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 over-estimation of electricity reduction by at least 50%.
- We show that the over-estimation works mainly through **an adverse selection effect**, in which firms bid low to win auctions when they anticipate low electricity consumption.

Introduction

- Demand response (DR) programs inform users about market conditions and give them incentives to reduce electricity consumption when it is in short supply. However, 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).
- A DR auction collects bids and reduction targets from participants and finds a market-clearing price to balance the DR market. Participants with bids lower than the auction price will win the auction, and each of them will receive a reward based on the amount of their electricity reduction and their winning bid.
- 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.
- **Research questions**: Do firms bid strategically in DR auctions? If so, what is the treatment effect of winning DR auctions on the reduction of electricity consumption?

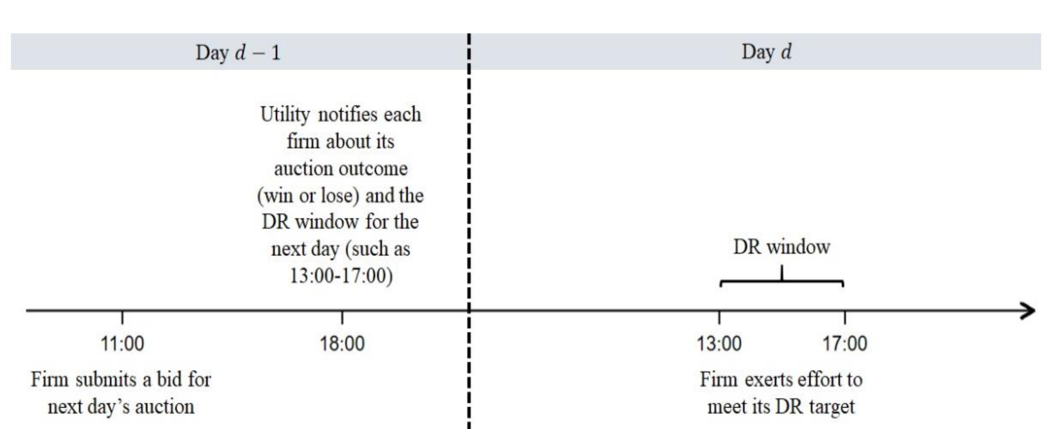

Figure 1. The Timeline of a Demand Response Auction

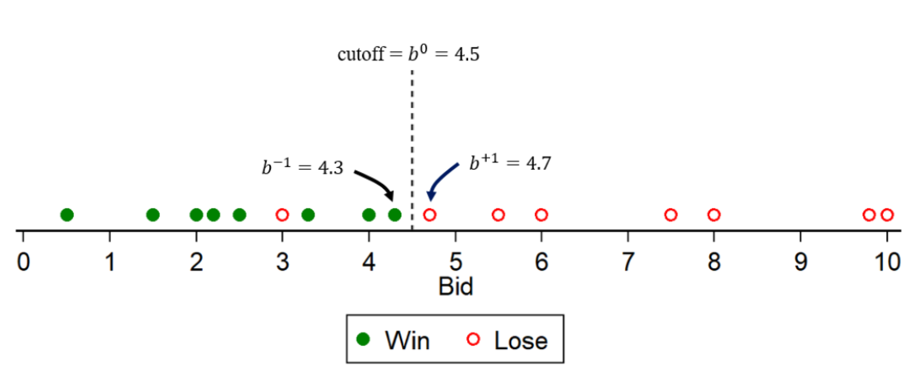

Figure 2. Construction of the Auction Price

Methods

- **Setting**: We study 39 Taiwan steel producers' behavior in participating daily pay-as-bid DR auctions for two years.
- **DR auctions**
  - Customer baseline load (CBL): electricity consumption on the previous five **losing** workdays
  - Rewards: bid × (CBL − actual consumption)
- **Data**: daily bids, auction outcomes, and hourly electricity consumption at the firm level
- **Estimating strategy**: We 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.
- **Testing channels of the strategic bidding effect**
- **Adverse selection effect**: when a firm places a low bid and consequently wins an auction on a day when it has scheduled maintenance.
- **Moral hazard effect**: when a firm deliberately manipulates its baseline consumption to boost its DR performance
- To test the adverse selection and the moral hazard effects, we 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.

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Results

- 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%).
- **Strategic bidding effect**: Once we control for the bids, the estimated load reduction in column (4) declines to 0.173 log points (16%). In column (5), 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.
- **Adverse selection effect**: Lower bid segments are associated with lower electricity consumption (column (4)). In particular, firms tend to submit their bids in the lowest bid segment (Bid ≤ 2.5) when their electricity consumption is the lowest (column (5)).
- **Moral hazard 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 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 relationship between electricity consumption and baseline eligibility. We do not find evidence of the moral hazard effect in any of the specifications.

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

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

Table 1. The Effect of Receiving a DR Request on Electricity Consumption

	(1)	(2)	(3)	(4)	(5)
Win in window	-0.465**	-0.524**	-0.588**	-0.173**	-0.182**
	(0.039)	(0.040)	(0.039)	(0.038)	(0.039)
Win outside window	-0.406**	-0.467**	-0.441**	-0.037	-0.045
	(0.033)	(0.035)	(0.034)	(0.035)	(0.037)
Bid				0.078**	
				(0.006)	
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**	7.422**
	(0.007)	(0.144)	(0.145)	(0.144)	(0.148)
Firm by hour-of-day fixed effects?	No	No	Yes	Yes	Yes
Control variables	No	Yes	Yes	Yes	Yes
Observations	138652	138652	138652	138652	138652

Notes: The dependent variable is a firm's logged hourly load. 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 2. 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 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. $^{+}\ p < 0.10$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$.

Discussion

- 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 estimates show that failing to account for the strategic bidding effect leads the program to overestimate its load reduction by at least 50% (Figure 3). The program's CBL-based price elasticity is also three to four times higher than our estimates that account for firms' strategic bidding behavior (Table 3).

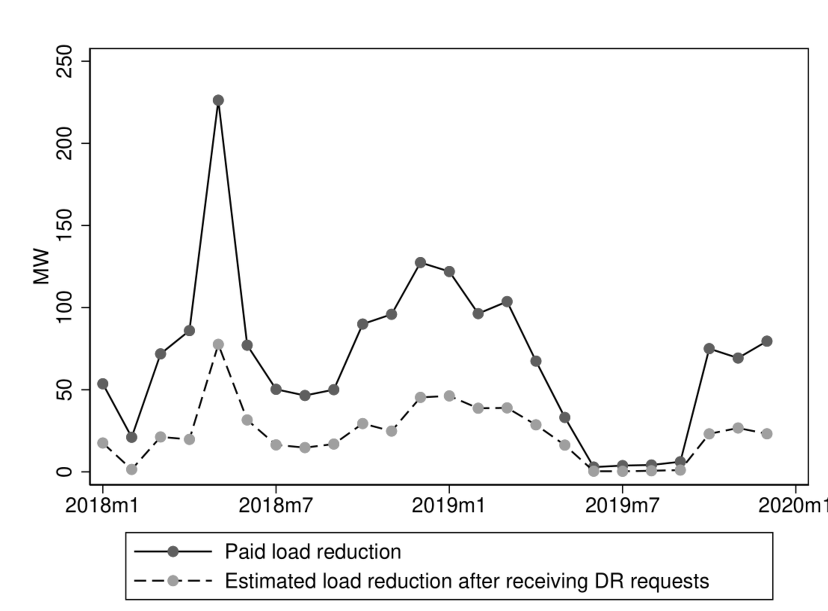

Figure 3. Estimated Average Monthly Load Reduction

Table 3. 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 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 3, respectively. $^{+}\ p < 0.10$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$.

Conclusion

- 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.
- 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.

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