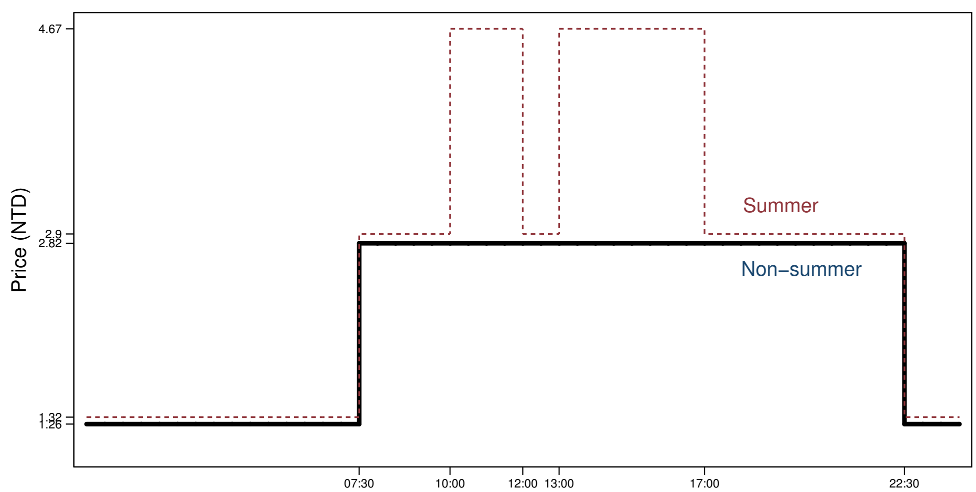
	Load based on CBL		Predicted load		
	(1)	(2)	(3)	(4)	(5)
Treated	-0.684**				
	(0.017)				
ln(price)		-0.858**	-0.245**	-0.181**	-0.256**
		(0.036)	(0.004)	(0.003)	(0.004)
Constant	8.236**	9.053**	7.422**	7.286**	7.437**
	(0.012)	(0.050)	(0.006)	(0.004)	(0.006)
Observations	5316	5316	5316	5316	5316

Notes: The dependent variable is 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 results in columns (4) to (6) of Table 2, respectively. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Figure B2: Retail Price



(a) Two-period Pricing Schedule



(b) Three-period Pricing Schedule

C Sample Representativeness

The consumption sample has a good coverage on participants who won the most auctions. Figure C1 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 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 C2 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.

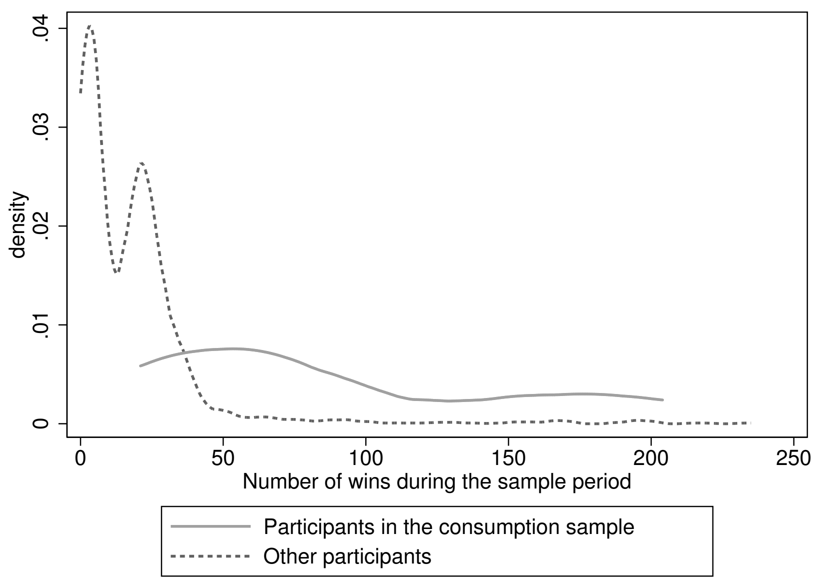


Figure C1: Number of Wins During the Sample Period

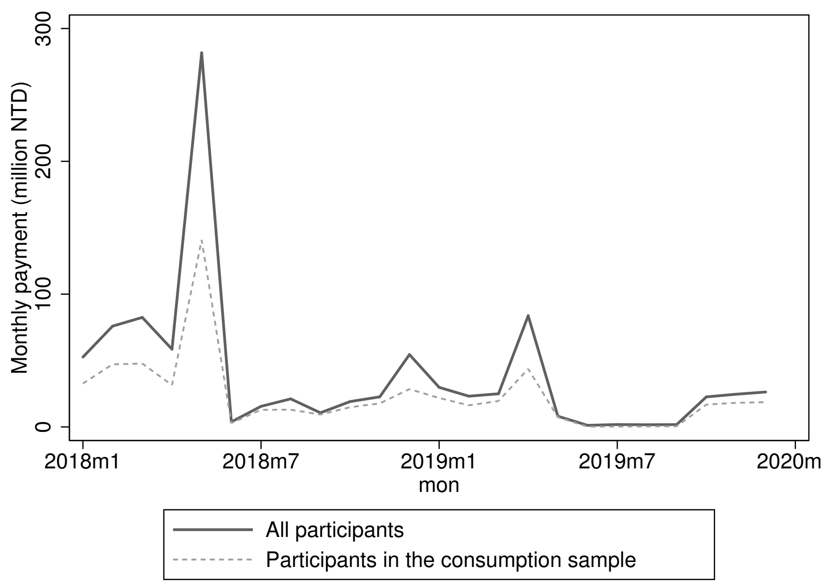


Figure C2: Monthly Payment

D A Hypothetical Example for the Counterfactual Analysis

In this section, we provide an example to illustrate how adjusted bids are used in our counterfactual analysis. Suppose we have an auction with three firms, whose attributes are shown in Table D1. We note that firm 1 is a 'nonsaver' as its estimated performance ratio is zero. To calculate each firm's estimated load reduction, we multiply its target by its estimated performance ratio, while the payment to each firm after sending a DR request is calculated by multiplying its target by its official performance ratio and bid. In an ideal situation, a firm that contributes more in payments and less in DR should be placed towards the back of the merit order in the DR auction. Based on this cost-effective criterion, the merit order in the DR auction for these three firms would be firm 3, followed by firm 2, and then firm 1. We note that the formula for adjusted bids $b_i^a = \bar{r}_i b_i / \hat{\beta}_i$ is designed exactly to achieve this cost-effective merit order.[17]

Table D2 presents the outcomes of the auction using the original bids and the adjusted bids. In the observed auction outcome using the original bids, firms 1 and 2 are winners in the auction, generating a total of 10 units of DR and 120 units of total payments. Then, we consider using alternative bids to determine winners in auctions in our counterfactual exercises. Note that under the adjusted bids, i.e., $(b_1^a, b_2^a, b_3^a) = (2000, 10, 2)$, we obtain the cost-effective merit order. The first counterfactual exercise shows that we can achieve the same total load reduction by making firm 3 the only winner of the auction and reducing the total payment to 20 units. By contrast, the second counterfactual exercise shows that under the same budget constraint, we can increase load reduction by making firms 1 and 2 the winners of the auction.

[17] For firm 1, we multiply its bid by a large number (i.e., 10000) to obtain its adjusted bid.

Table D1: Attributes of Firms for the Hypothetical Example

Firm	Type	Target	$\hat{\beta}$	$\bar{r}$	b	Contribution	
						DR	Payment
	(1)	(2)	(3)	(4)	(5)	(6) = (2) × (3)	(7) = (2) × (4) × (5)
1	Nonsaver	50	0	2	0.2	0	20
2	Saver	100	0.1	1	1	10	100
3	Saver	10	1	1	2	10	20

Notes: $\hat{\beta}$, $\bar{r}$, and b represent the estimated performance ratio, the official performance ratio, and the actual bid, respectively.

Table D2: Counterfactuals for the Hypothetical Example

Firm	b	Observed outcome			b^a	Target: total reduction			Target: total payment		
		Win	DR	Payment		Win	DR	Payment	Win	DR	Payment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1	0.2	1	0	20	2000	0	0	0	0	0	0
2	1	1	10	100	10	0	0	0	1	10	100
3	2	0	0	0	2	1	10	20	1	10	20
Total			10	120			10	20		20	120

Notes: b and b^a represents the observed bid and the adjusted bid, respectively.