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Abstract

My thesis is aimed at understanding how market design and policy affect firms' competition in the context of U.S. electricity markets and, based on the findings, how policies can be altered to improve welfare. The U.S. deregulated electricity markets are organized through multi-unit auctions and they are of interest for two reasons: (1) they are undergoing constant changes in market design, which provides a rare experimental field to enrich economists' understanding of important topics such as complex auction mechanisms and information friction; and (2) as an essential part of the ongoing global energy transformation, electricity markets, operated with a lot of money at stake, have significant implications for private and social welfare.

I study several important evolutions in electricity markets. These evolutions include renewable energy development, which implies a change of the paradigm in electricity market competition; capacity market design, which aims to provide additional payment and incentives for thermal capacity to stay operational; and retail deregulation, which allows more flexible retail pricing and demand-side strategy. Each of these papers is described in detail below.

In the first chapter, "The Value of Wind Information in Wholesale Electricity Market: Evidence from U.S. Midwest," I study how wind forecasting information affects strategic competition among electricity producers. In the Midwest market, firms that operate both thermal and wind plants have better forecasts about wind generation than firms that only own thermal plants. In theory, there is no a *priori* answer to whether wind uncertainty would lead to more or less efficient competition. Using detailed price and bid data, I find empirical

evidence that wind generation not only brings significant uncertainty to market supply, but also affects local market structures through transmission congestion. I also find that thermal bidding is more responsive to wind realization for firms that have better wind information. I then construct a strategic bidding model to estimate firms' private wind information, which determines their beliefs about local competition and explains their supply bids. I find that my model — with estimated information parameters — predicts firms' bidding behaviors and actual market results better than the standard oligopoly model of price competition. Using the model, I predict that when all firms are provided accurate wind information, it would greatly increase consumer surplus and market efficiency.

The second chapter is titled "Paying for Scarcity at the Right Time: Evidence from PJM Capacity Market Reform." In the U.S. deregulated electricity market, capacity market payment is designed as additional compensation for keeping sufficient capacity to stay operational. However, its traditional design of constant yearly payment detaches from actual generation performance and does not reflect real-time scarcity for capacity. As the result, it has little binding effects for generators to actually be available in electricity production. This paper investigates a recent capacity market reform in the Pennsylvania-New Jersey-Maryland (PJM) market, which added performance incentives that adjust producers' capacity payment based on actual output and market demand needs. Using PJM's staggered transition to this new design and generators in its neighboring market with the similar old design as a control group, the matched difference-in-differences results show that the reform mitigated strategic bidding incentives for generators and reduced their average bid price by 10%. This greatly improved allocative efficiency in PJM market production and led to large savings in total production cost. A preliminary estimate on the net benefit of the reform is about 1.5 billion dollars for PJM in 2016, after combining both the capacity payment increase in capacity market and production cost savings in energy market.

In the third chapter, "Does Retail Deregulation Create Strategic Wholesale Buyers? Evidence from the U.S. Midwest Electricity Market," I focus on how demand-side deregulation affects the electricity market. Specifically, I study whether electricity retail deregulation brought strategic buyers into the wholesale market with sequential market settings. I find that electricity buyers in retail-deregulated regions strategically split their purchase between the day-ahead market and the spot market. Specifically, they tend to underbid more in the day-ahead market when the day-ahead price premium is higher. In contrast, no such strategic behaviors are found for buyers in retail-regulated regions. This is consistent with deregulated buyers' incentives to minimize procurement costs. The increased flexibility in the demand-side bidding also helps mitigate some of the producers' market power that created the day-ahead price premium in the first place. By exploiting a retail policy change in Illinois which greatly increased the power purchased by competitive retailers, I find their strategic bidding in the wholesale market results in lower market prices when compared to retail regulated regions. This finding suggests the potential benefits of demand-side deregulation for improving production efficiency and consumer welfare.

Chapter 1

The Value of Wind Information in Wholesale Electricity Market: Evidence from U.S. Midwest

1.1 Introduction

The U.S. electricity market is experiencing a rapid rise in the generation capacity of wind power. Wind is the top energy source adding to electricity capacity in the U.S. in 2019,[1] and the total installed wind capacity in the U.S. is approaching 100 gigawatts, accounting for about 17% of electricity generation.[2] However, the significant penetration of this energy source has introduced challenges to the market due to its intermittency. Wind power production relies on the wind, which by its nature is volatile. This creates significant uncertainty in market competition. For example, in the U.S. Midwest market, wind generation can vary from 0% to 30% of market demand within days.

1. U.S. Energy Information Administration (EIA). See Figure A.15 that maps out the electricity capacity additions by energy source.

2. "States' Renewable Energy Ambitions", National Conference of State Legislatures, 2019, "http://www.ncsl.org/research/energy/states-renewable-energy-ambitions.aspx".

Due to its variability, wind generation is costly to predict and a wind forecast is not commonly available for all market players. Good location-specific forecasts for wind generation require massive amounts of data, computing power, and human resources to develop a forecasting model. Currently, in some electricity markets, market organizers only provide such forecasts to firms owning wind farms to facilitate wind power planning and dispatch. Firms owning only thermal plants,[3] in contrast, do not have access to such forecasts and must compete in wholesale electricity auctions with little knowledge about potential wind generation. The goal of this paper is to understand how wind uncertainty and wind information which reduces that uncertainty affect market competition and market efficiency. From a policy perspective, this paper specifically addresses the question: should all firms be given accurate wind forecasts when they compete in wholesale electricity market?

In wholesale electricity market, all power producers compete by bidding full supply curves in a centrally organized auction to meet demand every hour. Since auctions are scheduling market production hours in the future, actual market conditions such as demand and wind generation are unknown to producers at the time they bid. But wind generation has important implications on market competition; it not only brings uncertainty to market supply, but also affects market structure through transmission congestion.[4] When transmission lines between regions are congested, firms are segmented into separate local markets with different local competition and market prices. A firm in the congested region faces less competition and can further push up the market price for increased profit if it can predict wind generation and the resulting congestion before it happens. This paper utilizes the richness of marginal cost and bidding data to identify the role of wind information in firms' strategic behaviors. Specifically, for power producers, what is the value of wind information in learning about their competition and improving profit? For consumers and the market, will

3. Thermal power plants include steam-turbine, combustion-turbine and combine-cycle generation units, fuelled by coal, natural gas, oil, or nuclear.

4. In markets with rapid wind development, wind power is one of the main drivers for the changes in power flow and transmission congestion across hours. See Figure A.16 from GENSCAPE showing that wind power development increases transmission constraint frequency in Midwestern states.

more informative wind forecast improve market efficiency and reduce consumers' electricity costs?

The welfare implications of market players holding more information are theoretically ambiguous when considering the strategic behaviors of firms. Many empirical studies in industrial organization focused on market inefficiency when firms use the information about competition to their advantage and exercise market power. However, imperfect information can also generate inefficiencies when it makes firms deviate from the oligopolistic behaviors predicted in a full-information model. In the paper, I theoretically show that the price effect of increased wind information is unclear when comparing the bidding from an informed firm and an uninformed firm. In fact, informed bids that best respond to different market conditions could lead to either more or less inefficiency (higher or lower market price on average) than uninformed bids that best respond to the expectation, depending on the magnitude of the uncertainty created by wind in residual demands. This motivates my empirical analysis to quantify the welfare implications of wind information.

I conduct my analysis in the U.S. Midwest market (MISO), which operates with more than 20% of wind capacity in the U.S. I start by using detailed price data to infer local market definitions as determined by transmission congestion in each hour, and use the market definitions to explore the effect of wind generation on market structure. I find that wind generation has significant impacts in shaping market structure, which determines a firm's local competition. In particular, this impact is load-dependent: when demand is relatively low, wind generation is the main driver of congestion; however, when demand is high and the market is already congested, additional wind generation adds to local supply and alleviates congestion.

Based on this data-driven evidence of the wind generation effect on congestion, I test if firms respond in bidding when wind generation changes their local competition and steepens or flattens their residual demand. More importantly, I test how such a response might differ by whether wind forecast information is available to the firm or not. I track the supply curves of 15 major firms from 2012 to 2016 in the MISO real-time market, seven of which own both thermal and wind units, thus were provided wind generation forecasts by MISO. Eight firms lack such information as they do not own wind units. I find that both types of firms respond to higher demand by submitting a less competitive bid, while only firms with wind units also respond to wind supply shocks. Specifically, how they adjust their bidding slopes at different demand levels closely tracks the load-dependent patterns of wind impacts on market structure. This strongly suggests that firms with wind information do recognize this complicated impact of wind generation and act on it. The results are robust to controlling for firms' own wind generation, confirming that the direct effect of wind generation on firms' supply and its indirect effect on market structure play different roles in shaping firms' bidding strategy.

To better explain the bidding strategy of firms with different wind information, I construct a formal structural model of strategic bidding where firms best respond to their own beliefs about market competition given the information they possess. In the model, firms first approximate residual demands they expect for the actual hour from a mixture of informed and uninformed distributions of the previous auctions. The informed distribution consists of residual demands in the previous auctions that are matched by both ex-post demand and wind information, so it is closer to the ex-post market conditions that a firm will face. Meanwhile, the uninformed distribution matches only with ex-post demand information, so it is approximating actual residual demands with much less precision. Then firms choose best-response bids while they weigh the expected residual demands from the two distributions differently given the wind information they have. In this way, the model takes into account the impact of wind information in firms' belief and bidding formation, as better-informed firms will put more weights on residual demands drawn from the informed distribution. Fitting the optimal bids solved for different weights to the actual bidding, I can recover the optimal weight as each firm's information parameter, which represents the extent of wind information for each firm.

The estimation from my structural model shows that firms with wind units bid as if they are putting a weight of 0.88 on the informed distribution, which is close to ex-post, and a weight of 0.12 on the uninformed distribution. To the contrary, firms without wind units bid as if they weight the informed distribution by 0.26 and the uninformed distribution by 0.74, consistent with the lack of wind forecast information when they bid. I also show that my model with the estimated information parameters predicts the actual auction clearing price for each firm better than the ex-post optimal price predicted using the standard oligopoly pricing model.

I use the structural model to quantify profit and welfare impacts of wind information in two counterfactual simulations. First, I explore the changes to each firm's private profits when unilaterally changing their bid from considering no wind information to considering perfect wind information. For both types of firms, I find that giving perfect information to a single firm could reduce its losses by 35%-47% compared to ex-post optimal profit. Second, I simulate the changes to market welfare when moving from a baseline case of only wind firms having perfect wind information to a policy counterfactual when all firms are given perfect wind information. I find significant welfare improvements from this policy change in both consumer surplus and market production efficiency. The policy counterfactual reduces the market price by 3.4% on average, which is equivalent to a reduction in wholesale power procurement cost of $45,000 per hour. In addition, as major firms on average bid more competitively and produce more when given perfect information, this replaces costly production from small firms and reduces the total production cost especially during peak demand hours. As the result, the market production cost decreases by 2.8%. This reveals a potentially large improvement in electricity market efficiency from what would be a straightforward policy of providing wind forecast information to all production firms.[5]

5. The magnitude is substantial even when compared to a bigger policy change that happened in many electricity markets during 1999-2012: according to the estimation in Cicala [2017], the transition from command-and-control operations to the wholesale electricity market design reduced total production cost by 5-8% in the U.S.

Related Literature.— This paper makes several contributions to the previous literature. First, it relates to the economic literature studying the impacts of renewable energy, but focuses on the information and competition channels, which are less examined. Previous literature in this vein includes Fell et al. [2018] and Bushnell and Novan [2019] that focus on the direct welfare impacts of renewable energy on market price and pollution, when renewable supply replaces thermal generation. Specifically, they note that transmission constraints might prevent the full realization of social welfare improvement from renewable energy growth. In addition, several studies examine the competitive behaviors of wind farms and firms that own wind units. The theoretical work by Acemoglu et al. [2017] considers the changes in firms' optimal strategy when wind source is added to their thermal generation fleet; Ito and Reguant [2016] finds empirical evidence that independent wind farms use their information advantage about their actual production to arbitrage between day-ahead and real-time prices in the Spanish electricity market. My study documents that wind generation, through its impacts on transmission congestion, has broad implications for all production firms. I further test and confirm that firms do recognize the impact of wind and respond to it when possessing wind information.

Second, this paper contributes to the industrial organization literature on how uncertainty or information friction affects firms' bidding strategies in the auction setting. The theoretical work dates back to Klemperer and Meyer [1989], and recent empirical studies include Hortaçsu and Kastl [2012] that finds financial traders use their customers' information to their own advantage and extract additional profits in the Canadian treasury bond market. Several studies particularly focus on the welfare implications of increased information for firms in energy market auctions. Henricks and Porter [1988] and Fabra and Llobet [2019] find that when firms have good information in an auction, it facilitates seemingly collusive equilibria, while Vives [2011] and Holmberg and Wolak [2018] show market competition can be enhanced when private information is made public. In my study, I focus on a case where firms have different private information about wind generation in electricity market auctions.

Empirically I do not find that the firms with information advantage coordinate their bids with each other. Instead, the results show that more information induces more competition in bidding than less information, thus improving market efficiency and consumers' welfare.

Third, my study adds to the electricity market research that examines power producers' strategic behaviors in the auction-based market. Pioneer work from Wolak [2000], Borenstein, Bushnell and Wolak [2002] and Wolak [2003] highlights the susceptibility of wholesale electricity market to market power exercises from power producers and measures this market power in oligopoly competition models. The later work in this literature further develops the model to better characterize firms' bidding behaviors in this market. For example, Gans and Wolak [2008] and Bushnell, Mansur and Saravia [2008]) examine how firms' forward contract affect their incentives to exercise market power and their bidding strategies; Hortaçsu and Puller [2008] and Hortaçsu et al [2019] consider firms' different sophistication levels in their optimization and finds that large and more sophisticated firms bid close to profit-maximizing oligopoly model, while small and less sophisticated firms significantly deviate from the model prediction; Reguant [2014] studies the Spanish electricity market and demonstrates the importance of considering the complementarity between startup cost and marginal cost in measuring firms' market power exercise and explaining their seemingly sub-optimal behaviors. My paper adds to this literature and explores how information friction can also induce differences in firms' bidding and their deviations from optimal strategies, in the context that newly-developed wind power introduces significant uncertainty to market competition. I show that a large part of heterogeneity in firms' bidding can be explained by different information available to them when forming their beliefs and optimizing their bids based on the beliefs. I also provide empirical evidence that lack of information could induce more deviation and more inefficiency beyond firms' market power exercises that are traditionally considered in full-information or symmetric-information models. My study closely relates to recent empirical IO research that tries to understand how firms compete in complex and fast-changing market environments, such as Doraszelski, Lewis and Pakes

[2019], which demonstrates that the models of adaptive learning and fictitious play better predict firms' behaviors in the U.K. electricity frequency response market than a perfect information equilibrium model does.

The rest of the paper is organized as follows. Section 1.2 gives background and institutional details about wholesale electricity market competition and wind power operation in the U.S. Midwest. Section 1.3 presents an analytical framework and discusses the theoretical prediction of how bidding with uncertainty might affect market efficiency. Section 1.4 describes the data and reports how hourly local market definition is estimated using price data and a machine learning technique. Section 1.5 presents reduced-form evidence on the impacts of wind supply on market structure and firms' bidding strategies. Section 1.6 presents the structural model of firms' optimal bidding and explains how the wind information they possess is estimated from the model. Section 1.7 presents the results of the counterfactual simulations using the structural model, and finally Section 1.8 concludes.

1.2 Institutional Background

1.2.1 Production Competition in Midwest Electricity Market

I study the biggest restructured electricity market in the U.S. Midwest (MISO), which began in 2005 after electricity market deregulation divested traditionally integrated electric utilities into separate firms for power generation, transmission/distribution, and retailing. A profit-neutral system operator organizes the wholesale market in which firms that own power plants sell wholesale power to transmission and distribution utilities through centrally organized auctions. Based on the auction results, the system operator will centrally dispatch production to meet demand at every location across a vast integrated electricity grid covering over 13 states in the U.S.. The MISO market includes central, north and south regions. This study only focuses on the central and north region, as the south region only joined the market very recently with no wind capacity and limited transmission connection to the central and north.

The auction proceeds in multi-unit uniform-price format, in which each generation of firms first submit supply bids, the system operator calls firms to produce in increasing price order until total demand is met, and pays all accepted output at the highest accepted price offer. Firms are allowed to bid up to 10 price-quantity pairs for each generation unit they own; therefore, they have very flexible strategy spaces in their supply bid, which essentially is a full supply function consisting of a set of price-quantity steps.

Most electricity markets plan and schedule power production long before it actual happens. Months before the operating day, there is a bilateral contract market, where power producers can sign long-term forward contracts with utility firms. One day before the operating day, there is a day-ahead market, where producers and utilities bid in the auction, and based on the auction results, they make initial plans of power delivery for the next day. The final market before actual production is the real-time market, for which firms need to submit their final bids by 11:30 pm before the operating day.[6] Then after actual demand and wind generation are realized on the operating day, real-time market clears with firms' real-time supply bids, actual wind supply, and actual demand. Firms then start production and get payment, according to the real-time market clearing results in each hour.

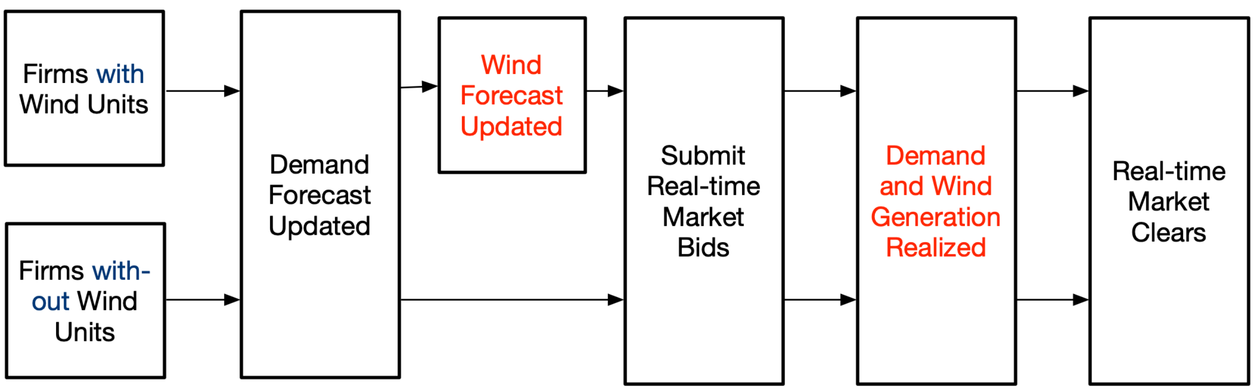
In the following analysis, I will focus on firms' bidding behaviors in the real-time market, although the impacts of forward contracts and the day-ahead market on the real-time supply bids will still be considered. The real-time market is most relevant to this study for two reasons: (1) it is the only market that clears with actual demand and wind supply, so accurate demand and wind forecasts are most useful. In contrast, the day-ahead market clears with demand bids and wind units' bids, which could deviate significantly from the actual quantity or the forecasting quantity; (2) real-time market allows me to focus on firms'

6. Theoretically, firms are allowed to change their real-time bids until half an hour before each operating hour on the operating day. However, the data shows that very few firms do so, except for the wind units, which need to adjust their bids to wind fluctuation from one hour to another. This is consistent with the industry reports from generating firms that it usually takes hours to prepare the bids; therefore, it might be difficult to further update their bids based on any last-minute information.

response in bidding when holding their supply capacity fixed. In the day-ahead market, different wind and demand forecasts could also lead to different start-up decisions of each generator. Incorporating start-up decisions in firms' strategies requires a dynamic model and accurate measures of startup costs, which are beyond the scope of this study.

The sequence of events for real-time market competition are summarized in Figure 1.1. All firms submit real-time bids without knowing actual demand or wind supply. While demand forecasts are commonly available to all firms when they bid, the wind forecasts are not. Specifically, for firms with wind units, MISO provides wind forecasting information on their market portal. Firms without wind units do not have access to such information. After firms submit their bids, real-time market clears in each operating hour, when actual demand and wind generation are realized.

Figure 1.1: MISO Market Timelines



Notes: The figure shows the timeline of production firms' participation in MISO real-time wholesale market up until the actual production. Source: Midcontinent Independent System Operator (MISO), "Business Practice Manual Vol.2: Energy and Operating Reserve Markets", 2018.

One supplemental note for demand-side participation in the wholesale market is that utility firms can also submit demand bids with price-quantity pairs in the day-ahead market. However, because of the lack of real-time pricing in electricity retail, in general, real-time demand is considered inelastic. Therefore, for real-time market auctions, firms are only allowed to bid the final demand quantity they need. For power generation firms, the more relevant demand measure is residual demand, which is the inelastic total market demand minus the supply offers of all other competing suppliers. The slope of the residual demand is determined by the willingness to produce by other available suppliers at different market prices. The more elastic the slope, the more price-sensitive other competitors' production, and the more difficult it is for the firm to exercise market power (raise price markups or withhold output).

1.2.2 Wind Power and Transmission Congestion

More than 40% of the total wind capacity in the U.S. has been installed in the Midwest region, because of its rich wind resources. In the MISO, installed wind capacity is approaching 20 GW in 2019. The current record for wind production was on March 15, 2019, when wind generation peaked at 16.3 GW, representing about 29% demand in MISO north and central region in that hour.[7] Wind capacity continues to grow, with more than 30 GW in MISO's interconnection queue waiting for approval and installation.

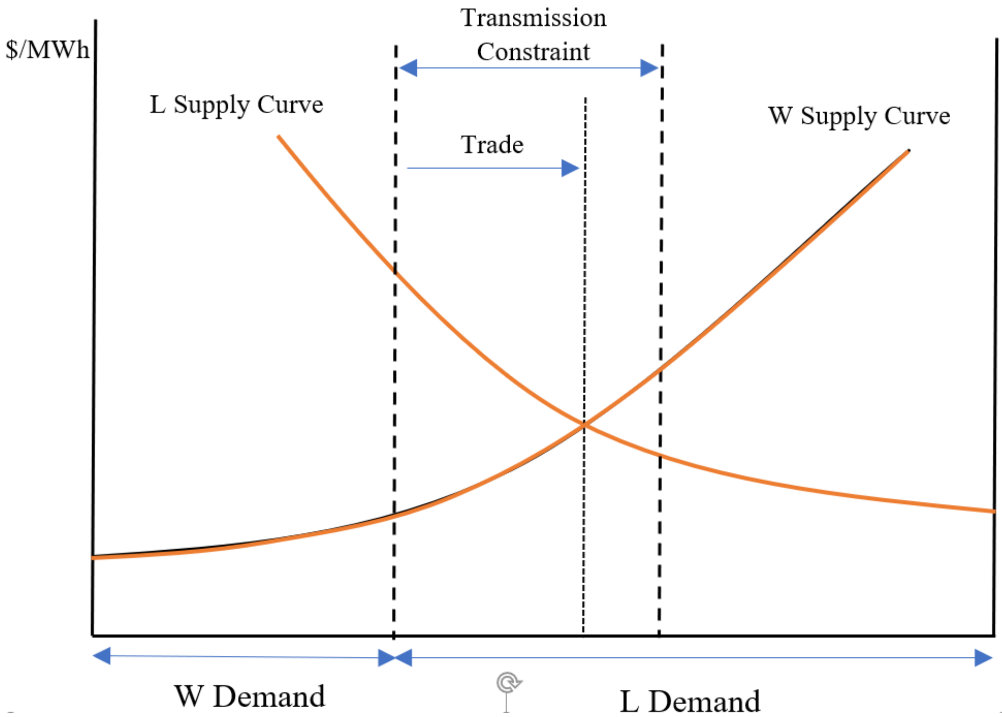
The large penetration of wind power has great impact on power flow in the electric grid. On one hand, wind power is supplied with zero or even negative price; hence, it is always dispatched first. On the other hand, wind generation is volatile; therefore, the dispatch of other resources could be quite different from one hour to another, even when market demand is unchanged. To see how this directly relates to congestion and market structure, I illustrate in Figure 1.2 using the power trade between two regions, similar to the model in Cicala [2017]. Congestion is a grid condition in which power flow is limited across a power line because of insufficient transmission capacity. When congestion occurs, any further power flow on the constrained line becomes impossible, and the two local regions connected by the line are segmented.

Figure 1.2 depicts two regions: region W is where wind units are located and region L is the demand center. The width of x-axis represents the total demand, which consists of two

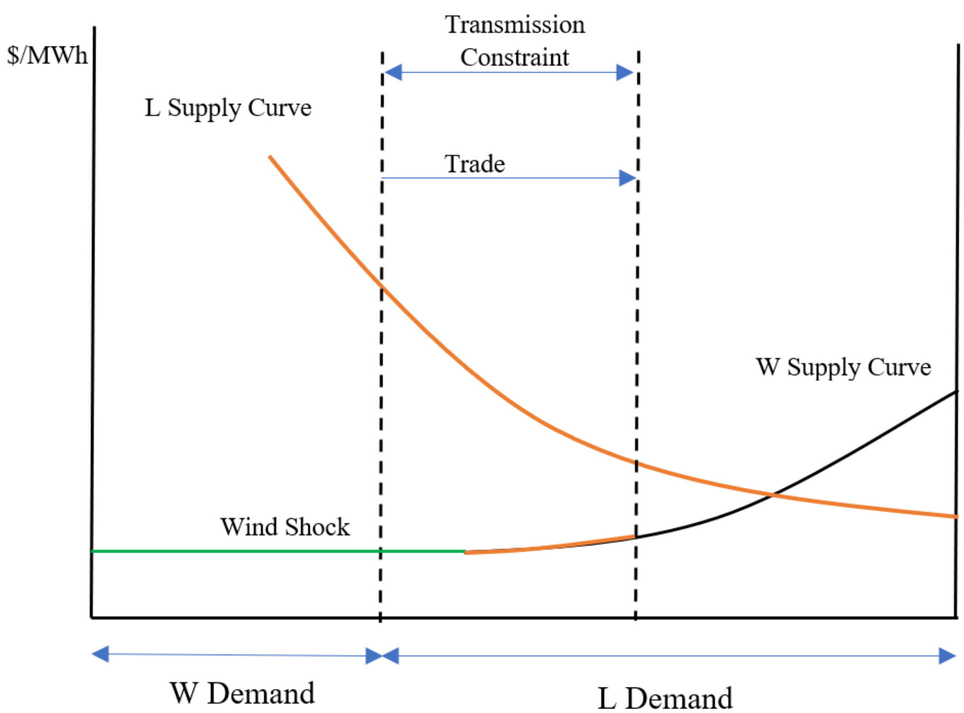
7. MISO IMM Quarterly Report: Spring 2019, Potomac Economics, 2019. *https://www.potomaceconomics.com/wp-content/uploads/2019/06/IMM-Quarterly-Report*$_{S}$*pring* – 2019$_{F}$*inal.pdf*

Figure 1.2: Two Region Illustration of Transmission Congestion

(a) When market is not congested



(b) When market is congested



Notes: The figure shows a two-region power trade model. Panel A illustrates a case with no congestion between region W and region L. Panel B shows a case with congestion between the regions. The part marked with orange color in two regions' supply curves represents thermal competition a firm in region L faces in each scenario.

local demands from W and L. The total production cost of meeting these local demands can be minimized when the two regions trade supply. However, the amount of power that can be traded is constrained by the transmission lines connecting them, and is at most the width between the two vertical dashed lines. Panel A in Figure 1.2 shows when the transmission is not constrained and the whole market clears at the intersection of the supply curve in region L and the supply curve in region W. The trade allows lower-cost region W producers to supply more than their local demand and export to load center L, reducing the market clearing price and total production cost. Panel B shows when additional wind supply surges in region W, the transmission is constrained by excessive supply trying to transport through the line. This results in two local regions becoming congested with different local clearing prices; the price in region W is lower, which incentivizes firms to produce less, while region L is priced up to encourage more local production.

Firms under these two scenarios face very different competition. When the two regions are uncongested as in Panel A, a firm in region L is competing with all other suppliers in the market. However, in the congested case in Panel B, some generation in region W (marked in black in region W's aggregate supply curve) is blocked from competing with the firm. Consequently, the firm faces a less elastic local residual demand, enabling it to exercise more market power.

Alternatively, congestion can also be created by demand increase in a local region. Such increase in demand leads to local supply shortage and higher local prices, attracting more generation transported into the region. This would block further transmission and create congestion in the imported transmission lines.

1.2.3 Wind Generation Forecasting in MISO

MISO started to develop and use the wind power forecasting in market operation since 2011. The forecasts are generated at the pricing node level (where one or multiple wind units locate) as well as the region and market levels. The hourly updated forecast looks forward to the next six days, and the more granular five-minute forecasts are for the next six hours.[8]

From the central dispatch perspective, MISO relies on the data to manage transmission constraints and outages to maintain the reliability of the grid. MISO also provides such information on the market portals of wind unit owners, in case the owner does not have their own forecasting, or their forecasting deviates much from the MISO prediction, to ensure the wind bids are close to what they can produce the next day.

It is generally costly to come up with such forecasting, especially for firms that do not operate wind units. Wind Forecasts are the combination of different models and diverse set of input data. First, high-definition real-time satellite data is necessary to develop wind weather forecasts around the certain heights where wind farms operate. Second, on-site operating specifics and metering data from each wind turbine are required, including accurate location, hub height, turbine historical performance, and production curve. Finally, different physical and statistical models are constructed and simulated to predict each unit's production, given the weather forecasts.

MISO constantly collects all the operating information from wind unit owners and contracts with a third-party vendor to develop the wind forecasting. In 2015, MISO' budget was 31.4 million dollars for the "outside services", among which wind forecasting was one of the main expenses.[9] With the investment, MISO gets relatively accurate hourly wind generation forecast. In 2015, the forecasting error on average is around 5.4% one day ahead, and around 4.6% four hours ahead.[10]

8. Porter and Rogers [2012], National Renewable Energy Lab (NREL) report, 2012.

9. "MISO 2016-2018 Budget Planning Presentation", MISO, December 10, 2015, "https://cdn.misoenergy.org/20151210%20BOD%20Item%2007a%20Operating%20and%20Capital%20Budgets110764.pdf"

10. "Uncertainty Management in MISO Real-Time Systems: Needs, Opportunities and Challenges ", MISO, June 2017, "https://www.ferc.gov/CalendarFiles/20170623124115-RT_Uncertainty_MISO.pdf"

1.3 Analytical Framework

I now characterize a firm's optimal bidding strategy following share auction bidding framework in Wilson [1979] and Hortaçsu and Puller [2008]. The purpose of this model section is two-folds: First, I demonstrate that a firm's bidding strategy depends on the shape of residual demand, which is derived based on local competition and market structure. Thus when wind generation or market demand affect the market structure, the firm that has this information should adjust its bidding accordingly. Second, for a firm that is uninformed about the realization of wind generation and is bidding against uncertain wind realizations, I use the model to understand whether its bidding will, in expectation, lead to higher or lower market price and market quantity than an informed firm's bids.

1.3.1 Model Setup

I discuss a simplified model with a monopoly firm facing uncertainty about the two states of the world. Later in the structural estimation section, this is extended to a formal strategic bidding model with more realistic characterization of firms' market competition.

Assume there are two states of market structure: uncongested and congested. In the uncongested state, firm i faces more elastic residual demands, which is the inelastic total demand minus bids by all other suppliers. In the congested state, firm i faces less elastic residual demands as some suppliers are blocked by congestion to compete with firm i. In each state, residual demand is shifted by total demand variation, which is assumed to follow an uniform distribution from $[d_L, d_H]$. I hold this demand distribution fixed for both states; therefore different slopes in residual demands can be considered as driven only by high or low wind generation, with the intuition discussed in the previous section.

For all the following results, with quantity (S) on the x axis and price (p) on the y axis, I denote a function as steeper if $|S'(p)|$ is smaller or $|p'(S)|$ is larger. Formally I define linear residual demands in the two states of market structure as follows:

(1) Flat residual demand (uncongested):

$D_1(p, d) = -b_1 p + \eta$

(2) Steep residual demand (congested):

$D_2(p, \delta) = -b_2 p + \delta$, where $b_1 > b_2 > 0$

η and δ represent uncertainty in total demand that shifts the residual demand. The distribution of total demand is known to all firms. In the following, I separately discuss the bidding strategy of a firm that also knows the realization of wind supply, thus knows the realization of residual demand type, and the bidding strategy of a firm that is uncertain about the realization of residual demand type. The marginal cost of the firm is assumed to be 0.

1.3.2 Optimization Problem

Firm i, as a monopoly, will maximize expected profit, conditioning on the distribution of residual demands it faces. Specifically, the expected profit is taken over all possible realizations of market clearing price:

$$\underset{s_i(p)}{max} \int_{\underline{p}}^{\overline{p}} [p s_i(p) - c_i(s_i(p))] dH_i(p, s_i(p))$$

where $H_i(p, s_i(p))$ is the probability measure for market clearing price p^c being lower than p, i.e. $H_i(p, s_i(p)) = Pr(p^c \leq p | s_i(p))$.

The case $p^c < p$ is equivalent to there be excess supply at price p, so $H_i(p, s_i(p)$ can be rewritten as follows: $H_i(p, s_i(p)) = Pr(S_i(p) \geq D_i(p, d))$

Using integration by parts and the Euler-Lagrange necessary condition, the point-wise optimal supply schedule $s^*(p)$ follows (omit i):

$$p - c'(s^*(p)) = s^*(p) \frac{H_s(p, s^*(p))}{H_p(p, s^*(p))} \tag{1.1}$$

This condition is derived following the same procedures in Hortaçsu and Puller [2008].

1.3.3 Bidding Strategy for an Informed Firm

Now we take the functional form of residual demand into the probability measure $H_(p, s(p))$:

$$H(p, s(p)) = Pr(s(p) \geq -b_1 p + \eta) = \Gamma(s(p) + b_1 p)$$

when firm i knows the slope of residual demand is b_1. $\Gamma(\cdot)$ is the CDF of total demand uncertainty η. Denote $\gamma(\cdot)$ to be the pdf of d, we have $H_s = \gamma(s(p) + b_1 p)$, $H_p = \gamma(s(p) + b_1 p) \cdot b_1$.

Taking them into the equation 1.1, the optimal bid in response to residual demand with slope b_1 can be calculated as follows: $s_1(p) = b_1 p$. Similarly, for residual demand with slope b_2, the optimal bid is $s_2(p) = b_2 p$.

The results above show that, when market structure makes residual demands steeper or flatter, a profit-maximizing firm should bid a steeper or flatter supply curve in response. I use this prediction in the reduced-form analysis to test how firms' bid responsiveness to wind generation depends on information they have on wind forecasts.

1.3.4 Bidding Strategy for an Uninformed Firm

Now I consider an uninformed firm's strategy when it is uncertain about actual state realizations of residual demands and believes the two states are equally possible. In this case, the firm will bid against a mixture distribution. In our model, the probability measure becomes:

$$\begin{aligned} H(p, s(p)) &= Pr(b = b_1) Pr(s(p) \geq D_1(p, \eta)) + Pr(b = b_2) Pr(s(p) \geq D_2(p, \delta)) \\ &= \frac{1}{2}\Gamma(s(p) + b_1 p) + \frac{1}{2}\Gamma(s(p) + b_2 p) \end{aligned}$$

Therefore we have $H_s(p, s(p)) = \frac{1}{2}\gamma(s(p) + b_1 p) + \frac{1}{2}\gamma(s(p) + b_2 p)$ and $H_p(p, s(p)) =$

$\frac{1}{2}\gamma(s(p)+b_1p)b_1+\frac{1}{2}\gamma(s(p)+b_2p)b_2$. Because η, δ follow uniform distribution, the firm's bid strategy against the mixture distribution is simplified as follows:

$$s(p) = \frac{b_1+b_2}{2}p$$

Note that this derivation is only valid when both types of residual demands are possible. Since demand is bounded at $[d_0, d_1]$, the space in which two types of residual demands vary do not fully overlap. As illustrated in Figure 1.3, for anywhere below the lowest RD_2 line, only residual demands with slope b_1 are possible, the uncertain bid overlaps with S^1 for this part. For anywhere beyond the highest RD_1 line, only residual demands with slope b_2 is possible; therefore the uncertain bid overlaps with S^2 for that part.

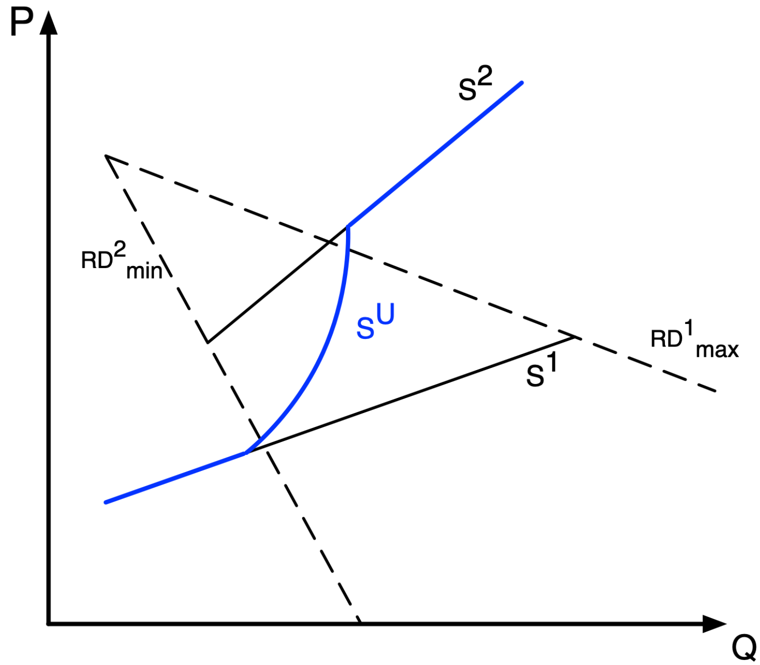
Using the two bids from the informed firms and the two residual demand lines, we can solve for the cutoff points for the three sections on the uncertain bid. A complete characterization of the uncertain firm's bidding strategy is as follows:

$$s^u(p) = \begin{cases} b_2 p & if\ p \geq \frac{d_1}{b_1+b_2} \\ \frac{b_1+b_2}{2}p & if\ \frac{d_0}{b_1+b_2} < p < \frac{d_1}{b_1+b_2} \\ b_1 p & if\ p \leq \frac{d_0}{b_1+b_2} \end{cases}$$

1.3.5 Intuition of Market Outcomes Under Uncertain Bid

Will an uninformed firm, in expectation, lead to higher prices and lower quantities than will an informed firm? This comparison can be illustrated in Figure 1.4. First, as shown in (a), when residual demands with b_1 are realized, the informed firm will bid S^1. Then, the uninformed firm with bid S^U will over-bid the price and under-bid the quantity compared to the informed firm. Second, as shown in (b), when residual demands with b_2 are realized, the informed firm will bid S^2. Then, the uninformed firm with bid S^U will under-bid the price and over-bid the quantity compared to the informed firm.

Figure 1.3: Illustration of Uncertain Firm's Bidding Strategy



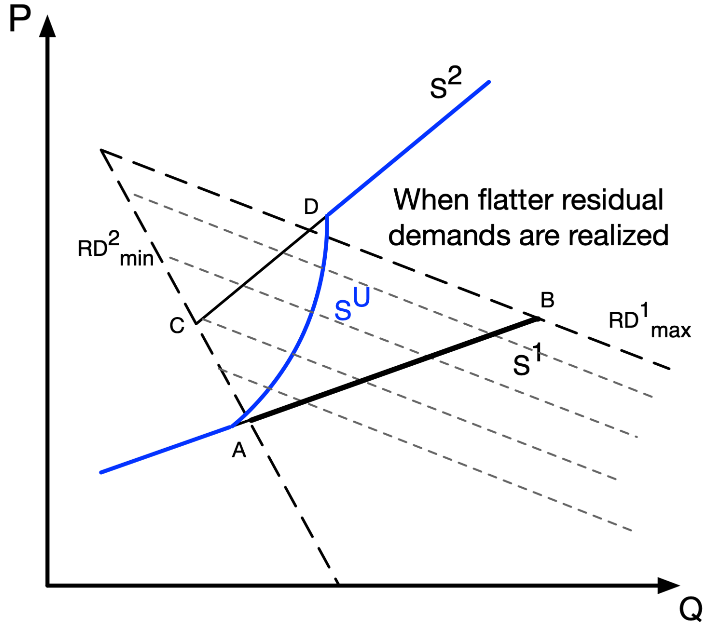
Notes: The figure illustrates the optimal bids for a firm certain about residual demand realizations and a firm uncertain about them. A certain firm will bid with S^1 in response to flatter type of residual demand realizations (RD^1), and bid with S^2 in response to steeper type of residual demand realizations (RD^2). A firm that is uncertain about the realizations of residual demand types will bid against a mixture distribution. Since demand variation is fixed and bounded, the two types of residual demands are not always overlapped. RD^1_{max} marked in the figure is the highest flatter residual demand (with highest demand realization), and RD^2_{min} is the lowest steeper residual demand (with lowest demand realization). So the uncertain firm will bid as same as S^1 for the space below RD^2_{min}, bid as same as S^2 for the space beyond RD^1_{max}, and bid in the middle for the space between (where both types of residual demands are possible).

Therefore whether the uncertain bid would increase or decrease market price depends on whether the overpriced cases under residual demands with b_1 dominates the underpriced cases under b_2. In Figure 1.4, this is the comparison between the residual demand realizations that pass through AB on S^1 and those that pass through CD on S^2. Higher the relative size of AB/CD, more residual demands with b_1 will pass through AB relative to residual demands with b_2 that pass through CD. Then, the uncertain bid is more likely to result in higher market prices on average.

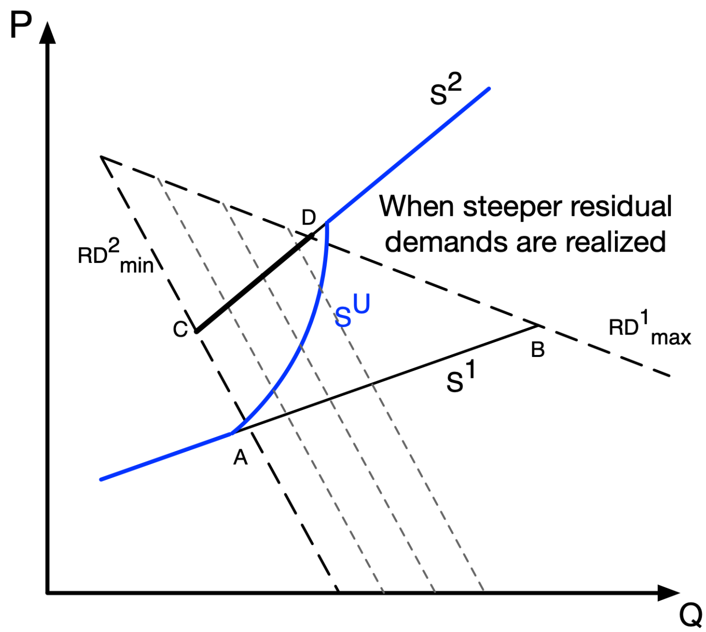
The interpretation of the relative size AB/CD is straightforward. This ratio is determined by the ratio of b_1/b_2, the slopes of two types of residual demand. When this ratio is higher,

Figure 1.4: Comparisons between Informed Bid and Uncertain Bid

(a) When residual demands with b_1 realized



(b) When residual demands with b_2 realized



Notes: The figure illustrates the intuition when comparing market results under the certain and the uncertain bid. The comparison should be focused on the parts where the uncertain bid is not overlapped with the certain bid. Thus whether the aggregate impact of uncertain bid would increase or decrease market price depends on the differences in market results under the residual demand realizations that pass through AB on S^1 and those that pass through CD on S^2. Higher the relative size of AB/CD, more often the uncertain firm will overbid the price under residual demands of b_1 type than underbid the price under residual demands of b_2 type. Then the uncertain bid is more likely to result in higher market price.

it means wind creates more uncertainty in the slopes of residual demands, and then the uncertain bid from the uninformed firm will more likely increase market prices, following the intuition above. In Appendix A, I analytically solve and compare the average market price and average market quantity between the informed firm's bids and the uninformed firm's bids. The results show that the uncertain bid will lead to lower market quantity, and higher average price on average when the slope ratio of b_1/b_2 is sufficiently large. Hence, it is an empirical question whether uncertainty about wind generation will increase or decrease prices on average, and this motivates my empirical analysis, presented as follows.

1.4 Data and Market Clustering

1.4.1 Data

The main data set used in this paper is the bidding data of production firms in MISO, which is publicly available on MISO's website. It contains a set of price-quantity pairs each firm submits for each of its units in hourly real-time auctions from 2013 to 2016. It also contains auction results for each unit in each hour, including cleared quantity and locational marginal price (LMP). This panel data has around five million observations each year, allowing me to track each generation unit's bidding behaviors over time.

This paper also benefits from detailed unit-level characteristics data and fuel cost data from U.S. Energy Information Administration (EIA): EIA-860 form and EIA-923 form.[11] These data can be linked to the bidding units in MISO data, which allows me to calculate the daily marginal cost measures for each thermal unit. Specifically, coal price is collected from the monthly transaction price of each plant in the EIA-923 "fuel receipts and cost" section, natural gas price is from EIA daily Henry Hub natural gas spot price and oil price is from EIA daily New York harbor No. 2 heating oil spot price. I combined fuel price data

11. I accessed this data through SNL Financial, an independent data company which verifies and cleans up the original EIA data.

with monthly operating heat rate data from EIA-923 to construct the cost data for each firm's coal, natural gas and oil fired generation units.

I focus on top 15 major producers in MISO central and north region during my study period. In total, they represent about 70% of the market share in market thermal capacity; 7 of them own wind capacity, and in total, they represent 80% market wind capacity. They have access to MISO's wind forecasts through their own market-bidding portal, and this study refers to them as "informed firms" or "wind firms". The other 8 firms only owned thermal power plants during my study period. They do not have access to MISO's wind generation forecasts before bidding in day-ahead and real-time market; thus referred as "uninformed firms" or "non-wind firms" throughout the paper.

Table 1.1 reports summary statistics for the two types of firms. "Wind firms" and "non-wind firms" are similar in a range of aspects listed in the table, including the states located, number of thermal power plants, and generation capacity in different energy sources.

Additionally, I use real-time market price, load and wind generation data posted by MISO in local market definition exercise, reduced-form analysis and structural simulation section. Real-time market price data reports nodal price or LMP at each pricing node every five minutes. Each node on the generation side represents the location of one generation unit or multiple generation units from the same power plant in the transmission grid. Each LMP contains three parts: the energy component, which is the same across the market, the congestion component, and the transmission loss component, which vary by each node depending on local transmission conditions. Real-time load and wind generation data are reported hourly at the regional level (MISO central, north, and south).

1.4.2 Local Market Definition

MISO and most other electricity markets use the "nodal-pricing" system, which segments market clearing and spot prices in different clusters of transmission nodes, according to transmission line constraints. In MISO north and central region, there are over 1,000

Table 1.1: Summary of Top 15 Major Generation Firms in MISO

	Wind Firms	Non-wind Firms
Number of firms	7	8
Plants locations	IA, IL, MI, MN, ND, SD, WI	IA, IL, IN, MI, MO, OH, WI
Number of thermal plants	121	95
Thermal capacity (MW)		
Largest	11,943	10,418
Smallest	3,805	2,946
Average	8,067	6,268
Avg. coal capacity	3,106	3,668
Avg. gas capacity	2,382	2,024
Wind capacity (MW)		
Largest	3,565	-
Smallest	335	-
Average	2,041	-

Note: This table summarizes several characteristics of top 15 major firms in MISO Central and North region, as of the end of 2015. They are defined into firms with wind units (wind firms) and firms without wind units (non-wind firms). Each unit's operating capacity is collected from the maximum available capacity reported in unit-level offer data in 2015. Thermal capacity includes steam-turbine, combustion-turbine and combine-cycle units, fuelled by coal, natural gas, oil, or nuclear.

different pricing nodes for generation units, and the LMP at each of the nodes determines the generators' payoff of their production. When there is no congestion, the prices across nodes are very similar.[12] However, there could also be significant price dispersion across the nodes during the hours of severe transmission congestion.

When congestion problems are prominent, the whole market can be considered as splitting into a set of local markets, in which the most competition a local producer faces comes from the local region. Thus, it has opportunity to exercise more market power than it would when competing in an uncongested market. Recent studies provide strong evidence that firms' strategic conducts in response to the transmission constraints have negative impacts on market efficiency and welfare, e.g., Davis and Hausman [2016] on the California electricity market, Ryan [2017] on the Indian electricity market and Woerman [2019] on the Texas electricity market.

It is important to account for the actual local markets in each hour, broken-off by congestion when modeling firms' bidding strategy; however, such local market definition is not readily available. Ideally, I would use the actual topology of the transmission grid in real time to define local markets, but that data is highly confidential to the public. Even if I do have the data, the computation for the whole market considering with binding transmission constraints would be enormous.

I instead exploit a statistical approach to define the local markets in each hour, following a similar method used in Zheng [2016] and Mercadal [2018]. Namely, this hierarchical clustering technique uses the fact that congestion creates price dispersion across different local markets, while the units in the same local market face similar transmission condition and receive similar prices.

Hierarchical clustering is a widely-used machine learning technique for finding groups in large datasets. In the context of local market divisions in the electricity market, each

12. In this case, prices can still vary because of transmission loss charge. This part is usually much smaller than congestion charge.

generation node initially represents one local market, or, in the jargon of the clustering method, a cluster. At each step, the two most similar nodes are merged into one cluster, based on a pre-defined similarity measure, which is measured by the price correlation between nodes. When each cluster has more than one node, a representative price for the cluster is calculated to minimize the within-cluster variance. Then the pair of clusters with minimum between-cluster price difference is merged first. This procedure is iterated until all nodes are in one cluster, or in my case, one market without congestion.

The richness of nodal pricing data in MISO facilitates this statistical approach. The real-time market clears every 5 minutes. Therefore, for each hour, there are 12 set of prices at each generation node, where each set of prices consist of energy price, congestion price, and transmission loss charge. In nodal pricing design, energy price is always the same across all units, reflecting the ideal results of market clearing without congestion. Congestion price and transmission loss price differ across locations. If the two nodes belong to the same local market in one hour, we would expect they coincide in their congestion components and transmission loss components in 12 prices over the course of the hour. The clustering method will assign them into the same cluster based on this.

The hierarchical clustering algorithm returns a set of potential market definitions. To find the best market definition that approximates the actual market structure most closely, I follow Mercadal [2018] and define a measure of fit for each market definition. Specifically, I calculate the market clearing price for each defined cluster (local market) using the aggregate supply bids and demand belonging to each cluster. Then, for each market definition, I calculate the objective function as the average difference between actual nodal prices and simulated nodal prices of generation units. The optimal market definition in each hour is the one that minimizes the objective function.

To summarize, I define local markets in each hour of real-time market using the following three steps:

1. Use similarities between nodal prices (12 congestion price + 12 transmission loss price

every 5 minutes for each hour) to cluster generation nodes into a set of potential local markets;

2. For a given definition, clear each local market using local demand and supply bids, and predict clearing prices for each node;

3. Choose the best market definition in each hour under which the simulated results best predict the actual results: $\underset{\boldsymbol{\tau}}{min}\ \frac{1}{N}\sum_i |\frac{\hat{p_i}^{\boldsymbol{\tau}} - p_i^{ob}}{p_i^{ob}}|$.

Table 1.2 reports the summary statistics of clustering results for all 8,744 hours in 2015.[13] The average prediction error, as measured by the difference between simulated and observed price, is quite small. For about 85% of hours, this prediction error is less than 10%. Considering the volatile nature of real-time market operation, the local market definition from the clustering algorithm captures the actual market segments reasonably well.

Table 1.2 reveals variations in local market size and local competition across hours. The market can be segmented into more than 74 local markets, with no more than 3 firms and 8 units in the smallest local market. Consequently, firms face very different competition over time.

Table 1.2: Summary Statistics of Market Clustering in 2015

Statistic	Mean	St. Dev.	Pct(1)	Pct(25)	Median	Pct(75)	Pct(99)
Across all hours							
Prediction error	6.1%	9.0%	0.0%	0.5%	3.0%	8.1%	47.8%
Number of mkts	8	13	1	1	3	9	74
Across all local markets							
Number of firms	60	45	3	18	42	118	127
Number of units	260	207	8	68	184	513	596
Capacity (MW)	32,754	26,246	987	8,595	23,848	62,097	81,071

Note: This table reports hourly local market definition results in 2015. 8744 hours are included in the table, with 16 of 8760 hours in 2015 are dropped due to missing data errors from original MISO data. The upper panel reports summary statistics at hour level, and the lower panel reports summary statistics at local market level after pooling all local markets in each hour together.

13. I dropped 16 of 8760 hours in 2015 because of missing data errors from the original MISO data.

Figure 1.5 provides the clustering results for two example hours in 2015. Each dot represents one or multiple generation units in each pricing node, and different colors represent different local markets. The figures show a good match between the clustering result and geographic proximity, although the algorithm uses only price information, not geographic closeness between units, to define local markets.

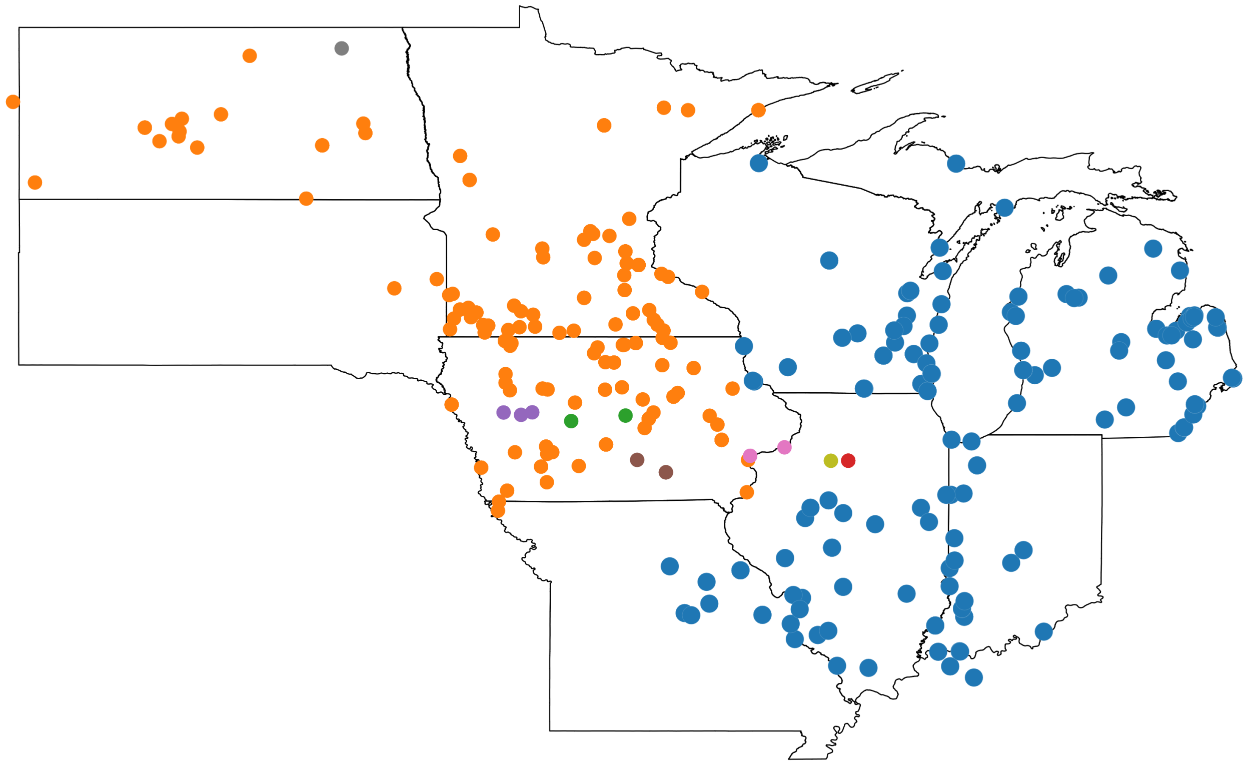
The fact that the clustering results manage to put together geographically close nodes is an important feature related to my later analysis. To see this, Figure 1.6 graphs time series of how generation capacity is split between largest local market and rest of the market in each day across 2015, at the whole market level and the individual firm level. When we look at the market-level capacity in the largest local market compared to total market capacity (left panel, red line), this ratio varies dramatically from day to day, between 50% to 100%, consistent with congestion segmenting markets into many clusters. However, since the plants from one individual firm are usually located close to each other, the market division does not split each firm's capacity significantly. As shown in the mid (green) and right (blue) panel in the Figure, the largest local market capacity for each wind firm or non-wind firm rarely drops below 90% of their total capacity. This means a change in market structure mostly results in local competition that the firm faces, rather than change in its own capacity. This greatly simplifies the complexity in my structural simulation, where I can fix firms' capacity for each day and consider how the bidding strategy changes in response to possible changes in local competition, as characterized by residual demands in different shapes.

1.5 Reduced-form Evidence of Wind Supply Impacts on Market and Firms

In this section, I first use the market clustering results obtained from the previous section to explore how wind supply affects transmission congestion and local market definition. Then, I present reduced-form evidence, which shows that firms with different information about

Figure 1.5: Example Hours of Market Divisions from Clustering Algorithm

(a) March 28, 2015, Hour 18



(b) July 03, 2015, Hour 18

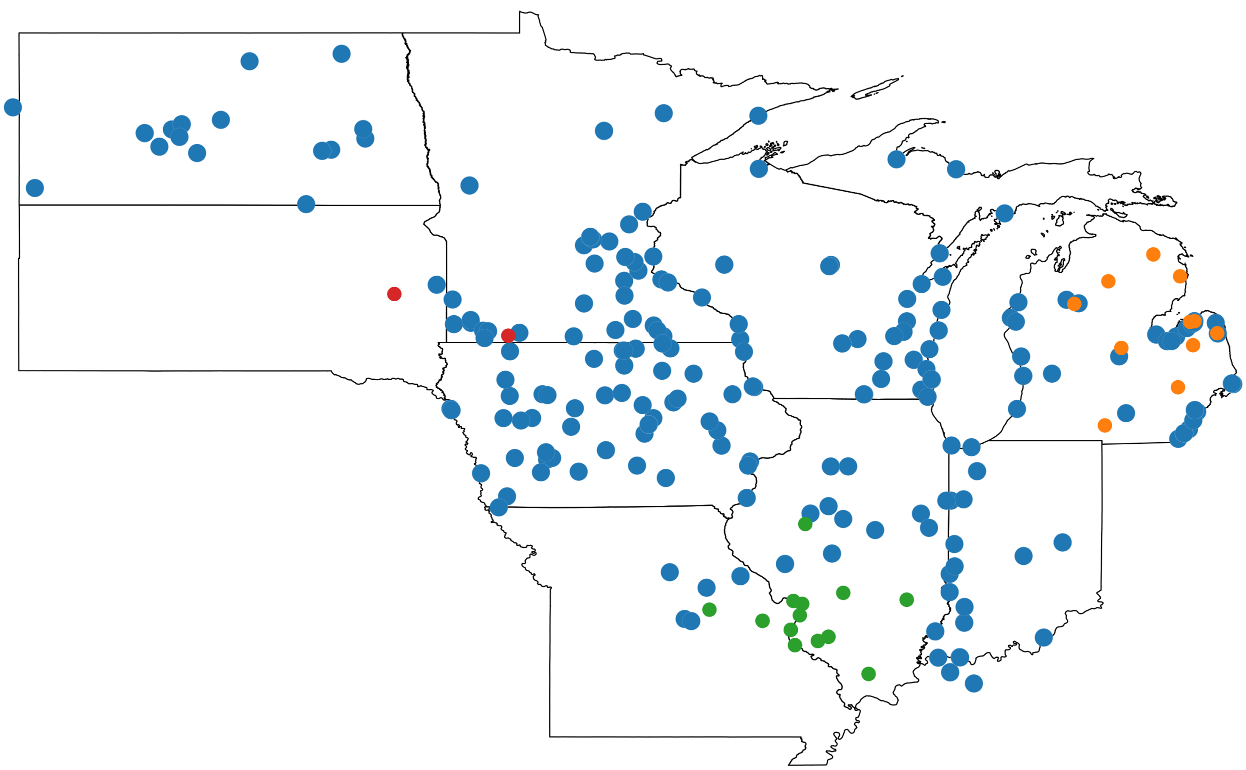
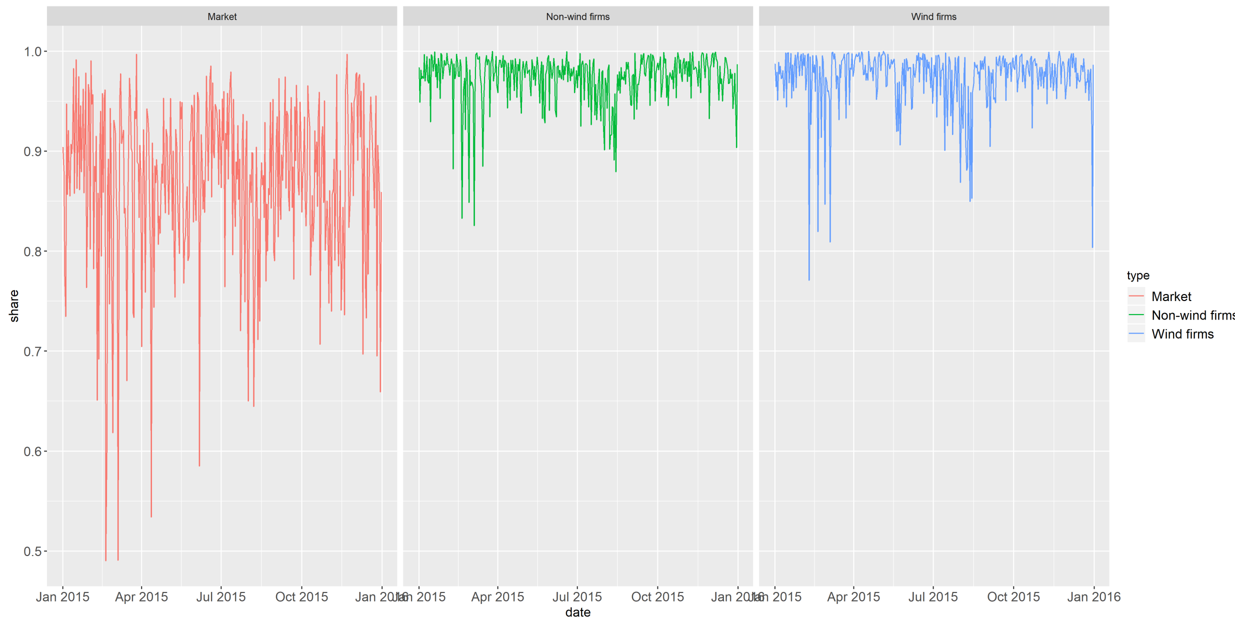


Figure 1.6: Time Series: Share of Largest Local Capacity Compared to Total Capacity



Notes: The figure shows share of generation capacity in the largest local market compared to total capacity, for market total (left), individual non-wind firms (middle) and wind firms (right) in 2015. The market is constantly split into multiple local markets. For each of major firms, however, its capacity is not split as much, since power plants for the same firm are usually geographically close to each other.

wind generation bid differently in the data.

1.5.1 Impacts of Wind Supply on Local Market Structure

I use time-series regressions to study how market definition and market structure change under different wind and load conditions in 2015. I include hourly market-level wind generation, demand, and their interaction term in the regressions, along with monthly and hourly fixed effects to control for the general trends in market conditions at different times of the year/day. The results are reported in Table 1.3. The dependent variables are constructed from market clustering results, including: the number of local markets (column 1); average market size in local markets measured by the local production capacity available (column 2); market size in the largest local market in each hour (column 3); and number of firms competing in the largest local market in each hour (column 4).

When ignoring the interaction term, the results of row 1 and 2 in Table 1.3 are consistent across all four measures. They show that higher wind generation and demand create more transmission congestion and lead to a more divisive market. Specifically, in each measure, this means more local markets, smaller available capacity in the largest/average local market, and fewer firms competing in the local market. However, the coefficients of the interaction terms, as reported in row 3, indicates that this is not the full picture. In fact, the opposite directions of the interaction coefficients mean that the impacts of wind generation on market structure depend on demand levels; the seemingly congestion effect in wind generation diminishes and could even reverse as the demand increases.

Table 1.3: The Impact of Wind and Load on Market Structure

	Dependent Variables in Each Column			
	(1)	(2)	(3)	(4)
	# of Local Mkt	Avg. Mkt Size (GW)	Max Local Mkt Size (GW)	# of Firms in Max Local Mkt
Real-time Wind (GWh)	8.53***	-12.84***	-9.06***	-23.70***
	(0.48)	(0.70)	(0.40)	(1.50)
Real-time Load (GWh)	0.76***	-0.83***	-0.12***	-2.06***
	(0.05)	(0.07)	(0.04)	(0.15)
1 GWh RT Wind × 1 GWh RT Load	-0.14***	199.03***	157.81***	0.36***
	(0.01)	(12.20)	(6.96)	(0.03)
Month fixed effects	Yes	Yes	Yes	Yes
Hour fixed effects	Yes	Yes	Yes	Yes
Observations	8,744	8,744	8,744	8,744

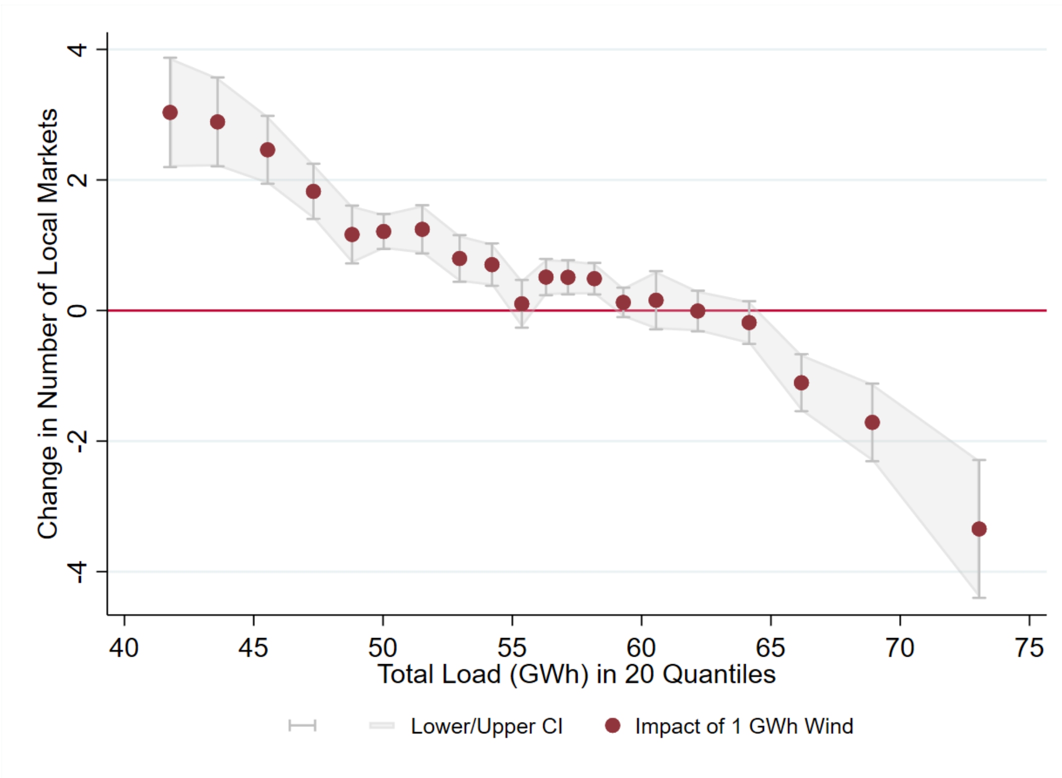
Note: This table reports regression results using hourly data in real-time market in 2015. Dependent variables are number of local markets, average local market generation capacity (GW), generation capacity (GW) in maximum local market and number of firms in maximum local market. Real-time wind generation and real-time demand are measured in GWh.
Robust standard errors are in parentheses with *p<0.1; **p<0.05; ***p<0.01.

To further understand this relationship, I run the regressions of market structure measures on real-time wind generation and demand by each of the 20 evenly-divided demand quantile groups. As shown in Figure 1.7 and Figure 1.8, a 1-GWh[14] increase in wind supply first

14. 1 GWh = 1000 MWh

increases number of local markets (positive coefficient) by 3, and reduces local competing capacity by 3 GW; however, these effects gradually diminish in magnitude, and eventually reverse in direction as total demand increases. When market demand surpasses 80% of its peak level, more wind supply will alleviate congestion, reducing the number of local markets and increasing local supply competition.

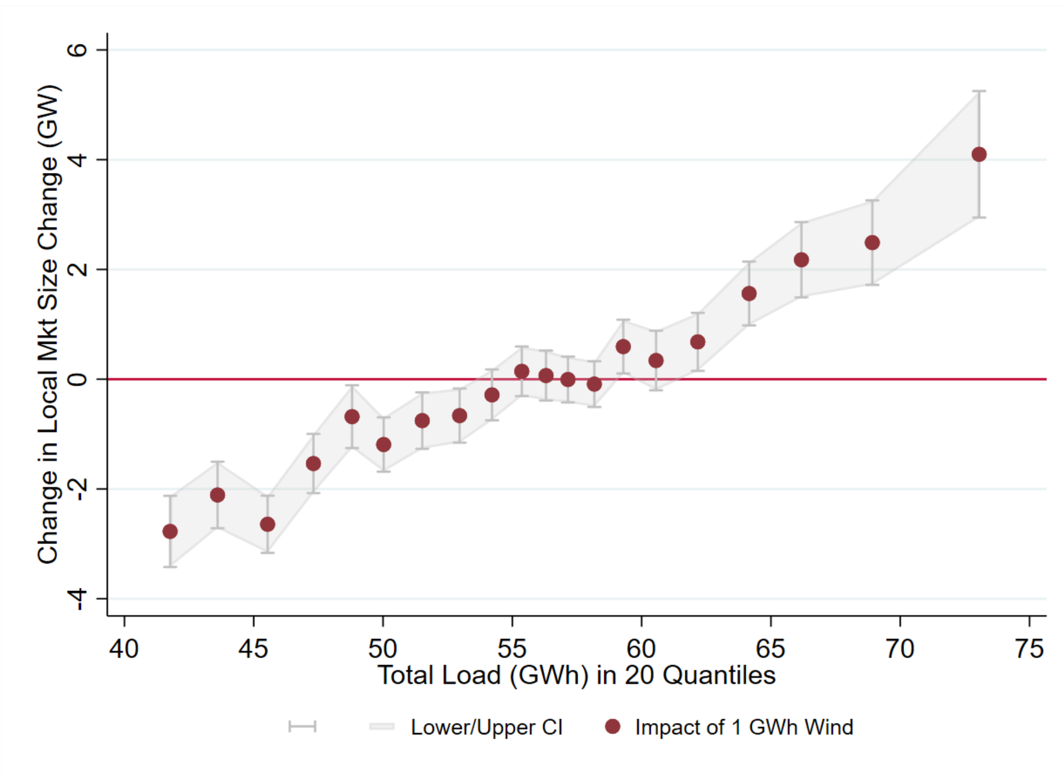
Figure 1.7: Marginal Effect of Wind Supply (1 GWh) on Number of Local Markets by Load Quantiles



Notes: The figure shows the regression results of number of local markets on real-time wind generation by each of the 20 evenly-divided demand quantile groups, after controlling for real-time demand and monthly fixed effect. A 1-GWh increase in wind supply first increases number of local market (positive coefficient) by 3, but the effect gradually diminishes in magnitude, and eventually reverse in direction as total demand increases.

This load-dependent impact of wind generation is consistent with the intuition. Consider a region with a bunch of wind farms. When total demand is low, a surge in wind generation from strong wind blow cannot be accommodated by local demand and will likely export to other regions. This could quickly take up transmission capacity and make the region

Figure 1.8: Marginal Effect of Wind Supply (1 GWh) on Local Market Size (GW) by Load Quantiles



Notes: The figure shows the regression results of local generation capacity (the largest local market in each hour) on real-time wind generation by each of the 20 evenly-divided demand quantile groups, after controlling for real-time demand and monthly fixed effect. A 1-GWh increase in wind supply first reduces average competing capacity in local markets by 3 GW, but the effect gradually diminishes in magnitude, and eventually reverse in direction as total demand increases.

"export-constrained". This means that wind increase is likely to create congestion in the low demand case. However, in the high demand case, local supply is in shortage, which requires importing generation from outside. Then the local market could be congested by "import-constrained". In this case, more wind supply actually will help the situation, as it increases the local supply and reduces the imported power flow that creates congestion.

1.5.2 Differential Responses to Wind Shocks for Wind and Non-wind Firms

In the previous section, I have showed that wind generation has significant impacts on market structure. When higher wind generation alleviates congestion under the high demand case, this will increase local market competition. Firms that recognize this wind supply impact would expect a more elastic residual demand, and bid a flatter slope (larger dS/dp) in response. Similarly, we can consider the impact of demand on the bidding slope. When demand increases congestion, less supply competes in the local market. Consequently, firms should expect a less elastic residual demand, and bid a steeper slope (smaller dS/dp) instead. In this section, I follow this logic and examine in panel regressions whether firms respond to change in wind supply, and how that response depends on different information held by wind firms and non-wind firms.

In this analysis, I exploit exogenous variations in hourly demand and wind generation in the market. All firms submit real-time bids without knowing the realizations of demand and wind generation; however, demand forecasts are available to all firms, while wind forecasts are exclusive to wind firms before they bid. Because of the sequential market setting, the real-time demand and wind is essentially separated into two parts: their day-ahead schedule cleared in day-ahead auction, and their real-time deviation, which is the difference between actual realization and day-ahead schedule. I separately control for these two parts, and test if firms incorporate information of both parts in their real-time supply bids.[15] The panel-

15. In real-time market, firms are required to bid a full supply function for all their capacity, regardless of

data regression with fixed effects is estimated for wind firms and non-wind firms separately as follows:

$$\begin{aligned} bid\_slope_{it} = \alpha + \beta_1 DA\_Wind_{it} + \beta_2 RT\_Wind\_Shock_{it} + \gamma_1 DA\_Load_{it} + \gamma_2 RT\_Load\_Shock_{it} \\ + \phi MC\_slope_{it} + \mu_i + \delta_y + \eta_h + \epsilon_{it} \end{aligned}$$

I track hourly bids of the 15 major firms over a long panel from January 2012 to December 2016. In particular, since each firm's bid in an hour is a step function, I approximate the bidding slope by fitting a B-spline polynomial, and calculate the local slope ($bid\_slope_{it} = (dS/dp)_{it}$) around the market clearing price. Besides the demand and wind supply in day-ahead and real-time, I further control for the change in the slope of firms' own marginal cost function ($MC\_slope_{it} = (dq/dmc)_{it}$), which is also approximated using B-spline polynomials. I also account for yearly (δ_y), hourly (η_h), and firm (μ_i) fixed effects.

The results are shown in Table 1.4. Column (1) and (2) show that, both "wind firms" and "non-wind firms" submit a steeper bid function (i.e. dS/dp goes down) in response to an increase in load (real-time load especially). They also bid steeper for a steeper marginal cost function. However, only "wind firms" also respond to changes in day-ahead and real-time wind supply: they submit a flatter bid function when wind supply is higher. All these results are robust after controlling for the firm and time fixed effects.

To explore the load-dependent feature of wind supply impacts, I run the regressions at each of the 20 demand quantile groups. As Figure 1.9 and Figure 1.10 show, I find how wind firms adjust their bidding slope coincides with the way in which wind supply affects market structure at different demand levels, as Figure 1.8 shows. When wind is likely to decrease local competition at the low demand level, firms tend to bid less competitively (reduce dS/dp), and when wind is likely to increase local competition at the high demand

whether any of them has been scheduled in the day-ahead market

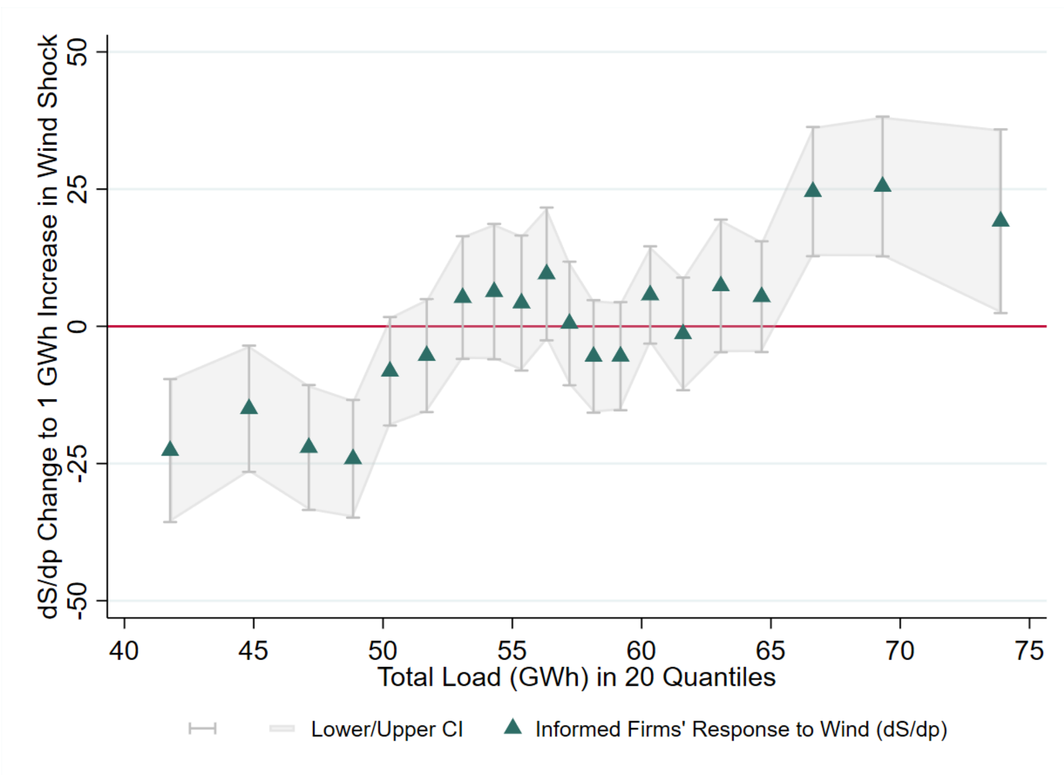
Table 1.4: Response in Bidding Slope to Demand and Wind Shocks

	Dep Var: Firm's Bid Slope (dS/dp)			
	(1)	(2)	(3)	(4)
	Wind Firms	Nonwind Firms	Wind Firms	Nonwind Firms
Day-ahead Wind	0.004***	0.00004	0.0005	0.0005
	(0.001)	(0.001)	(0.001)	(0.0005)
Real-time Wind Shock	0.009***	-0.002	0.007***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Day-ahead Load	-0.002***	0.002***	-0.002***	0.002***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Real-time Load Shock	-0.002***	-0.007***	-0.002***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Slope of Own MC	0.001***	0.022***	0.0004***	0.002***
	(0.00004)	(0.001)	(0.00003)	(0.0003)
Firm fixed effects	No	No	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Hour fixed effects	Yes	Yes	Yes	Yes
Observations	267,638	300,695	267,638	300,695

Note: This table reports regression results using hourly data in real-time market from 2012 through 2016. Dependent variable is each firm's bid slope (dS/dp) around market clearing price in each hour, approximated from B-spline regressions. For regressors, real-time wind generation (demand) is divided into day-ahead wind (demand) schedule and real-time wind demand) shock, which is the deviation of actual wind generation (demand) from day-ahead schedule. All demand and wind generation are measured in MWh. Slope of each firm's marginal cost curve is also approximated from B-spline regressions.
Robust standard errors are in parentheses with *p<0.1; **p<0.05; ***p<0.01.

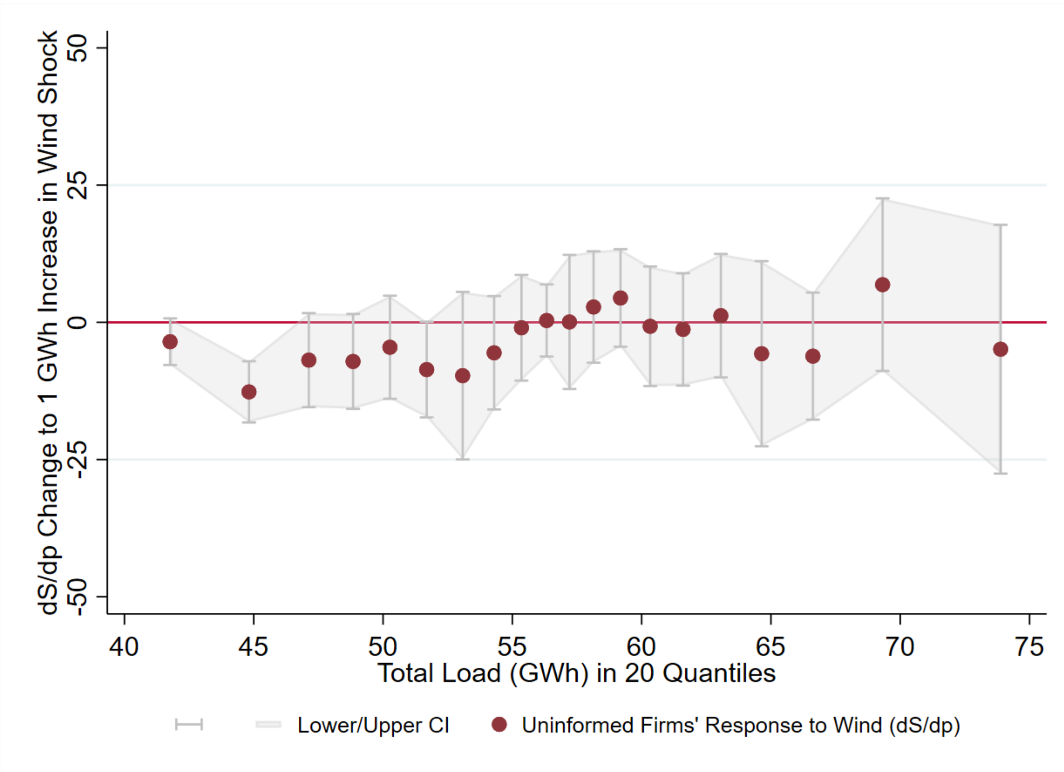
level, firms also tend to bid more competitively (increase dS/dp). Note that this consistent pattern in wind firms' bidding response does not rely on market structure measures in the previous subsection since they are not used in the regressions here. This finding suggests that with good wind information, wind firms are very aware of the complicated wind impacts on market structure and act on it by adjusting their bid functions accordingly. By contrast, the responses of non-wind firms are not different from 0 at all demand levels but one.

Figure 1.9: Bid Slope (dS/dp) Response to Wind at Different Load: Wind Firms



Notes: The figure shows the regression results of wind firms' bid slope (dS/dp) on real-time wind shocks at each of the 20 demand quantile groups, after controlling for day-ahead wind, day-ahead demand, slope of marginal cost and firm fixed effects. It shows the way in which wind firms adjust their bidding slope coincides with the way in which wind supply affects market structure at different demand levels: when wind is likely to decrease local competition at low demand level, wind firms tend to bid less competitively (reduce dS/dp), and when wind is likely to increase local competition at high demand level, wind firms also tend to bid more competitively (increase dS/dp).

Figure 1.10: Bid Slope (dS/dp) Response to Wind at Different Load: Non-wind Firms



Notes: The figure shows the regression results of non-wind firms' bid slope (dS/dp) on real-time wind shocks at each of the 20 demand quantile groups, after controlling for day-ahead wind, day-ahead demand, slope of marginal cost and firm fixed effects. It shows non-wind firms' responses are not different from 0 at all demand levels but one.

1.5.3 Direct and Indirect Impacts of Wind Generation on Firms' Bidding Strategy

The analysis above presents empirical evidence of wind impacts on firms' bidding through changing market structure and local residual demands faced by firms. A more direct impact of wind generation on firms' generation capacity has not been considered. Theoretically, firms will respond to this direct impact differently from the way they respond to market structure change. When higher wind generation adds to wind firms' total generation capacity, they will have more incentives to push up market price as marginal profit of doing so increases from the expansion of their infra-marginal capacity.

To differentiate this direct effect of wind generation from its indirect effect found in the previous analysis, I rerun the regressions in section 1.5.2 with wind firms, while including each firm's hourly own wind generation as an additional control. By adding this control, I can separate firms' response to the changes in market structure and those in their own supply curve. Table 1.5 shows the results. Across different specifications with different fixed effects, I still find strong impacts of market wind supply and market demand on wind firms' bidding slope, which are of the same directions and magnitudes as those in regressions without own wind generation control. In addition, the estimated impact of own wind generation on bid slope is negative, which is consistent with the theoretical prediction: higher wind supply increases the infra-marginal capacity that a firm owns; therefore, the firm will earn more profit with the expanded capacity if pushing up the market price. As the result, the firm will bid less competitively, that is, with smaller dS/dp in slope.

1.5.4 Robustness Checks

The analysis in section 1.5.1 shows non-linear impacts of wind generation on local market structure, and the regressions in section 1.5.2 further show that firms with wind information bid strategically in response to wind-induced market structure change, while firms without

Table 1.5: Wind Information Effect on Wind Firms' Bidding: Robustness to Own Wind Generation

	Dep Var: Firm's Bid Slope (dS/dp)		
	(1)	(2)	(3)
	Wind Firms	Wind Firms	Wind Firms
Day-ahead Wind	0.008***	0.008***	0.0002
	(0.001)	(0.001)	(0.0006)
Real-time Wind Shock	0.014***	0.014***	0.006***
	(0.001)	(0.001)	(0.001)
Day-ahead Load	-0.002***	-0.002***	-0.002***
	(0.0001)	(0.0002)	(0.0002)
Real-time Load Shock	-0.001*	-0.0014**	-0.0013**
	(0.0005)	(0.0006)	(0.0006)
Slope of Own MC	0.001***	0.001***	0.0004***
	(0.00003)	(0.00003)	(0.00002)
Own Wind Generation	-0.079***	-0.079***	-0.001
	(0.002)	(0.002)	(0.003)
Year fixed effects	Yes	Yes	Yes
Hour fixed effects	No	Yes	Yes
Firm fixed effects	No	No	Yes
Observations	265,020	265,020	265,020

Note: This table reports regression results using hourly data in real-time market from 2012 through 2016. Dependent variable is each firm's bid slope (dS/dp) around market clearing price in each hour, approximated from B-spline regressions. Regressors are day-ahead wind schedule, real-time wind deviation, day-ahead demand schedule, real-time demand deviation, slope of marginal cost around market price, and each firm's own real-time wind generation in each hour.
Robust standard errors are in parentheses with *p<0.1; **p<0.05; ***p<0.01.

such information do not. Section 1.5.3 separates the direct impact of wind generation on wind firms' total supply, and the indirect impact of wind generation on market structure, as they play different roles in affecting firms' bidding strategy. In this subsection, I address some potential concerns that remain in these analyses.

First, one concern is that the non-linear impact of wind generation on market structure might heavily rely on the local market definitions I measure from the hierarchical clustering approach. To ensure that the result does not generate from any potential measure errors in the market definition, I run a robustness check using another measure for market divisions inferred from MISO marginal fuel data. MISO provides marginal units' fuel information for each 5 minute interval in the real-time market every hour. The number of marginal units vary from one 5-minute interval to another because of the variation in local markets dynamically defined by transmission congestion. Although generators' identities are not available in the marginal fuel data, and differences in the unit of time can lead to discrepancy in market definition between this report and my approach, I can still use number of marginal units reported by MISO as a proxy for how divided the market is. I then explore how wind generation and demand affect this number of marginal units measure, and compare the results to my findings in section 1.5.1. The regression results are reported in Table 1.6. I show that the similar non-linear impact from wind generation is estimated using this alternative measure for market division from MISO official reports. This indicates that the results of wind impact on market structure are robust to different approaches in the measurement of the market divisions.

Second, for the analysis in section 1.5.2, one concern is that if the plants of non-wind firms are very far away from all wind units, they are unlikely to be affected by wind generation. To show that this is not the case, I calculate the distance between each firm's thermal plants and each major wind project location. Those major wind project locations have wind units with at least 300 MW of installed capacity during my study period.[16] In Figure 1.11, I

16. For some locations, I combine different companies' wind projects together as they reside at the same

Table 1.6: Wind's Impact on MISO-report Market Division Measure

	Dependent Variables in Each Column	
	(1)	(2)
	# of Marginal Units (hrly. avg.)	# of Marginal Units (every 5-min)
Real-time Wind (GWh)	0.83***	0.83***
	(0.05)	(0.02)
Real-time Load (GWh)	0.08***	0.08***
	(0.005)	(0.002)
1 GWh RT Wind × 1 GWh RT Load	-0.005***	-0.005***
	(0.001)	(0.0003)
Hour fixed effects	Yes	Yes
Observations	8,744	104,928

Note: This table reports regression results using real-time 5-min marginal fuel data in 2015. Dependent variables are average number of marginal units in each hour, and number of marginal units in each 5 minutes. The regressions include 8744 hours, same as reported in previous exercises of market clustering. Real-time wind generation and real-time demand are measured in GWh. Robust standard errors are in parentheses with *p<0.1; **p<0.05; ***p<0.01.

graph the distribution of these distances by wind firms and non-wind firms separately. One observation by comparing the two distributions is that more thermal plants in wind firms are located very close to wind projects than those in non-wind firms. This is as expected, as all power plants from one firm (wind firm) usually operate close to each other. However, we still see about 70% of plants from wind firms located farther than 200 miles, and they overlap with most thermal plants from non-wind firms located within 600 miles of wind projects. These are reasonable distances for the plants to be in the same local market with wind projects. Moreover, transmission constraints can have extensive impacts on market structure. Therefore, even when a plant is not in the same local market with wind projects, it is unlikely to be totally immune to wind impacts on local market structure.

1.6 Structural Model of Bidding with Imperfect Wind Information

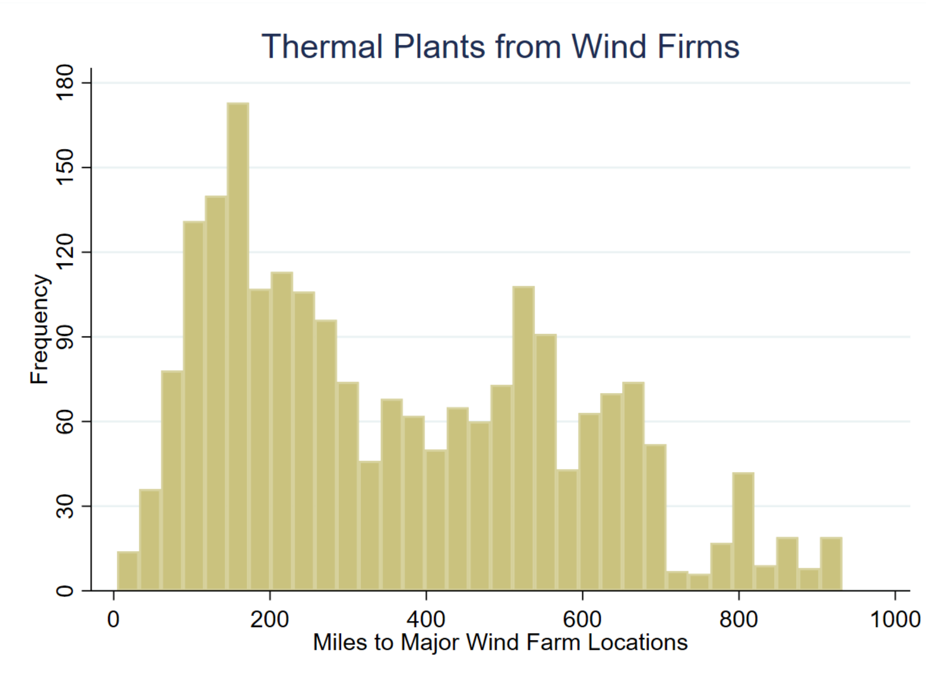
1.6.1 Model of Firms' Beliefs and Strategic Bidding

To better explain the bidding strategies from firms with different wind information, I construct a model of best-response bidding where firms maximize expected payoffs given beliefs about residual demands as determined by the information they possess. This type of model is widely used in IO literature, especially under multi-unit auction settings, where solving for firms' full equilibrium supply curves and beliefs is intractable except for a few special cases. Instead, the model assumes that firms approximate their rivals' actions by using ex-post results or the results in the past under similar market conditions. By construction, this approximation makes firms' beliefs consistent with what their rivals' actually do and has been proved very useful in characterizing firms' profit maximizing behaviors in the previous literature. See, for example, Gans and Wolak [2008], Hortaçsu and McAdams [2010], Reguant

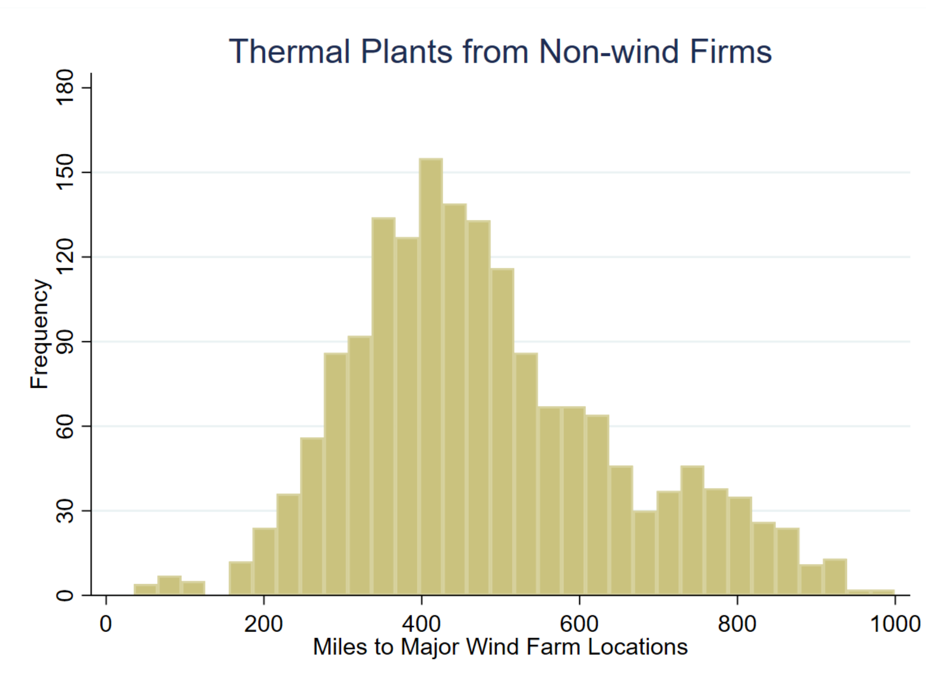
longitude and latitude coordinate according to EIA data.

Figure 1.11: Distance Between Firms' Thermal Plants and Major Wind Project Locations

(a) Distance of Wind Firms' Plants to Wind Project Locations



(b) Distance of Non-wind Firms' Plants to Wind Project Locations



Notes: The figure shows the distribution of the distance between each of major wind project locations and each thermal plant owned by wind firms (Panel A) or non-wind firms (Panel B). The observation used in the figure is the distance in miles calculated for each thermal plant-wind location pair. 70% of thermal plants from wind firms are overlapped with most thermal plants from non-wind firms within the distance range between 200 and 800 miles.

[2014], and Doraszelski, Lewis and Pakes [2019]).[17]

The key feature I add to this model in my specific setting is how much wind information firms have will affect their beliefs about the residual demands to which they best respond. That is, based on different wind information, some firms will form noisier distributions of residual demands, while others will form more precise ones. So in the model, their beliefs about their rivals might not be correct or consistent to what will actually happen, due to the information friction. However, each firm still rationally best-responds given its beliefs.

So in the model, when firms need to predict market structure and rivals' bids to construct residual demands, they will learn from the bidding data in the past, of the auctions that they believe were under the similar market conditions (demand, wind generation, hours) as what they will face next. This is a valid behavioral assumption from my reduced-form analysis, as I find when firms have good information about demand and wind generation, they indeed predict the changes in market structure well and respond strategically to them.

Specifically, for a particular hour h in day t, firm i forms expectations of residual demands from the similar hourly auctions in the most recent three months ($[t-90, t-1]$). For each similar auction, all rivals' bids, local market definitions and local demand in that auction are used to construct a residual demand curve, which represents a potential situation firm i expects to face for an actual hour the next day. Formally, the residual demand is constructed as:

$$RD_{ith}(p|\Theta_{ih'}) = \sum_{d \in \Theta_{ih'}} q_{dh'}(p) - \sum_{jh', j \in \Theta_{ih'}} b_{jh'}(p)$$

where h' represents the similar auction (hour) in the past; $\Theta_{ih'}$ is the local market (defined

17. Gans and Wolak [2008] draws sample analogue for the distribution of residual demand uncertainty for each firm each day from the auctions in the previous, current, and following month which have daily peak demand closest to actual demand for that day; Hortaçsu and McAdams [2010] estimates the distribution of the bidder's residual supply by resampling from past auctions in Turkish treasury bond auctions; Reguant [2014] estimates firms' expectations of residual demands by bootstrapping the past similar days in the Spanish electricity market; Doraszelski, Lewis and Pakes [2019] samples from the past bids to estimate firms' expectations of rivals' bid price in a discriminatory auction in UK frequency response market.

by transmission congestion) where firm i is located during hour h'; $q_{dh'}$ are the local demand bids; and $b_{jh'}$ are the local supply bids except for firm i's own bids in hour h'.

In the reduced-form analysis, I find there are differences among firms for wind information they have, while not much for demand information. Motivated by this finding, wind information becomes the key to formalizing firms' beliefs about residual demands. For a firm that is perfectly informed about wind generation, it can use both demand forecasts and wind forecasts to construct the distribution of residual demands. Albeit having some uncertainty, this distribution should be precise and close to what happens ex-post. On the other hand, for a firm that has no information about wind generation, it can only rely on publicly available demand forecasts to form its beliefs. The distribution of residual demands constructed by that firm would then be more general and imprecise.

The informed distribution and the uninformed distribution of residual demands mentioned above represent two extreme cases of firms' wind information possession. A less extreme firm would face a mixture distribution that combines the informed and the uninformed distributions. How much wind information the firm possesses is reflected in the weights between the two distributions in that mixture. A firm with more information about wind generation would put more weights on the informed distribution relative to the uninformed distribution. Using this structure, I can estimate firm's wind information as a one-dimensional information parameter, which is denoted as γ for the rest of the paper: it determines the extent of wind information for each firm.

Specifically, the informed distribution consists of hourly auctions in the past that are matched with same hour of day, ex-post market demand and ex-post wind generation in the next-day actual hour. The uninformed distribution consists of the auctions matched only with hour of day and ex-post market demand. Given the information parameter of each firm as the weight between these two distributions, the mixture distribution of residual demands are formalized. Then firms will optimize their supply bids that best respond to the expected profit over this mixture distribution of residual demands. Formally, the firm solves a mixed integer programming problem (MIP):

$$\max_{\boldsymbol{b}(q_{ths})} \; E\Pi_t(\boldsymbol{b}(q_{ths})) = \sum_{s=1}^{S_t} \{[\gamma\tau + (1-\gamma)(1-\tau)] \cdot [DR^{\tau}_{ths}(b_{ths}) \cdot b_{ths} - C_t(q_{ths}) - b_{ths} \cdot QC_t]\} \tag{1.2}$$

s.t.

[Balance constraint] $\quad \mathrm{DR}^{\tau}_{ths}(b_{ths}) = q_{ths}, \forall s, h, \tau$

[Capacity constraint] $\quad \underline{\mathrm{Q}} \leq q_{ths} \leq \overline{Q}, \forall t, h, s$

[Monotonic supply function] $\quad \mathrm{b}_{ths} \leq b_{th's'} \Rightarrow q_{ths} \leq q_{th's'} \forall t, h, h', s, s'$

For each day, the firm's expected profit is maximized over all residual demand draws (s) from the mixture distribution, where τ indicates whether the residual demand DR^{τ} is drawn from the informed distribution ($\tau = 1$), or the uninformed distribution ($\tau = 0$), and γ indicates the weight put on the draws from the informed distribution. C_t represents the firm's marginal cost function, which is updated every day as fuel price, heat rate and generation capacity can change from one day to another. The firm's generation capacity may vary especially when it owns wind units. In this way, I incorporate the impact of own wind generation into the calculation of the firm's optimal bidding. QC_t represents forward contract position, for which the firm gets payments at pre-determined forward contract prices. My data does not contain the forward contract information. However, I can use each firm's bidding and marginal cost data to back out their forward contract positions on each day, following Hortaçsu and Puller [2008]. An explanation of the approach can be found in Appendix B.

The optimal bid function $\boldsymbol{b}(q)$ is solved subject to three market bidding constraints: (1) balance constraint: quantity produced by each firm equals the residual demand it faces at its bid price; (2) capacity constraint: each firm cannot produce beyond its operating capacity limits; (3) monotonic supply function: each firm's bid price needs to be increasing in its production quantity. The firm's optimal bid curve is obtained by connecting all the solved

(b^*_{ths}, q^*_{ths}) pairs.

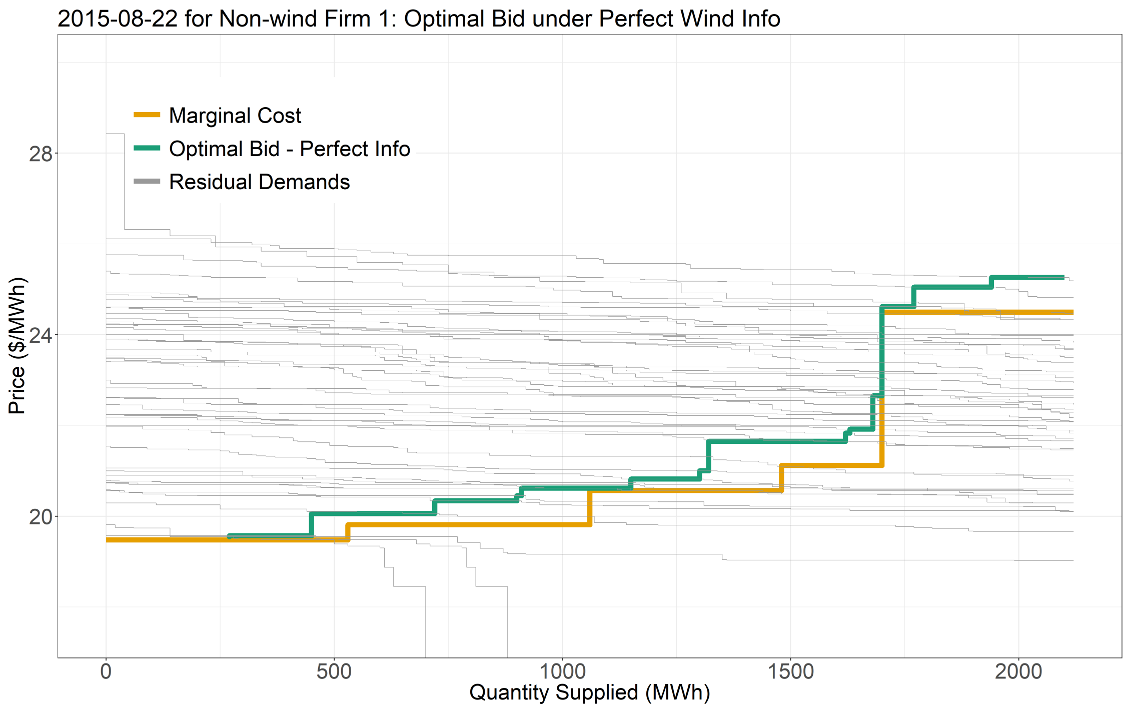
The information parameter γ is identified by fitting the optimal bid predicted by the model to each firm's actual bid and finding the one model with a particular γ that have the best fit. Figure 1.12 provides an example of how to calculate optimal bids under each γ and how to choose the optimal γ for a non-wind firm on a particular day. Part (a) shows the optimal bids solved in $\gamma = 1$ model: all the residual demands are drawn from the informed distribution; the optimal bid in green color is solved the MIP problem, which maximizes the expected profits over these residual demands. Part (b) illustrates $\gamma = 0$ model: all residual demands are sampled from the uninformed distribution, which are clearly much more widespread than the residual demands sampled from the informed distribution; Based on the residual demands, $\gamma = 0$ model will solve for the optimal bid curve. Part (c) shows that if we compare the bids predicted by the two models to the firm's actual bid, $\gamma = 0$ model is a better fit. In the formal estimation, I also search for γ between 0 and 1. In those cases, both sets of residual demands from (a) and (b) are used in generating optimal bid curve, while different γ determines the weight of each type of residual demands in the MIP's objective function. In general, we would expect the bids with $\gamma \in (0, 1)$ to lie between $\gamma = 1$ and $\gamma = 0$ bids.

The structural model described above formulates the best-response bidding for a strategic firm, given the beliefs estimated for the firm. This is different from an equilibrium model where firms' beliefs are mutually consistent with each other's play. It has been established in auction literature that the explicit analysis of such an imperfect-information, asymmetric supply function equilibrium is generally infeasible. Previous literature has only provided a few special cases in symmetric models (e.g. Hortaçsu and Puller [2008] and Vives [2011]).[18] When considering the interaction between firms' bidding and transmission congestion, this

18. Hortaçsu and Puller [2008] solves for a SFE in which firms hold private information about contract position. The complexity of the Bayesian-Nash equilibrium is greatly simplified by assuming that other firms' private information does not change a given firm's ex-post optimal bid. Vives [2011] solves for a SFE where ex-ante symmetric firms have imperfect information about costs and offer linear supply functions.

Figure 1.12: Example of Fitting A Non-wind Firm's Bid with Model

(a) Residual demands and Prediction under $\gamma = 1$



(b) Residual demands and Prediction under $\gamma = 0$

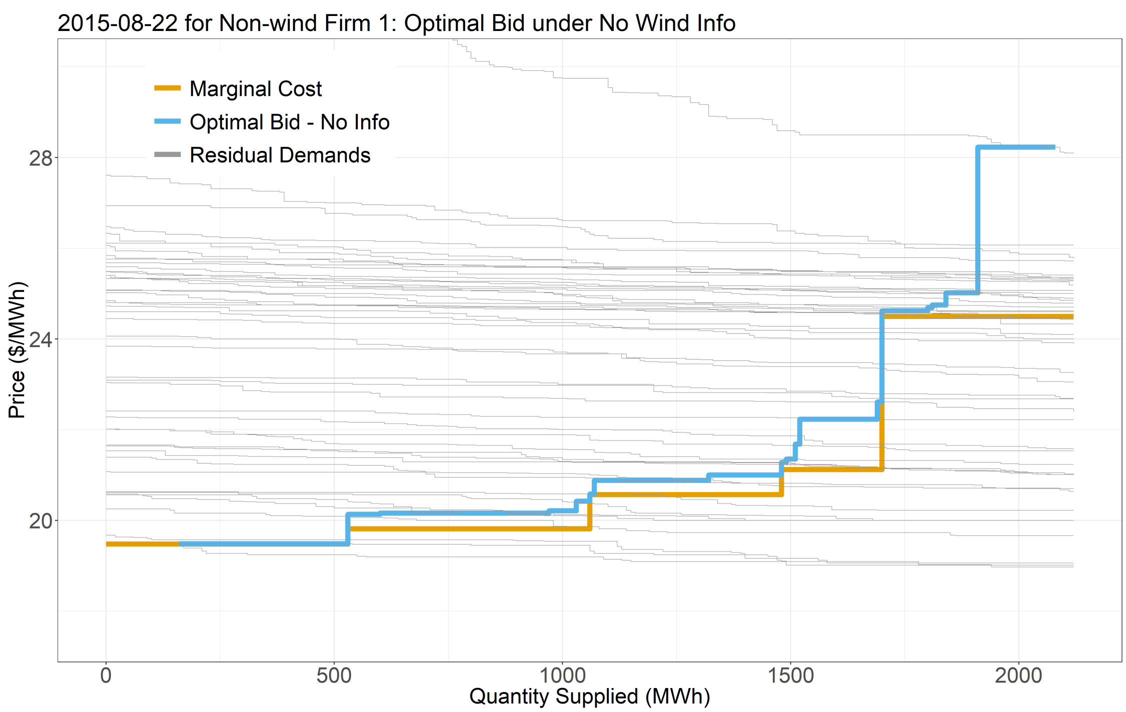
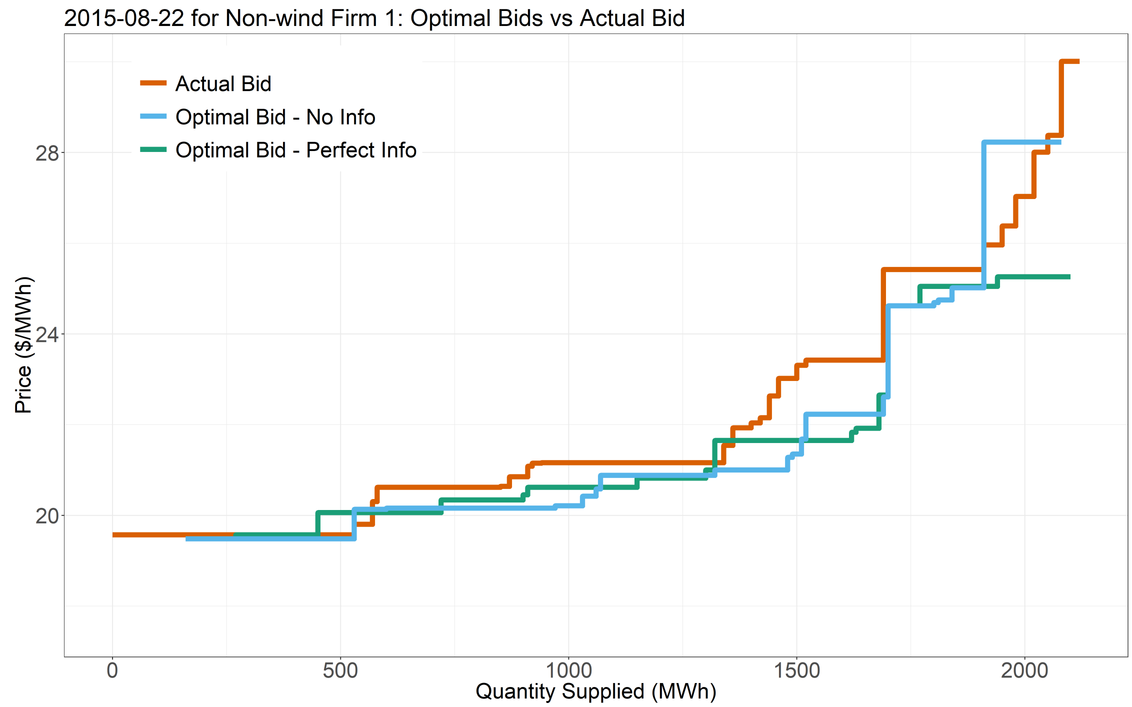


Figure 1.12: Example of Fitting A Non-wind Firm's Bid with Model (Cont.)

(c) $\gamma = 0$ model is a better fit than $\gamma = 1$ model



Notes: Figure 1.12 shows a series of graphs as an example of how the structural model works to fit a firm's supply bid in each day and estimate the information parameter γ. First, given residual demands drawn from informed distribution and uninformed distribution, the MIP solver calculates the firm's optimal bid given marginal cost and forward contract position for $\gamma = 1$ model (Panel A) and $\gamma = 0$ model (Panel B). The actual estimation process also involves calculating optimal bids under the model with $\gamma \in (0,1)$, when the firm best responds to the mixture of two residual demand samples with γ as the weight. Finally, as shown in Panel C, each solved optimal bid is compared to the firm's actual bid on the same day, and the optimal γ is estimated when the optimal bid best fits the actual bid.

problem becomes even more challenging (Wilson [2008]).[19] Given this reason, the behavioral assumptions I make in my model seem to be more realistic for firms' operation. As quoted from Wilson [2008], "if the conditions for an equilibrium are so complicated as to impede academic and policy studies, then perhaps it is implausible to suppose that firms' bidding strategies approximate an equilibrium."

From a practical point, it is within major firms' ability to use historical data and information they possess to approximate real-time market conditions. It is also made possible by MISO since it updates unit-level historical bid data for all market participants on their bidding platform. Hortaçsu and Puller [2008] provides an example in the early years of Texas electricity market that, if firms just best respond to the most recent rivals' bids, their profits will be very close to the ex-post optimal profits.

1.6.2 Estimation Procedures

To sum up, the estimation of information parameter γ in the model takes the following three steps:

1. Construct firms' expectations on residual demand by sampling in the mixture distributions.

   Specifically, for a given firm i and each hour in auction day t:

   (1) Pool similar hours in the past 90 days [t-90,t-1], by matching:

   - Same time of the day ($\pm$2 hours);

   - Same load (($\pm$ 2000 MW or $\pm$5%);

   to obtain the uninformed distribution for day t;

   and add the following in the matching to get the informed distribution for day t:

   - same wind condition ($\pm$ 250 MW or $\pm$5%);

   (2) Randomly draw S similar hours from the informed distribution and S similar hours

19. Wilson [2008] characterizes a symmetric SFE when transmission constraints could bind in a nodal pricing system, using the calculus of variations. Still, the computation of such equilibrium results is extremely challenging.

from the uninformed distribution without replacement;

(3) For each sampled hour, use the local market structure, local demand bids, and rivals' bids to construct the residual demand curve.

2. With the random sample of residual demand curves, solve for the ex-ante optimal supply curve that maximizes expected profits over all residual demands, with γ as the weight in the objective function for residual demands from the informed distribution, and 1-γ as the weight for residual demands from the uninformed distribution. The solution follows the mixed integer programming approach specified in (1.2).

3. In the outer loop, search for the information parameter γ, from which the solved optimal bid best fits the firm's observed bid curve on day t. The measure of fit is the mean square prediction errors (MSE) of bid price at each bid step (10 MWh), as traditionally used in measuring model performance:

$$\hat{\gamma} = \underset{\gamma}{argmin} \, (\sum_q [b_{it}^{data}(q) - b_{it}^{model(\gamma)}(q)]^2)$$

As the objective function is non-linear and not perfectly convex in γ, I use a grid search to ensure the global optimum is found. Specifically, I first search with 0.05 interval, and then around the local minimum, I switch to a finer interval of 0.01 and obtain the final estimation of γ.

1.6.3 Estimation Results

I apply the estimation procedures to the data from April 2015 through September 2015. In these six months, there are 172 daily auctions in total, after excluding 10 days in which the empty set comes up when matching with both demand and wind in the past 90 days.

The information parameter γ captures the likelihood of firms believing that the residual demands drawn from the informed distribution will realize ex-post. Higher γ means the firm puts more weight on the residual demands drawn from the informed distribution; therefore, it will get firms' expectations closer to what is actually realized ex-post.

I estimate the average information parameter γ for each type of firms (wind/non-wind). In Figure 1.13, I show the grid search results at 0.05 accuracy for γ from [0,1]. Panel A graphs the average MSE (objective value) over all wind firms at each search step of γ, and Panel B is the average MSE by γ for non-wind firms. Because some firms are better predicted than are others, the mean levels of MSE differ across firms. To ensure the average result is not the artifact of one or two firms with large MSEs, I standardize each firm's MSE at each γ and each day, before averaging them to generate the figures at each γ for each type.

Once I obtain the estimate of γ for each type of firms at 0.05 accuracy, I further search at 0.01 accuracy around the local minimum in the 0.05 search. Figure 1.14 graphs the average MSE of each type in the 0.01 search.

The estimated parameter for wind firms is 0.88, indicating they weigh highly on the informed distribution that is close to what happens ex-post. On the contrary, the estimated parameter for non-wind firms is 0.26, consistent with the fact that they do not possess much forecasting information about wind generation.

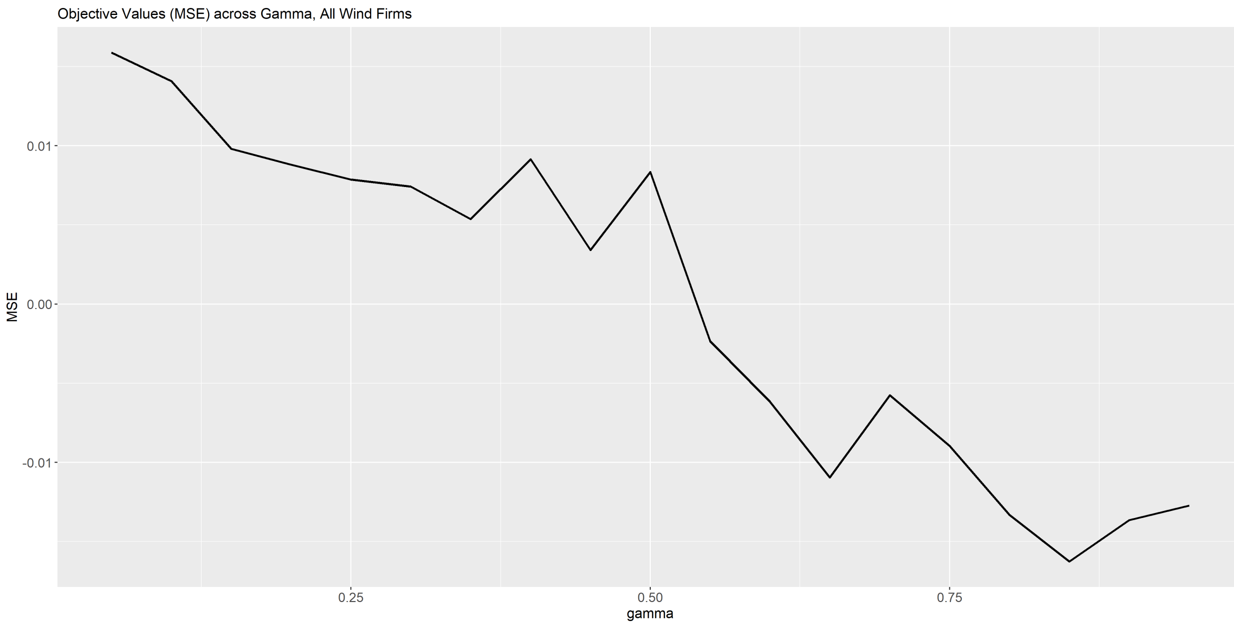
1.6.4 Model Fit

In this section, I show that my model, with the estimated information parameter, better predicts the actual clearing price for each firm than ex-post optimal price predicted using standard oligopoly pricing model. The ex-post optimal price is produced using ex-post optimal bid, with which each firm best responds to ex-post actual residual demands in each hour.

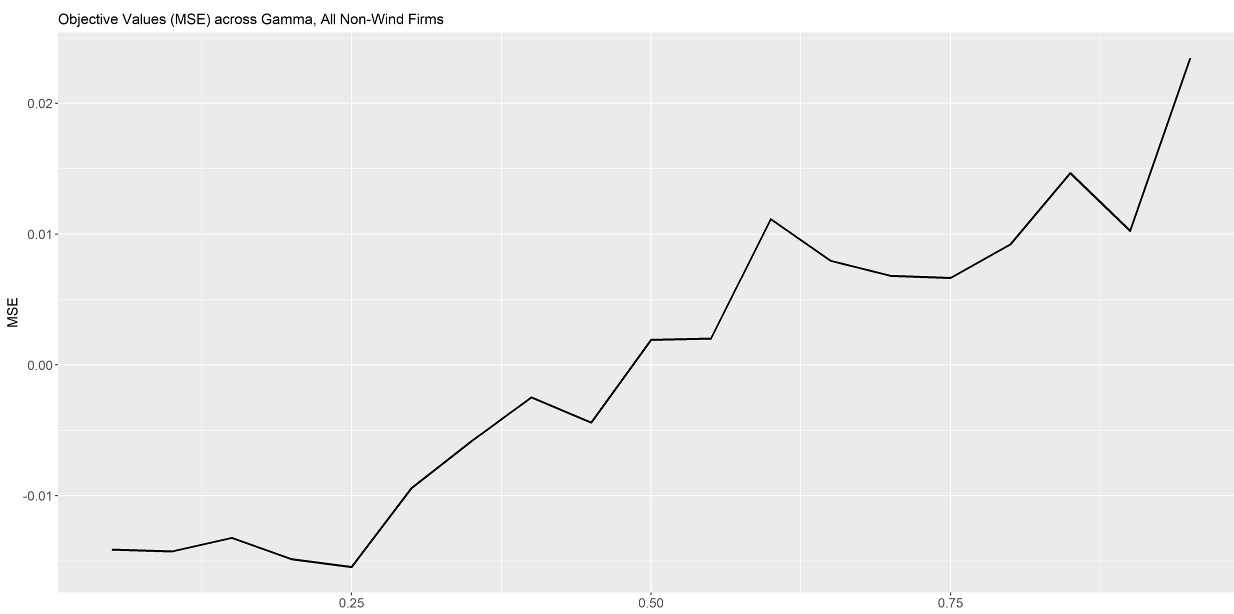
In Table 1.7, I regress the actual price for each firm in each hour on the model predicted price from the best-fit γ for each type, and the predicted price from the ex-post optimal bid. The results show that, for both wind firms (column (1) and (3)) and non-wind firms (column (4) and (6)), my model with the estimated γ explains the majority of variation in

Figure 1.13: Grid Search Results for Wind Firms' and Non-wind Firms' γ, 0.05 Interval

(a) Wind Firms



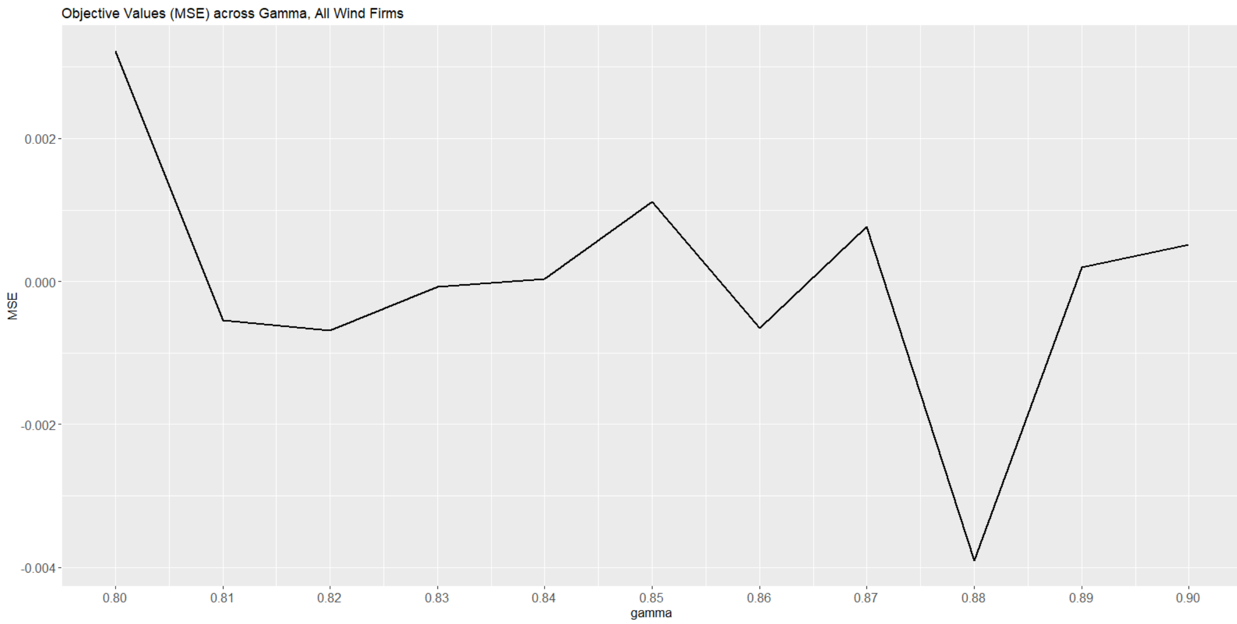
(b) Non-wind Firms



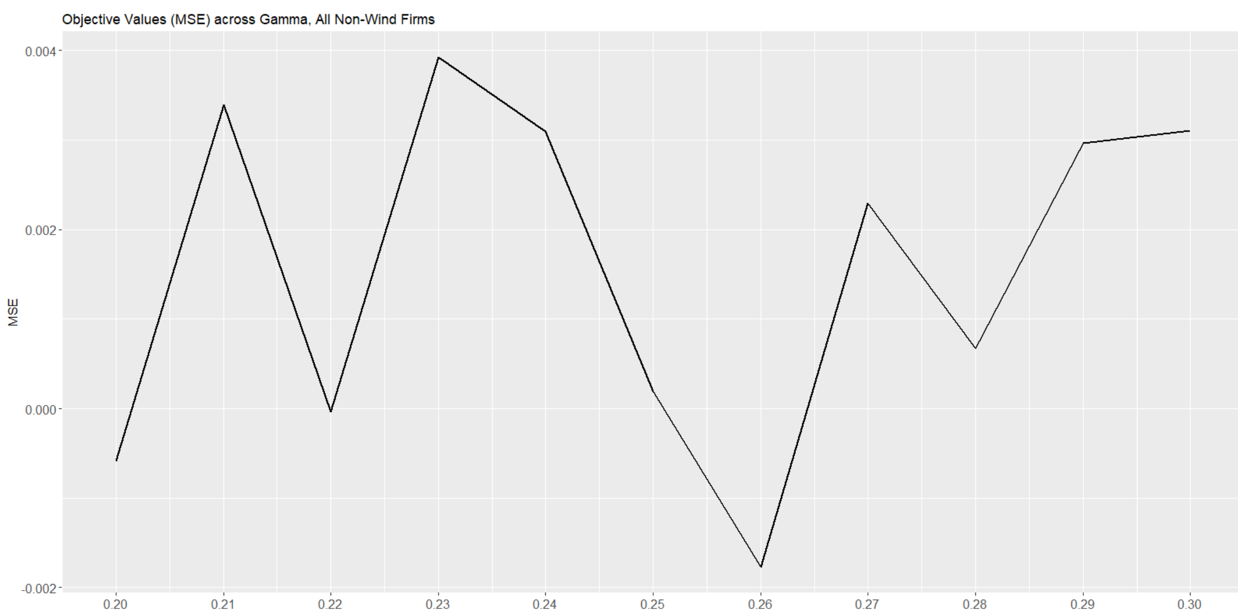
Notes: The figure shows grid search results of information parameter γ from 0 to 1 with 0.05 interval, for each type of firms (wind/non-wind). The prediction errors (MSE) for different γ between modeled bids and actual bids are first calculated for each firm each day. To avoid firms' heterogeneity to affect average result, the MSEs are standardized within each type-γ-day, and then averaged over all days and firms in each type.

Figure 1.14: Grid Search Results for Wind Firms' and Non-wind Firms' γ, 0.01 Interval

(a) Wind Firms



(b) Non-wind Firms



Notes: The figure shows grid search results with 0.01 interval for information parameter γ for each type of firms (wind/non-wind), around the local minimums obtained from the grid search using 0.05 interval. The prediction errors (MSE) for different γ between modeled bids and actual bids are first calculated for each firm each day. To avoid firms' heterogeneity to affect average result, the MSEs are standardized within each type-γ-day, and then averaged over all days and firms in each type.

actual price, and the price from ex-post optimal bid has little prediction power. In addition, comparing column (2) with column (5) reveals that prices from the ex-post optimal bid are more correlated with actual bids for wind firms. By contrast, for non-wind firms, even using this price as a single predictor, it does a poor job in fitting the actual price. This shows that wind firms that hold better wind information indeed bid much closer to the optimal bid than do non-wind firms.

Table 1.7: Compare Best-fit γ to Ex-post Optimal Bid Model

	Dependent variable:					
	Market Clearing Price from Actual Bids					
	(1)	(2)	(3)	(4)	(5)	(6)
	Wind	Wind	Wind	Non-wind	Non-wind	Non-wind
Price from best-fit γ	0.91***		0.89***	0.81***		0.96***
	(0.04)		(0.08)	(0.08)		(0.004)
Price from ex-post optimal		0.57***	0.04		0.08*	0.0001
		(0.07)	(0.04)		(0.04)	(0.001)
Constant	1.89**	9.10***	1.45*	4.13**	20.07***	0.91***
	(0.74)	(1.46)	(0.81)	(1.64)	(0.88)	(0.10)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Hour fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,797	26,404	26,404	30,241	29,249	29,249
R^2	0.95	0.78	0.96	0.88	0.52	0.98

Note: The table shows the fit of the wind information model to market clearing price in real-time market from April 2015 through September 2015. The dependent variable is market price each firm receives in each hour, calculated from their actual bids and actual residual demand in the local market. The independent variables are market price calculated using the information model with the best-fit γ for each type of firms, and market price calculated using ex-post optimal bid in response to actual residual demand in the local market. Column (1)-(3) are regression results on the sample of wind firms, and column (4)-(6) are regression results on the sample of non-wind firms.

Standard errors clustered at the date-level are in parentheses with $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

1.7 Counterfactual Analysis

In this section, I use the structural model to simulate and quantify the profit and welfare impacts of wind information in two counterfactual simulations. First, I explore the change to each firm's private profits when each unilaterally changes its own bid from knowing no wind information to knowing perfect wind information; Second, I simulate the changes to consumer welfare and market efficiency when all firms are given perfect wind information, compared to a baseline case in which only about half of the firms have perfect information about wind generation.

The calculations of these two simulations are straightforward using my structural model results: each firm's $\gamma = 1$ bid is calculated as a best-response supply bid after drawing expected residual demands from the informed distribution. Similarly, each firm's $\gamma = 0$ bid is calculated using residual demand draws from the uninformed distribution. For both simulations, I use ex-post local market definitions and local demand to calculate market results. Therefore, the counterfactual results for each firm and each hour are calculated by clearing each local market with actual demand and hypothetical supply bids predicted in the model. Because of the best-response model setting, firms' hypothetical supply bids respond to changes in wind information they possess, but not respond to changes in other firms' bidding behaviors. So this exercise should be considered as a simulation of firms' short-term adjustments to wind information variation, rather than equilibrium results they might finally converge to after a longer-run learning process.[20] I plan to work on this long-run aspect in my future research.

20. In a complex setting such as electricity market auctions with rapidly changing market conditions, as pointed out in Doraszelski, Lewis and Pakes [2019], "... convergence to equilibrium after a perturbation may not be swift or indeed certain". They actually find that it took about 6 years for firms to get close to a complete information Nash equilibrium in frequency response auctions in the UK electricity system.

1.7.1 Profit Gains when A Single Firm Unilaterally Changes Bid

I first examine the profit that each firm would get if it is given perfect information about wind and unilaterally changes its supply bid according to what the $\gamma = 1$ model would predict; and the profit for each firm if no wind information is available and they bid according to $\gamma = 0$ model. These two profits are then compared to their actual profits. Conceptually, this exercise can elucidate firms' willingness to pay for a private wind forecasting service, when it will give them an informational advantage while keeping every other firm's information unchanged.

Specifically, I use the ex-post local market definition, actual residual demand (demand - rivals' bids) and each firm's counterfactual bids predicted in the model to simulate the cleared price, cleared quantity and firms' profits in each hour from April 2015 to September 2015. The profit measure requires knowledge of fixed contract price, which is not available in my data. Therefore, I use the ex-post optimal results as a benchmark, which is calculated using firms' ex-post optimal bids given actual residual demands. Comparing the two profits cancels out the contract revenue part. This difference is still informative, as it reveals how different models deviate from the maximum profits a firm can ever obtain.

Table 1.8 reports the average results for wind firms in Panel A and non-wind firms in Panel B separately. Column (1) shows the deviation from the ex-post optimal results if the firm bids with perfect wind information, i.e. $\gamma = 1$. Column (2) shows the deviation when the firm bids as $\gamma = 0$ model predicts. Column (3) shows the difference between market results from firms' actual bid in data and the ex-post optimal bid.

Comparing the average cleared quantity across the three columns reveals that for both types of firms, perfect wind information will make firms bid closer to the ex-post optimal result; no wind information, in contrast, will make firms withhold more quantity in their bids. This is consistent with the predictions in my analytical model when wind uncertainty leads to sufficiently large uncertainty in residual demands. In actual data in Column (3), non-wind firms indeed clear less quantity, while wind firms do not. Therefore, non-wind firms' actual bid is more consistent with the prediction of $\gamma = 0$ and wind firms' actual bid is more consistent with the prediction of $\gamma = 1$. This echoes the estimation results of the structural model, confirming that actual bid patterns are predicted well by each firm's information type.

Consequently, $\gamma = 0$ bids will lead to higher prices and higher profit losses than $\gamma = 1$ bids, for both types of firms. This highlights the value of wind information for firms' private profit. However, if comparing the profit under $\gamma = 1$ case and the actual profit, perfect information improves the actual results for non-wind firms, but not for wind firms. This indicates heterogeneity across firms within each type, which is not fully explained by this wind information model.

Finally, to approximate firms' willingness to pay for perfect wind information, I compare the profit loss measures between $\gamma = 1$ and $\gamma = 0$. The willingness to pay, or the value of perfect wind information to firms' profit, is \$579/hr for wind firms, with 35% increase from its $\gamma = 0$ profit. For non-wind firms, the willingness to pay is \$303/hr on averages, equivalent to 47% improvement from its $\gamma = 0$ profit. The results would be different when comparing $\gamma = 1$ results to the actual result, but it seems not all the profit loss in the actual case comes from wind information; therefore, that comparison would likely exaggerate the value of wind information. In general, the annual profit loss avoided by having perfect wind information ranges from \$2.7M to \$5.1M. Given that the estimate of wind forecasting expenses for MISO in 2015 was around \$16M, this private benefit is not very likely to pass the cost-benefit test for any single firm to invest in the wind forecasting individually. This might explain why we do not see those non-wind firms obtain wind information from other sources.

Table 1.8: Hourly Deviation of Different Types of Bids to Ex-post Optimal Bid

	Deviation from Ex-post Optimal Results		
	(1) $\gamma = 1$ type	(2) $\gamma = 0$ type	(3) Actual
A. Wind firms			
Average cleared quantity (MWh)	-3	-150	113
Average cleared price ($/MWh)	0.05	0.24	-0.17
Average profit loss ($/hr)	-1090	-1669	-890
B. Non-wind firms			
Average cleared quantity (MWh)	37	-111	-201
Average cleared price ($/MWh)	-0.20	-0.05	-0.12
Average profit loss ($/hr)	-335	-638	-1273

Note: The table presents simulation results in real-time market from April 2015 through September 2015 when each firm unilaterally changes its bid to $\gamma = 1$ model bid or $\gamma = 0$ model bid. Each result shown in the table is the deviation of the simulated result compared to ex-post optimal result, calculated using ex-post optimal bid in response to actual residual demand. Average results are calculated over all hours for each type of firms. Column (1) reports the results from simulating $\gamma = 1$ model, column (2) reports the results from simulating $\gamma = 0$ model, and column (3) reports the results from firms' actual bids. Panel A shows results for wind firms, and panel B shows results for non-wind firms. The results in each panel are simulated for each firm first, then averaged over all firms in each type.

1.7.2 Welfare Impact of Better Wind Information

In this section, I simulate a policy counterfactual in which all firms are given perfect information about wind generation,[21] and compare them to a baseline case in which wind firms bid with perfect wind information and non-wind firms bid with no wind information. I do not use actual results as the baseline, so I can isolate the wind information impact from the firm-level heterogeneity discussed before that cannot be fully explained by the levels of wind information.

As predicted by the analytical model, market efficiency and consumer welfare would increase if reduction in uncertainty leads to less quantity withholding from non-wind firms and brings lower-cost capacity into production. In addition, there are other potential channels for this information effect to impact efficiency. If the provision of wind forecasts to all firms in the market were public news, wind firms might predict that non-wind firms are likely to bid more competitively with less uncertainty; they might then respond by also submitting more elastic bids. This would further mitigate the market power exercise. Besides, changes in bidding are likely to reshape the market structure, for example, relieve some of the transmission constraints, or segment other local markets. These channels are not the scope of this simulation, as accounting for them requires an equilibrium model in which firms hold consistent beliefs about each other's behavioral changes and a transmission model that maps firms' bidding to market structure. These are both very challenging problems and I leave them to future research.

The simulation is conducted with the 15 major firms from April 2015 to September 2015. The remaining unmodeled firms are treated as fringe players which bid their marginal cost into the market, as they have limited ability to affect market price given the small capacity they hold. Therefore, I essentially use their actual bid price in the data as their marginal cost.

21. Note that this is not equivalent to giving firms perfect foresight on other firms' strategy. Firms still need to infer their rivals' bids from past play, but based on perfect information about actual wind generation.

In each hour, I take actual market structure, local demand, fringe firms' actual bids, and major firms' hypothetical supply bids predicted in the model to simulate the results for each local market. In the baseline case, all wind firms bid as $\gamma = 1$ and non-wind firms bid as $\gamma = 0$; In the policy counterfactual, both types of firms bid as $\gamma = 1$.

Table 1.9 reports and compares the simulated market outcomes under the baseline and the policy counterfactual. The simulation shows that, when all non-wind firms change their bids from $\gamma = 0$ to $\gamma = 1$ type, this leads to a 3.4% decrease in the market clearing price. Since real-time demand in the electricity market is inelastic, this reduction in price directly passes through to a reduction in wholesale electricity procurement cost by $45,000 per hour. This likely indicates an equivalent increase in consumer surplus, as most regulated utility companies just pass through the wholesale procurement costs to consumers through flat-rate retail pricing.

Market production cost also decreases by 2.8%. This is from production reshuffle between lower-cost production from major firms and higher-cost production from small firms. Although the average quantity being reshuffled is relatively small, the cost saving is significant, which is mostly concentrated during peak demand hours. During those hours, a small withholding from non-wind firms could induce highly costly fringe production to kick in. The magnitude of this reduction is substantial in electricity market context. For a comparison, the transition from command-and-control operations to the wholesale electricity market design in the U.S. during 1999-2012 reduced total production cost by 5-8% (Cicala [2017]).

Again, the number derived here needs to be taken with caution, since (1) the simulation assumes that wind production can be perfectly forecasted; (2) impacts of firms' bidding on market structure and heterogeneity within each type of firms are not fully considered. Nevertheless, the results suggest a potentially important improvement in electricity market efficiency from what would be a straightforward policy of making wind forecast information available to all firms.

Table 1.9: Hourly Welfare Comparison Between Baseline Case and Perfect Wind Info Case

	(1) Baseline	(2) All $\gamma = 1$	(3) Pct. Diff.
Mean Price (\$/MWh)	24.6	23.8	-3.4%
	(0.3)	(0.2)	(0.8%)
Consumer Cost	1356.7	1311.2	-3.5%
(000s \$/hr)	(24.3)	(19.8)	(0.8%)
Major Production	38.0	38.4	1.0%
(GWh)	(0.4)	(0.4)	(0.04%)
Fringe Production	16.2	15.8	-2.5%
(GWh)	(0.2)	(0.2)	(0.1%)
Major Production Cost	535.3	541.5	1.1%
(000s \$/hr)	(6.8)	(6.9)	(0.1%)
Fringe Production Cost	140.9	116.3	-21.2%
(000s \$/hr)	(12.9)	(8.4)	(5.7%)
Total Production Cost	676.3	657.9	-2.8%
(000s \$/hr)	(17.5)	(13.8)	(0.01%)

Note: The table presents simulation results in real-time market from April 2015 through September 2015. Average results are taken over all hours in each scenario. Column (1) reports the results when all wind firms bid with $\gamma = 1$ bid, and all nonw-wind firms bid with $\gamma = 0$ bid. Column (2) presents the results when all firms bid with $\gamma = 1$ bid. Column (3) calculates the percentage difference between (1) and (2): ((2)-(1)/(2)). Bootstrapped standard errors in parentheses are calculated using 1000 samples.

1.8 Conclusion

Renewable energy is the key to the ongoing transformation of the power market and energy systems. Simultaneously, the uncertainty it creates fundamentally changes the paradigm of market competition. The fluctuation in renewable capacity makes the market environment more uncertain, and requires all market participants to have better information when making optimal decisions in competition.

This paper contains a case study on the U.S. Midwest market where wind power sometimes generates as high as 30% of demand. In this market, wind generation has great impact on market competition and market structure through transmission congestion. I find that wind forecast information not only affects the private profit of production firms, but also has important implications on market efficiency.

Firms that do not own any wind units have limited wind information when bidding in the market, while firms that own wind units have information advantages. Consequently, I find that firms without wind units tend to respond less to wind supply changes and deviate more from the ex-post optimal bidding strategy. I then develop a strategic bidding model with a belief-formation process to explain firms' bidding differences using wind information. Based on the model, I run counterfactual simulations and show that firms that bid against the current uncertainty created by wind are more likely to withhold more production in the market. Hence, providing firms with better wind information could greatly improve consumer welfare and market efficiency. This suggests that electricity market policy and technology should work together in developing accurate renewable forecasting, and simultaneously, gain awareness from market participants in the use of such information.

Appendices

A.1.1 Market Result Comparison in A Two-state Analytical Model

In this appendix, based on the analytical model presented in Section 1.3, I derive and compare the market price and quantity results under informed firm's bidding and uninformed firm's bidding. The idea is to take expected market outcomes over all demand realizations under the two states for an informed firm and an uninformed firm, and see how the average market clearing price and quantity change under different bidding strategies.

For each state (b_1, b_2, the set of demand realizations (η,δ) can be divided into one part where the uncertain bid overlaps with one of the certain bids, and the other part where the uncertain bid falls between the two certain bids.

Follow the uniform distribution assumption, we can calculate the expected prices in b_1 state with uncertain bid ($s^u(p) = \frac{b_1+b_2}{2}p$) or certain bid with b_1 slope ($s_1(p) = b_1 p$):

$$E_1(p) = \int_{d_0}^{\frac{2b_1d_0}{b_1+b_2}} (\frac{\eta}{2b_1})f(\eta)d\eta + \int_{\frac{2b_1d_0}{b_1+b_2}}^{d_1} (\frac{\eta}{2b_1})f(\eta)d\eta$$

$$E_1^u(p) = \int_{d_0}^{\frac{2b_1d_0}{b_1+b_2}} (\frac{\eta}{2b_1})f(\eta)d\eta + \int_{\frac{2b_1d_0}{b_1+b_2}}^{d_1} (\frac{2\eta}{3b_1+b_2})f(\eta)d\eta$$

where $\eta \sim U[d_0, d_1]$.

So the average price difference is:

$$E_1(p) - E_1^u(p) = \frac{-(b_1-b_2)\Delta}{4b_1(3b_1+b_2)(d_1-d_0)}$$

where the term $d_1^2 - \frac{4b_1^2d_0^2}{(b_1+b_2)^2}$ is denoted by Δ.

Similarly, the expected prices in b_2 state with uncertain bid or certain bid with b_2 slope ($s_2(p) = b_2 p$) can be calculated as:

$$E_2(p) = \int_{d_0}^{\frac{2b_2d_1}{b_1+b_2}} (\frac{\delta}{2b_2})f(\delta)d\delta + \int_{\frac{2b_2d_1}{b_1+b_2}}^{d_1} (\frac{\delta}{2b_2})f(\delta)d\delta$$

$$E_2^u(p) = \int_{d_0}^{\frac{2b_2d_1}{b_1+b_2}} (\frac{2\delta}{b_1+3b_2}) f(\delta) d\delta + \int_{\frac{2b_2d_1}{b_1+b_2}}^{d_1} (\frac{\delta}{2b_2}) f(\delta) d\delta$$

where $\delta \sim U[d_0, d_1]$.

So the average price difference is:

$$E_2(p) - E_2^u(p) = \frac{(b_1 - b_2)\Phi}{4b_2(b_1+3b_2)(d_1-d_0)}$$

where the term $\frac{4b_2^2d_1^2}{(b_1+b_2)^2} - d_0^2$ is denoted by Φ.

I add these two parts together to compare the average prices (over all possible wind and load) between uncertain bid and certain bids:

$$\begin{aligned} & E_1(p) - E_1^u(p) + E_2(p) - E_2^u(p) \\ = & \frac{b_1 - b_2}{4(d_1-d_0)} [\frac{\Phi}{b_2(b_1+3b_2)} - \frac{\Delta}{b_1(3b_1+b_2)}] \end{aligned}$$

From this, it can be shown that:

$$\begin{aligned} E_1(p) + E_2(p) < E_1^u(p) + E_2^u(p) & \\ \iff \frac{\Delta}{\Phi} > \frac{b_1(3b_1+b_2)}{b_2(b_1+3b_2)} & \\ \iff \underbrace{\frac{(b_1+b_2)d_1 - 2b_1d_0}{2b_2d_1 - (b_1+b_2)d_0}}_{(1)} \cdot \underbrace{\frac{(b_1+b_2)d_1 + 2b_1d_0}{2b_2d_1 + (b_1+b_2)d_0}}_{(2)} > \frac{b_1}{b_2} \frac{(3b_1+b_2)}{(b_1+3b_2)} & \end{aligned}$$

where (2) $> \frac{(3b_1+b_2)}{(b_1+3b_2)}$ as long as $b_1 > b_2$ and $d_1 > d_0$, which are just our setup assumptions. Also, (1) $> \frac{b_1}{b_2}$ if and only if $b_1 > b_2$ and $\frac{b_1}{b_2} > \frac{d_1}{d_0}$.

So in our model setting, uncertain bid is likely to induce higher average price when $\frac{b_1}{b_2} > \frac{d_1}{d_0}$, i.e. the ratio of two residual demand slopes is greater than the ratio of upper and lower bound of demand.

This means, when the wind-induced uncertainty in residual demand is large enough, we will likely have a higher market clearing price on average. The intuition of this result is presented in Section 1.3.

Similarly we can compare the expected quantity under two wind scenarios and different bids:

$$E_1(q) = \int_{d_0}^{\frac{2b_1 d_0}{b_1+b_2}} (\frac{\eta}{2}) f(\eta) d\eta + \int_{\frac{2b_1 d_0}{b_1+b_2}}^{d_1} (\frac{\eta}{2}) f(\eta) d\eta$$

$$E_1^u(q) = \int_{d_0}^{\frac{2b_1 d_0}{b_1+b_2}} (\frac{\eta}{2}) f(\eta) d\eta + \int_{\frac{2b_1 d_0}{b_1+b_2}}^{d_1} (\frac{(b_1+b_2)\eta}{3b_1+b_2}) f(\eta) d\eta$$

$$E_2(q) = \int_{d_0}^{\frac{2b_2 d_1}{b_1+b_2}} (\frac{\delta}{2}) f(\delta) d\delta + \int_{\frac{2b_2 d_1}{b_1+b_2}}^{d_1} (\frac{\delta}{2}) f(\delta) d\delta$$

$$E_2^u(q) = \int_{d_0}^{\frac{2b_2 d_1}{b_1+b_2}} (\frac{(b_1+b_2)\delta}{b_1+3b_2}) f(\delta) d\delta + \int_{\frac{2b_2 d_1}{b_1+b_2}}^{d_1} (\frac{\delta}{2}) f(\delta) d\delta$$

Put them together to calculate the quantity difference under uncertain bid and certain bids:

$$E_1(q) - E_1^u(q) + E_2(q) - E_2^u(q) = \frac{b_1 - b_2}{4(d_1 - d_0)} [\frac{\Delta}{3b_1+b_2} - \frac{\Phi}{b_1+3b_2}]$$

and we have

$$\begin{aligned} & E_1(q) + E_2(q) > E_1^u(q) + E_2^u(q) \\ \Longleftrightarrow & \frac{\Delta}{\Phi} > \frac{3b_1+b_2}{b_1+3b_2} \end{aligned}$$

From the proof in price comparison, we already know that part (2) of $\frac{\Delta}{\Phi}$ is greater than $\frac{3b_1+b_2}{b_1+3b_2}$, and we can also show that part (1) of $\frac{\Delta}{\Phi}$ is greater than 1, so this last inequality is true. So we have $E_1(q) + E_2(q) > E_1^u(q) + E_2^u(q)$.

To sum up, when firms face uncertainty in wind supply, their uncertain bid in maximizing the expected situations is likely to decrease market efficiency by lowering clearing quantity and increasing market prices. A formal structural simulation in the paper shows a result consistent with this prediction.

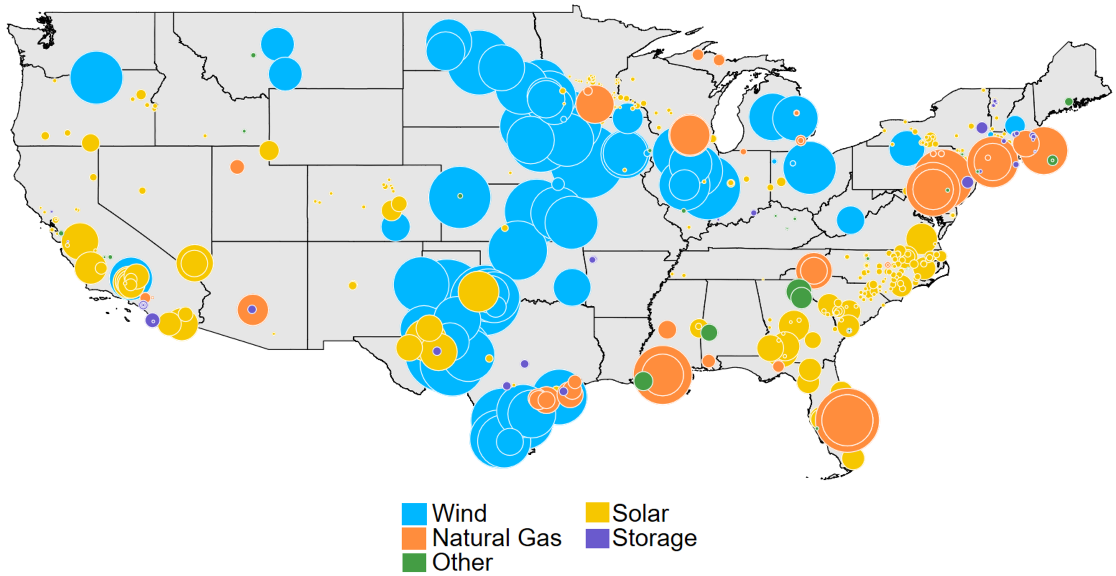
A.1.2 Estimation of Firms' Forward Contract Positions

My data does not contain each firm's forward contract information. However, as I observe each firm's marginal cost curves, I can back out their forward contract positions on each day, following a proposition derived in Hortaçsu and Puller [2008]. Recall the optimality condition in the analytical model: $p - c'(s^*(p)) = s^*(p)\frac{H_s(p,s^*(p))}{H_p(p,s^*(p))}$. When accounting for the firm's forward contract with QC reserved from its production at the contract price, the condition becomes: $p - c'(s^*(p)) = (s^*(p) - QC)\frac{H_s(p,s^*(p))}{H_p(p,s^*(p))}$. Then Hortaçsu and Puller [2008] proposes that QC can be calculated by finding the quantity where the supply function of the firm intersects its marginal cost function.

Intuitively, this approach is valid as long as the firm knows a basic bidding strategy that they should bid above (below) marginal cost when it is a net seller (buyer) after accounting for the forward contract. This is a reasonable assumption for major firms in my analysis. Besides, for major firms, their supply is very often on the margin, which gives them ability to greatly affect market price. Note that the approach only relies on firms' private information about their own contract positions, so no matter how much wind information firms have and whether they could bid an optimal markup, I can estimate their contract positions using this approach.

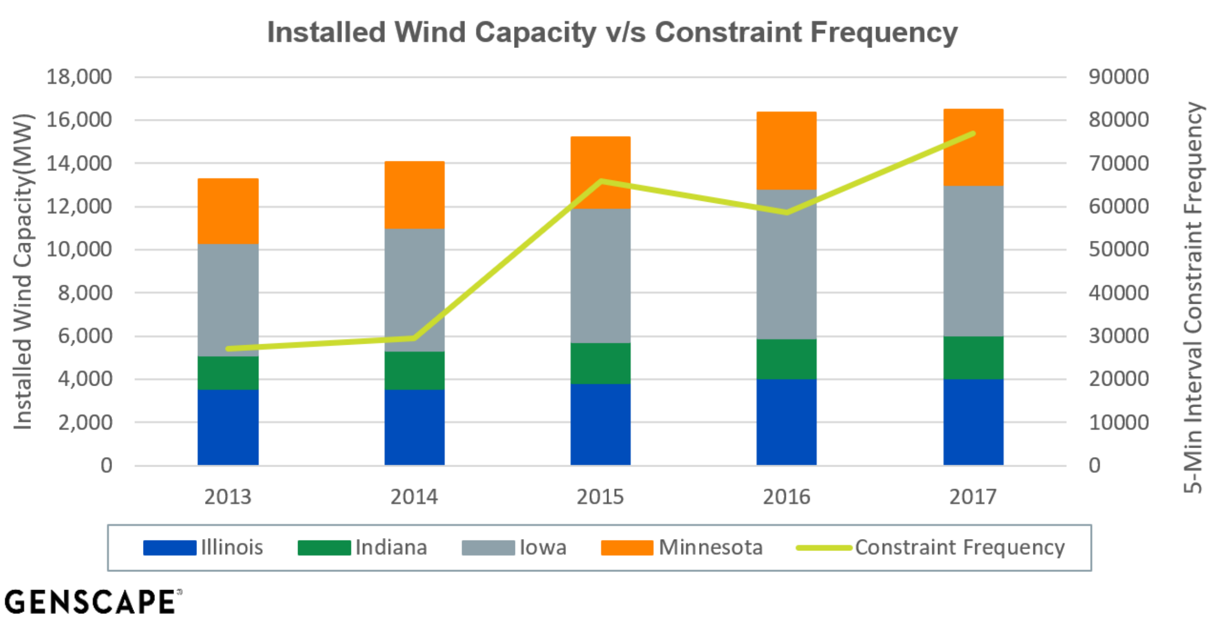
A.1.3 Additional Figures

Figure A.15: U.S. Electricity Capacity Addition in 2019, by Energy Source



Notes: The figure shows the location and capacity of generators planned to add to U.S. electricity market in 2019. It is created by the author using EIA-860 Form: proposed plants in 2019. Bubble size is scaled by the installed capacity of each generator.

Figure A.16: Installed Wind Capacity Increases Transmission Constraint Frequency



Notes: The figure shows trends in wind capacity development and frequency of transmission constraint in midwest states. Source: "Wind Farms are Blowing Up Congestion in Midwestern Electricity Markets", Genscape, 2019. *https://www.genscape.com/blog/wind-farms-are-blowing-congestion-midwestern-electricity-markets*

Chapter 2

Paying for Scarcity at the Right Time: Evidence from PJM Capacity Market Reform

2.1 Introduction

The core function of markets is to formalize prices to accurately reflect the scarcity value of goods or services. The price signal is vitally important to facilitate market demand and supply to meet, especially in the electricity market. Large fluctuations in electricity demand, and supply constraints arising from the fixed generation capacity, result in significant hourly and daily variations in the scarcity value of electricity. In wholesale electricity market, energy auctions featuring competitive hourly bidding provide such price signals and incentives for power plants to produce when needed. However, when capacity market is added to electricity market design to provide additional incentives, such concept of time-varying pricing is relegated to a vague notion.[1]

1. Regarding the terms commonly used in electricity market design, the market that distributes power plants' actual hourly production to meet real-time demand is defined as the "energy market", or "energy auction", while the market that ensures resource adequacy in the medium- and long-term is defined as the "capacity market". The capacity market in many regions—such as ISO New England, MISO, and PJM—

The capacity market operates in tandem with the energy market by generating additional revenue to compensate power producers if their revenues from the energy market are not sufficient to support both short-run operations and long-run investments. However, the originally conceived fixed payment system "did little more than transfer a rather arbitrary amount of money from load to generation" (Cramton, 2017, p. 45). The yearly installments do not attach to their hourly production and do not reflect the real-time capacity shortage. Therefore, the system adds little incentives for producers to make their power plants actually available in the energy market. Instead, it only ensures that there is sufficient "steel in the ground."

Historically, price signals in the energy market sufficed to stimulate electricity supply without additional incentives from the capacity market. Even for generators that do not operate all the time, the prices during high demand hours can rise high enough to cover both short-run production costs and long-run investment costs. However, in recent years, the rapid expansion of subsidized renewable energy and the decrease in natural gas prices have swiftly reduced energy market prices and producer revenue. Those generators who are only called on to produce for limited hours per year find it more and more difficult to get enough revenue. Consequently, there is an increasing reliance on the capacity market payment to cover the shortfall between the energy market revenue and their total costs. With this ongoing revenue shift from the energy market to the capacity market, there is an increasing need to deploy a capacity payment mechanism to ensure that producers have incentives to contribute when needed.

In this paper, I study the costs and benefits of integrating time-variant scarcity pricing with capacity market payment. On one hand, the time-variant capacity payment may provide a better signal of providing generation capacity under different market conditions, thereby increasing energy market efficiency. On the other hand, it may lead to higher capacity market costs, because producers may be inclined to offset the payment risks by raising base prices

operate only once a year.

paid to them in capacity auctions.

I empirically assess the effects of a recent policy change in the U.S. northeast electricity market, PJM.[2] In June 2016, PJM implemented a reform in its capacity market design by adjusting each generator's capacity payment to conform with actual performance during periods of peak demand. The performance of generators is assessed by their actual output during those hours when the system demand or supply is under stress, as compared with the output they had committed to in the capacity market. Any shortfall is subject to hourly penalty charges calculated from the capital costs of building new power plants each year—usually 10 to 20 times higher than the capacity price paid to current generators.

In a descriptive analysis, I find evidence that producers in the PJM market invested in a greater number of firm fuel contracts as well as maintenance to improve the reliability of their generators immediately before the capacity market reform took effect. I then study producers' bidding behaviors in wholesale auctions using detailed generator-level hourly data from 2015 to 2017. I track the change in their bidding before and after the reform, and compare it to the bidding from producers in the neighboring Midwest market, which operated according to the old capacity market design at the time of PJM's reform. The difference-in-difference regression results show that the bid price of the PJM generators decreases by 10% on average because of the reform, after controlling for fuel costs and general time trends. This effect is predominant in marginally producing gas-fired plants, which have strong incentives to withhold capacity and drive up market prices before. This indicates that the reform improves energy market efficiency by reducing producers' incentives to exercise market power.

In a welfare analysis of the capacity market reform, I consider both the benefits of reducing energy market costs and the potential cost implications in the capacity market. The impact of the reform on reducing costs in energy market production is measured using

2. The full name is Pennsylvania-New Jersey-Maryland Interconnection, and it serves all or part of 13 states and DC in the U.S.. More details are discussed in Section 2.2.

a predictive modeling approach, building upon the "generation regressions" of Davis and Hausman (2016) and Cicala (2017). First, I fit each generator's production schedule semi-parametrically with the its operating characteristics and demand conditions, making use of the historical data before the inception of the PJM reform. Then, I use the estimated model to predict the counterfactual production for each generator in the first year of the reform had the reform not been implemented. The impact of the reform on market production cost can be quantified by comparing the actual production outcomes and predicted counterfactuals. This approach is better suited in this context, because it would be difficult for a structural modeling and simulation approach to fully capture the complicated relationship between firms' bidding and market production allocation.

The results of the welfare analysis show that the capacity market reform resulted in lower production costs in the PJM, compared to what would be if not for the reform. The most significant reduction in the market production cost for PJM occurred during peak hours, during which the market is more susceptible to market power exercise. This is consistent with the findings of the reduced-form model, in that the reform mitigated the strategic bidding by marginal gas-fired producers. I quantify the reform's overall welfare implications by combining the energy production cost savings with the increased capacity payment in the capacity market. As a result of the reform, capacity payments increased by 2.5 billion dollars in the PJM 2016-2017 delivery year, while savings in the energy market production are estimated at 3.8 billion dollars. Therefore, the capacity market reform resulted in a net benefit of 1.5 billion dollars in the 2016-2017 delivery year.

This paper contributes to the previous studies on oligopoly competition and the exercising of market power in the electricity market. Following the pioneering work of Borenstein, Bushnell, and Wolak (2002), there have been studies on different mechanisms in electricity market designs to mitigate the exercising of market power, such as fixed-price forward contracts (Bushnell, Mansur, and Saravia, 2008), complementary bidding (Reguant, 2011), and time-variant retail pricing (Alcott, 2013). Whereas most discussions focus on energy market applications, less attention has been paid to the capacity market, which is currently the second largest source of power plants' revenue in over 33 states in the United States. This paper is one of the first studies to empirically evaluate market efficiency gains if combining time-variant scarcity pricing into capacity payment.

This paper also has bearing on the contentious debate in both academia and industry, over the optimal market design for achieving resource adequacy. The debate is mostly focused on the comparison of two approaches, the capacity market and the energy-only market encompassing scarcity pricing. In energy-only market design, there is no capacity market to provide additional compensation for producers. Instead, the scarcity pricing inflates the market price to a level far above the marginal production cost under scarcity conditions, providing better incentives when capacity would be especially needed. Up to this time, this design has only been implemented in the Texas electricity market (ERCOT). One critique of this design is that due to the inelastic demands in the electricity market, real-time scarcity pricing is susceptible to the exercising of market power, thereby making it difficult to distinguish between market power abuse and legitimate scarcity rents. Furthermore, extremely high peak-season retail prices from the scarcity pricing in consumers' bills are considered a political risk.

While these two designs have been discussed either theoretically (e.g., Bushnell (2005), Cramton and Stoft (2005), Joskow (2006), Bushnell, Flagg, and Mansur (2017)) or through simulation (e.g., Alcott (2013); Galetovic, Munoz, and Wolak (2015)), I use a real-world policy change in the PJM capacity market and present important new evidence. The combination of time-varying pricing with capacity payment in a capacity market design can ensure resource adequacy, at the same time counteracting the financial insecurity caused by the extreme price volatility in energy-only market design. This is of vital importance in energy policy, as this reformed capacity market design is currently being considered as the main policy revision in many electricity markets, including ISO New England, Southwest Power Pool, and California ISO.

The remainder of this paper is structured as follows: Section 2.2 provides an overview of the U.S. electricity market with an introduction to the PJM capacity design reform; Section 2.3 presents a two-step analytical model of energy and capacity supply, which predicts, in theory, the possible effects of the reform; Section 2.4 summarizes the data used in the empirical analysis; Section 2.5 describes the econometric approach used for evaluating the impacts of the reform. Section 2.6 presents the empirical findings regarding the impact on the producers' bidding behavior, production costs, and social welfare. Section 2.7 contains the conclusions of this study.

2.2 Institutional Background

2.2.1 U.S. Electricity Market

Historically, electricity utilities were vertically integrated and responsible for all types of services from generation, transmission, and distribution to end-use consumer retailing. Typically, they operated as regional monopolies subject to state-level cost-of-service regulations. Even though there was no competition, they were only allowed to keep the amount of profit that was a fixed share of their total cost expenditure. There was no market, so monopoly utilities used a command-and-control system to organize power plants' production to meet regional demand in the areas under their control.

During the late 1990s and early 2000s, the United States electricity market underwent major deregulation. The deregulation separated the transmission system from power generation and allowed independent power generators access to the grid. While utilities still own transmission and distribution networks, they relinquished control of the networks to regional transmission organizations (RTOs), or independent system operators (ISOs), which integrated multiple regions into wholesale markets and act as independent, nonprofit grid operators over each integrated market. In the RTO/ISO organized wholesale market, generation resources compete with each other in uniform-price auctions by submitting price-sensitive supply bids on an hourly basis to sell their power. RTO/ISO calls generators to produce in increasing price order until total market demand is met, and pays all accepted output at the highest accepted price offer.

Currently, two-thirds of the electricity produced in the United States is sold through wholesale markets. Major ISOs include California (CAISO), Midcontinent ISO (MISO), Texas (ERCOT), Pennsylvania-New Jersey-Maryland Interconnection (PJM), New England (ISO-NE) and New York (NYISO). Their market operations are regulated by Federal Energy Regulatory Commission (FERC). Among them, MISO and PJM are the largest, each controlling a large aggregated market over multiple states.

The capacity market was first created around 2007 in PJM, MISO, ISO-NE, and NYISO. The purpose of setting up this additional market was to comply with the FERC's resource adequacy requirement. In the yearly capacity auction, the system operator needs to plan and secure sufficient installed generation capacity for the next year's operation, whereby "sufficiency" is calculated by the predicted peak demand in the following year, plus the "planning reserve margin." The capacity auctions are in the format of yearly uniform-price auctions and generators that successfully bid in the capacity market commit to uninterrupted availability in the energy market for the following year. In return, they receive fixed capacity payments per year, which is based on the capacity auction price and the amount of capacity they commit to.

2.2.2 PJM Old and New Capacity Market Design

This paper focuses on two neighboring electricity markets, PJM and MISO, which had similar capacity market designs before June 2016. In June 2016, PJM initiated reform in its capacity market and began its transition to a "performance-based"capacity market design. Below, I compare PJM's old and new capacity market rules, focusing on the differences in generators' capacity obligations in the energy market.

Under PJM's old capacity market design, the chief obligations for generation resources include:[3]

1. Follow "Commitment Compliance":

   All generators with capacity market ("capacity resources") commitment are required to bid in day-ahead energy auctions every hour every day to the amount committed in capacity auctions.

2. Pass "Peak Hour Period Availability Test":

   This test assesses the average availability of capacity resources across pre-defined peak hours (June–August and January–February, with approximately 500 total hours). The capacity resource will be charged a penalty if its average outage rate is higher than its 5-year average in the past. The charge is the capacity payment received from the capacity auction proportional to this shortfall.

Under these rules, there was minimal risk to the generators of incurring such penalties. Thus, they had little incentives to ensure full production during all hours. This lack of incentives resulted in extremely high energy prices as shown in recent events that posed great threat to the reliability of the grid.

One such event was the Polar Vortex of January 2014, when much of the Midwest and East Coast faced record cold temperatures. During this time, in PJM regions, 22% of generation capacity (up to 30% for gas generators) was unavailable during the emergency, and consumers' January billings skyrocketed to as high as one-third of their entire year's total in 2013. Some of the generators' under-performance was due to the lack of maintenance or weatherization that exposed them to forced outages and startup failures. Another case related to gas generators, where they did not secure fuel delivery through firm contracts, so their gas supplies were cut off due to the high demand in other sectors. It has also been reported that some generators made false claims of having experienced outages, while in

3. Section 8.4.1, PJM Manual 18: PJM Capacity Market, July 2017

fact, they were uncertain as to their next-day operational profit given the high volatility in the spot price natural gas market.[4]

The new PJM capacity market design uses "Non-performance Assessment" to replace the "Peak Hour Period Availability Test". It enforces capacity obligations according to clear performance criteria, with penalties attached to the actual peak hours. The Non-performance Assessment compares the actual production of capacity resources to their commitments on an hourly basis under stressed market conditions. It is expressly stated that the assessment does not exempt the generator from eventualities only because its bidding price is higher than its cost.[5] Any shortfall will be subject to extreme penalty charges, priced according to "Net Cost of New Entry (Net CONE)." In 2016, this value was about $2000/MW-hour.

The new design highlights the value of ensuring generation capacity during hours of scarcity by penalizing providers that fail to do so. The hours of scarcity are only announced in real time, which could be any hour when demand is high. This is expected to disincentivize producers from strategically withholding capacity to push up market prices in times of high demand. At the same time, this new design is also expected to lead to changes in their capacity market behaviors. In order to fulfill the performance requirements in the energy market, some generators need additional investment to keep their plants in good condition. As a result, they may raise their prices in capacity auctions to offset the additional investment costs. They may also do so because they will face increasing financial risks from non-performance under the new capacity payment mechanism.

PJM has taken a phased approach to implementing their capacity performance rules. Since its inception in the 2016-17 delivery year[6], the number of megawatts cleared under the new performance-based design has increased each year until the delivery year 2020–21, when

4. PJM Staff Draft Problem Statement, "Problem Statement on PJM Capacity Performance Definition", August, 2014.

5. Section 8.4A, PJM Manual 18: PJM Capacity Market, July 2017.

6. Many electricity markets use the concept of "delivery year" instead of calendar year for planning purposes. Each delivery year refers to the 12 months beginning June 1 and extending through May 31 of the following year.

all PJM resources will be subject to the performance-based capacity requirements. PJM has transitioned 60% of capacity resources in 2016-17 and 70% of resources in 2017-18 in its commitment to the new design.

2.3 Model

This section details a two-stage model of a producer's energy and capacity supply decisions in PJM. The model serves as the theoretical basis to illustrate how the old and new capacity market design could lead to different behaviors from producers.

The model is set up as follows. In the first stage, firms decide whether to increase or decrease generation capacity when bidding in the yearly capacity market auction. Firms also decide whether to make additional investment to improve generators' performance, reflected in reduced outage rate. In the second stage, firms decide the quantities to sell in the hourly energy market and compete in a Cournot-Nash equilibrium. The model is presented following backward induction.

2.3.1 The Second Stage of Wholesale Supply

Consider a firm, i, which owns several generators in its generation fleet. In hour t of energy market, firm i needs to set the quantities to sell. Similar to Bushnell, Mansur and Saravia (2008), firm i is assumed to maximize its profits (in expectation) in a Cournot game, :

$$\underset{s_{it}}{max}\ \pi_{it} = p_t(q_{it}, \boldsymbol{q_{-it}}) \cdot q_{it} - c_{it} \cdot q_{it}$$

$$s.t.\ q_{it} = (1 - \alpha_i - s_{it}) \cdot k_i$$

where demand function is given and known to all producers, and the market price is determined by both firm i's quantity q_{it} and its rivals' quantities $\boldsymbol{q_{-it}}$. c_{it} is firm i's marginal production cost which is assumed to be constant. Firm i's total capacity is capped at k_i, but its actual production q_{it} is less than k_i, due to two reasons. First, some of its generators might experience forced outage, for which the rate in expectation equals α_i. Second, firm i can also strategically withhold some capacity in order to push up market price, which is denoted s_{it} in a percentage term.

For given α_i and k_i which are set in the first stage, firm i's strategic withholding ratio s_{it} needs to satisfy the following first-order condition:

$$\frac{\partial \pi_{it}}{\partial s_{it}} = p_t + q_{it}(s_{it})\frac{\partial p_t}{\partial q_{it}} - c_{it} = 0$$

By under-supplying by s_{it}, the firm essentially trades off between scheduling more quantities into the market (each additional unit of quantity gets p_t) and pushing up the market price by strategic withholding (all inframarginal quantities get $\frac{\partial p_t}{\partial q_{it}}$). Note that the forced outage rate α_i, and the "strategic" outage rate s_{it} are interchangeable here, which means firm i's strategic withholding can hide behind forced outages, since it is usually difficult for the system operator to observe real reasons for the outages.

In addition to the profit maximization described above, firm i also faces incentives from its capacity obligation. Under the old capacity market design, firms only take a penalty if their outage rate across the 500 pre-defined peak hours in summer and winter is more than the historical outage rate in the past 5 years. So firm i's aggregate profit (in expectation) over a year can be written as:

$$\Pi_i^{old} = \begin{cases} \sum_t \pi_{it} - (\alpha_i + \frac{\sum_{i \in dh} s_{it}}{N_{dh}} - \overline{\alpha}_0) \cdot N \cdot p^c \cdot k_i & if \ \alpha_i + \frac{\sum_{i \in dh} s_{it}}{N_{dh}} > \overline{\alpha}_0 \\ \sum_t \pi_{it} & if \ \alpha_i + \frac{\sum_{i \in dh} s_{it}}{N_{dh}} \leq \overline{\alpha}_0 \end{cases}$$

where $\overline{\alpha}_0$ is the baseline outage rate in the past 5 years, dh denotes the 500 pre-defined hours in summer and winter, N is total hours in a year, and p^c is the capacity auction price (in $\$/MWh$ unit), which is also the penalty rate in the old capacity market design. It is clear to see that the old capacity obligation has little binding effect on reducing firm i's strategic withholding s_{it}, since it is easy for firm i to control the average withholding rate during the pre-defined hours to not trigger the penalty, i.e. keeping $\frac{\sum_{i \in dh} s_{it}}{N_{dh}}$ below $\overline{\alpha}_0 - \alpha_i$.

Under the new design, however, non-performance penalty NP_{it} is calculated hour by hour when the market has a stressed situation. Since such stressed hours are only announced in real-time based on actual situations, this non-performance penalty is actually added into every hour with a positive probability:

$$\Pi_i^{new} = \sum_t (\underset{s_{it}}{max}\ \pi_{it} - NP_{it}) = \sum_t [\pi_{it} - Pr(q_{it} + \sum_{-i} q_{-it} < Q_t^d) \cdot r \cdot (s_{it} + \alpha_i - \overline{\alpha}_0) \cdot k_i]$$

$$s.t.\ q_{it} = (1 - \alpha_i - s_{it}) \cdot k_i$$

where Q_t^d is the target capacity need that ensures grid reliability, which is the predicted peak demand for the next few hours plus a reserve margin, and the probability of hour t being an emergency hour $Pr(q_{it} + \sum_{-i} q_{-it} < Q_t^d)$ is a decreasing function of $q_{it} + \sum_{-i} q_{-it} - Q_t^d$, the surplus in available supply compared to the target capacity need. r is the non-performance penalty rate, which is set at "net Cost of New Entry" (net CONE) updated by the system operator every year.

As described above, firm i needs to consider the potential non-performance penalty in its production decision every hour, so the new first-order condition becomes:

$$(p_t + q_{it}(s_{it}) \frac{\partial p_t}{\partial q_{it}} - c_{it}) - \frac{\partial \delta_{it}}{q_{it}} r \cdot (s_{it} + \alpha_i - \overline{\alpha}_0) \cdot k_i - \delta_{it} r = 0$$

where for simplicity, denote $Pr(q_{it} + \sum_{-i} q_{-it} < Q_t^d)$ as δ_{it}. The last two items are from the new capacity obligation, which are the additional costs firm i needs to consider when deciding how much capacity to withhold.

To sum up, comparing between the old and new capacity obligations, there are several important differences in the incentives they create for producers:

1. The old design only adds incentives during 5% of known hours throughout the year. Outsides these pre-defined hours, firms can optimally withhold capacity to exercise market power in the oligopoly competition without the need to consider their capacity obligations. Even within these pre-defined hours, they can strategically "distribute" outages across the hours to avoid any penalty. Under the new design, however, there is a positive probability of triggering non-performance assessment every hour. So the capacity obligation has binding effects on firms' production decision every hour. Moreover, the probability increases as market situation gets more stressed. This means the new design provides more incentives exactly when producers are more needed, reflecting the time-varying value of generation capacity.

2. In the old design, firms' capacity penalty exposure is capped at their capacity payment, while in the new design, the penalty can exceed the capacity payment firms receive. The penalty under the new design is based on net CONE, which is a much higher reference point for the value of capacity, compared to capacity auction price used under the old design. Hence, firms could lose significant revenue if they perform poorly under the new design.

Therefore, firms will likely bid more competitively and withhold less capacity under the new capacity market design, especially during the high-demand hours.

2.3.2 The First Stage of Capacity Supply

In capacity market auction, producers bid to commit to a reliability target equivalent to the predicted peak demand for the next year plus a reserve margin, ranging from 10% to 25% of the peak demand. Firm i makes decisions on how much capacity to commit (k_i) and how much to invest in improving generators' performance, i.e. reducing outage rate (α_i) in the model. If firm i's bid k_i is smaller than its current capacity k_i^0, then it means the firm will retire some units for the next year, since there is no point for the firm to hold on an asset it deems not economic anymore. If k_i is larger than firm's current capacity, the difference x_i is the new capacity the firm wants to add to its generation fleet. Under this scenario, a fixed investment cost will incur, denoted by $FC_i(x_i)$.

Similar as above, denote the energy market profits (excluding capacity penalty) that the firm earns in the second stage as $\Pi_i = \sum_t max\ \pi_{it}$. Then in the first stage, the firm solves capacity supply problem considering the expected profits from energy market Π_i, capacity market payoff and penalty, and other unaccounted costs, including operating costs of keeping its generators available $I_i \cdot k_i$, investment costs of adding new capacity $FC_i(k_i)$, and investment costs in reducing forced outages $FC_i(\alpha_i)$. Under the old design, the profit-maximization problem is:

$$\underset{\alpha_i, k_i}{max}\ \Pi_i + (1 - a_i) \cdot N \cdot p^c \cdot k_i - I_i \cdot k_i - FC_i(\alpha_i) - FC_i(x_i)$$

where

$$a_i = \begin{cases} 0 & if\ \alpha_i + \frac{\sum_{i \in dh} s_{it}}{N_{dh}} \leq \overline{\alpha}_0\, (no\ penalty) \\ \alpha_i + \frac{\sum_{i \in dh} s_{it}}{N_{dh}} - \overline{\alpha}_0 & if\ \alpha_i + \frac{\sum_{i \in dh} s_{it}}{N_{dh}} > \overline{\alpha}_0\, (penalty\ triggered) \end{cases}$$

Unlike energy market, I assume capacity auction is perfectly competitive. This should be a reasonable assumption because the capacity auction holds three years before the actual operating year, so this should give potential entrant firms an opportunity to compete with the incumbent firms in the capacity market.

Given the perfect competition, each firm should submit the capacity auction bids that make it break even in expectation. By replacing p^c with firm's bid b^c, and denoting $I_i \cdot k_i + FC_i(\alpha_i) + FC_i(x_i) - \Pi_i$ as net "going-forward" cost, or GFC_i^0, we have:

$$b^{old} = \frac{1}{(1 - a_i)} \overline{GFC_i^0}$$

where $\overline{GFC_i^0}$ is the net going-forward cost per MW per hour (divided by $N \cdot k_i$). So b^c is the per MW bid price, in $\$/MWh$ unit, same as p^c.

By comparison, under the new design, firm i's total profit is aggregated as:

$$\underset{\alpha_i, k_i}{max}\ \Pi_i + N \cdot p^c \cdot k_i - \sum_t [\delta_t \cdot r \cdot (s_{it} + \alpha_i - \overline{\alpha}_0) \cdot k_i] - I_i \cdot k_i - FC_i(\alpha_i) - FC_i(x_i)$$

where δ_t is the probability of triggering performance assessment hour, as discussed in the second stage of the model. Then we have firm i's capacity auction bid b^c as:

$$b^{new} = \overline{GFC_i^1} + \frac{1}{N} \sum_t \delta_t \cdot (s_{it} + \alpha_i - \overline{\alpha}_0) \cdot r$$

where $\overline{GFC_i^1}$ is per MWh net going-forward cost under the new design.

An immediate observation is that, b^{new} under the new design is very likely to be higher than b^{old}. This is because: (1) firms withhold less in energy market and drives down the energy price, causing net going-forward cost goes up, i.e. $\overline{GFC_i^1} > \overline{GFC_i^0}$; (2) it is easy to control the average outage rate to avoid penalty under the old design, so a_i is likely 0 in b^{old}; However, in b^{new}, the penalty r is more extreme and much harder to avoid by manipulation. So the firm is likely to incorporate a high risk premium in their capacity market bids (the second term in b^{new}) that reflects the potential penalty cost in the energy market.

The model also predicts that the reform's impacts on capacity investment choices differ for different firms. If a firm owns many inefficient units, it will need a much higher compensation from capacity market under the new design, since reduced energy price under the new design affects its energy market profit more, and its high outage rate is also likely to result in higher penalty, compared to more efficient firms. So it will be less favored in capacity market, and will be forced to retire some of its inefficient generators. For a firm that own more efficient units, on the contrary, higher capacity compensation under the new design might even allow an expansion in its generation capacity. In sum, this implies more efficient allocation of the capacity payment and more efficient generation fleets for the market.

2.4 Data and Descriptive Evidence

2.4.1 Data

I use two sets of data in the two analyses detailed in Section 2.5.

The first set of data is PJM and MISO wholesale market bidding data, which provide generator-level daily bid (price-quantity pairs) in day-ahead auctions and market outcomes, such as market clearing prices and quantity. The data includes some generator-level characteristics such as generation capacity and fuel type, but each generator's identity is masked by PJM.

The second set of data is the hourly generation data for power plants in the PJM and MISO from the Energy Information Administration (EIA) and Environmental Protection Agency (EPA). Specifically, the EPA's Continuous Emissions Monitoring System (CEMS) provides hourly gross production data for fossil fuel generators larger than 25 MW in capacity. EIA Form 923 allows me to match power plants' production data with their operational characteristics, such as operating heat rate and fuel type. Using this information, I construct marginal cost measures for each generator.

Table 2.1 presents descriptive information on the power plants under study in the PJM and MISO by their fuel types. For both markets, natural gas-fired plants have the largest market share. Column 2 shows the aggregate capacity of generators in each type that are matched with the EIA and CEMS information in the data, and column 3 shows the officially reported generation capacity under the dispatch of the PJM and MISO. The comparison of the two columns indicates that the generators studied in this paper are representative of the producers in both markets.

Table 2.1: Generation Capacity By Fuel Type in PJM and MISO

	No. of Plants in Data	Implied Capacity in Data (MW)[1]	Official Capacity in 2016 (MW)[2]
PJM			
Coal-fired	61	50,916	54,369
Gas-fired	137	61,170	64,458
Oil-fired	28	8,719	9,028
MISO (Central & North)			
Coal-fired	68	47,730	48,471
Gas-fired	99	29,931	32,367
Oil-fired	18	2,667	2,063

Notes: [1] Plant-level maximum hourly generation in CEMS from 2015 to 2017.
[2] PJM data is from 2016/2017 capacity auction (RPM Base Residual Auction). MISO data is from 2016 State of Market Report of MISO.

2.4.2 Graphical Analysis

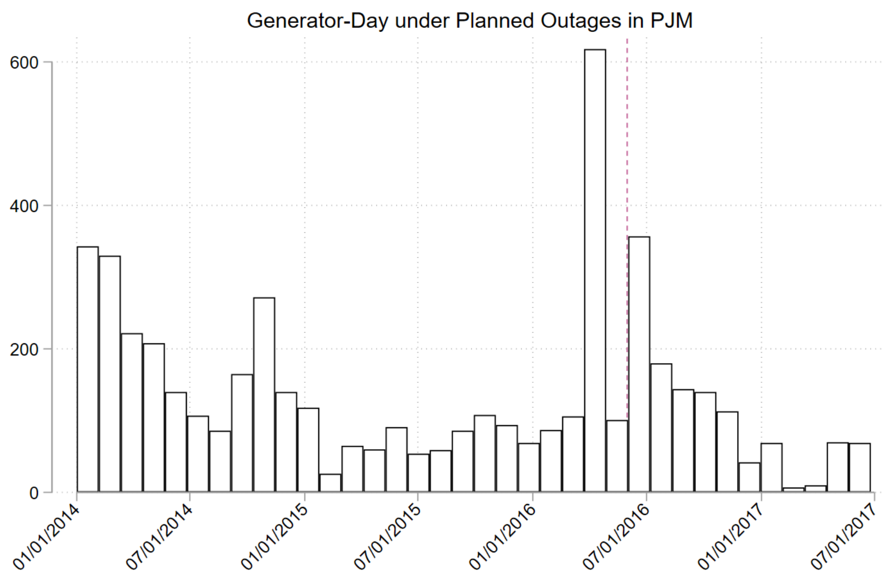
Before conducting the formal empirical analysis, I first use raw data to show some evidence that the PJM's reform has induced additional investment by power plants to reduce the risk of forced outages. As previously discussed, most forced outages are due to a lack of maintenance or fuel. I find in the data that the reform incentivized generators to invest in operational and fuel reliability, which is also confirmed by the official PJM surveys.[7]

Specifically, Figure 2.1 shows a sudden increase in generators' planned outages right before the new performance-based design started in June 2016. The planned outages are power plants' pre-scheduled arrangements, during which generators are taken offline for major repairs, maintenance, and upgrades. As I only found a cluster of planned maintenance around the inception of the reform, as opposed to other periods before and after, it is consistent with the explanation that, in expectation of the reform, generators took measures to improve their operational reliability to reduce the non-performance risks.

Figure 2.2 plots the share of natural gas supply under "firm contracts" relative to

7. PJM, "Capacity Performance Driven Investments", October 24, 2016.

Figure 2.1: More Generators Off-line For Maintenance Before the Reform



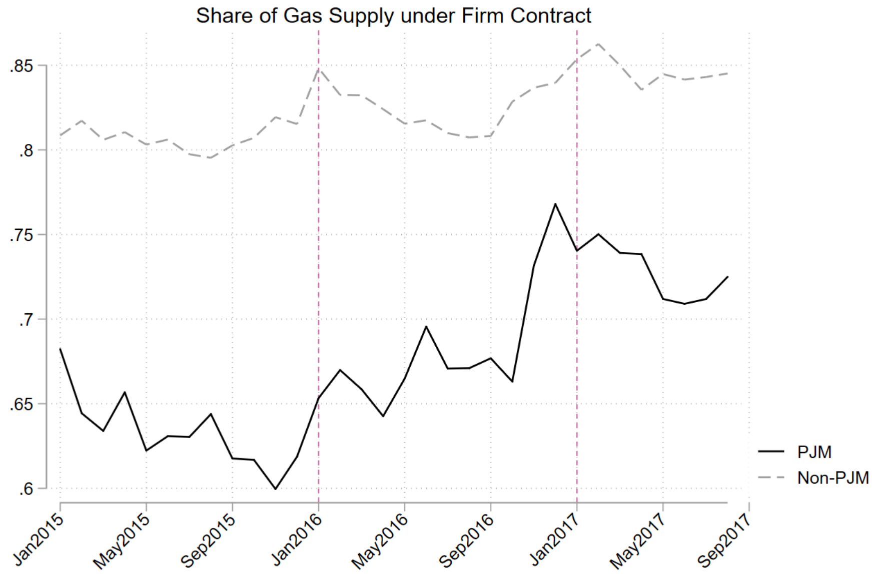
Source: PJM Daily Day-ahead Generation Offer Data. The vertical red line marks June 2016.

"interruptible contracts" for gas-fired power plants in the PJM and non-PJM regions. For a firm contract of natural gas, the plant needs to pay an extra monthly reservation fee. However, in return, it will enjoy the prioritized fuel transportation service without any interruptions, even in high demand situations. A 15% increase in firm contract utilization is observed in the PJM region within one year after the reform started, compared to minimal change in non-PJM regions. This indicates that the PJM reform likely encouraged more investments to improve the fuel reliability and reduce outages due to a fuel shortage.

2.5 Empirical Strategies

In estimating the effect of the PJM capacity market reform, I use two empirical approaches that serve different purposes and rely on different assumptions about the expected outcomes if generators in the PJM were not subject to new capacity obligations. The first approach is difference-in-difference estimation, which focuses on the impact on generators' bidding behavior. It compares the before-and-after trends of the generators' bid price between the

Figure 2.2: Share of PJM Generators' Gas Supply under Firm Contracts



Source: EIA-923 Form. The vertical red lines mark transition year of 2016.

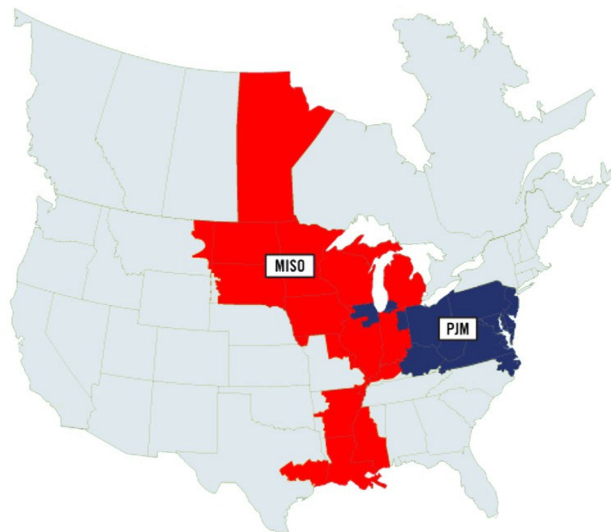
PJM and its neighboring market, MISO (Figure 2.3). The second approach is "generation regressions", which are used to construct predictions about the expected aggregate generation results in the absence of the reform. This approach focuses on the effect of the reform on the actual production results, thereby capturing the broader effect of the reform compared to the first analysis on generators' bidding, for example, the reform's effect on reducing generators' forced/strategic outages.

2.5.1 Difference-in-Difference Analysis

The richness of wholesale market data allows me to track each generator's daily bids over time to study how their bid prices change in response to the capacity market reform. The staggered timing of the reform implementation in June 2016 and the similarity in operations of old capacity market in the PJM and MISO motivated a difference-in-difference approach to estimate the causal impact of the performance-based capacity market design on generators' bidding behaviors.

In this context, the MISO region provides an ideal comparison with the PJM. As shown in

Figure 2.3: PJM-MISO Market Map



Source: PJM-MISO Joint and Common Market

Figure 2.3, MISO and PJM share a similar market size and are neighbors in four states with a few power companies owning plants in both regions. Moreover, the original capacity market designs in the two regions were very similar until the PJM implemented their reform in 2016. This control region allowed me to isolate the effect of the reform from other time-varying factors, such as changes in federal or state policies and company operations.

Specifically, generator bids in the MISO are used to estimate counterfactual outcomes for the PJM after adjusting for common shocks and time-invariant differences:

$$y_{it} = \beta D_{it} + \gamma fc_{it} + \lambda D_{it} \cdot PJM_i + \alpha f(load_{it}) + \delta_i + \mu_s + \epsilon_{it}$$

where the dependent variable y_{it} is the average bid price for generator i on day t. The observations on PJM's generator bids are at a daily level, as the PJM's rules before 2018 require each generator to offer its production with a single bid curve that applies to all 24 hours of the same day. Since the MISO allows generators to bid different hourly prices across each day, I average the hourly bid price for each unit per day in the MISO for the analysis.

In the data, I found that less than 25% of units changed their hourly bids on the same day; thus, this data treatment is not likely to affect the estimation results.

D_{it} is an indicator equal to one if the auction occurred after the PJM capacity reform (June 2016). The primary variable of interest is λ, the coefficient for the interaction term of the reform timing dummy D_{it} and PJM_i dummy. It measures the change in the generator's bid price in the PJM after the reform, compared to the generators in the MISO market.

The regression controls for time-invariant difference between the two markets using a dummy variable PJM_i, which equals 1 if generator i belongs to the PJM region, and 0 if generator i belongs to the MISO region. In the preferred specification, I also added a control for the generation unit's fixed effects to account for the time-invariant difference. Other control variables for common shocks in the two markets include fc_{it} the daily fuel cost, month-of-year fixed effects μ_s, and daily PJM/MISO demand $load_{it}$ in quadratic polynomials $f(load_{it})$.

The validity of this approach relies on two findings: (1) there are no other major changes in the PJM/MISO market design coinciding with PJM's capacity market reform; (2) the PJM's reform did not prompt the generators strategically switching markets between the two regions as a direct result. The first is confirmed from the FERC records because all major market design proposals in the PJM and MISO must be submitted to the FERC to obtain their approval. The second is assured by the fact that generators are constrained by geographical location and interconnection costs in switching markets. In addition, the time needed to exit one market and interconnecting to another usually takes more than a year of evaluation and preparation, therefore I did not observe any major switch during the period of my study from 2015 to 2017.

I also explore a matched difference-in-difference approach to improve over the standard DiD estimate. Specifically, I used the nearest neighbor matching estimator to match the units that: (1) have the same fuel type (coal, gas or oil); (2) have similar historical bidding patterns, that is, a PJM unit is matched to a MISO unit if the absolute difference in their average bid prices in the pre-reform period is less than the threshold of \$5/MWh (for a robustness check, I also tried \$10/MWh).

One caveat for this approach is that the estimated effect is an "intent to treat"(ITT) estimator, as 2016 was still a phase of the reform when only 60%∼70% of generators operated under the new capacity obligations (while the others operated under the old design). I consider my estimate as the lower bound of the true effect of the reform when it is fully implemented.

2.5.2 Generation Regression Approach

The difference-in-difference analysis in the previous section aims to show how the capacity market reform changes generator bidding behaviors in the energy market. Thereafter, I investigate to what extent the reform might improve the market efficiency and reduce the cost of electricity production. When generators under the new capacity market design bid more competitively in keeping with its marginal cost, market production is expected to be scheduled more closely to the "merit-order" (i.e. lower-cost units get scheduled first), thus production efficiency is improved. However, other reasons could also contribute to an improvement in production efficiency. For example, when additional investments from producers are induced by the capacity market reform, generators might be able to produce at lower marginal costs, thus reducing the market production cost. In addition, if generators become more reliable and report less outages (for either strategic or practical reasons), the total production cost is also expected to decrease. Improvements such as mentioned cannot be captured from the previous analysis on the auction bidding data.

Therefore, I use actual production data from the CEMS and "generation regressions"' approach to study the overall effect on market production efficiency. The "generation regressions"' analysis closely tracks Davis and Hausman (2016) and Cicala (2017), with the central idea of using historical patterns in the pre-reform period to predict how market production would be allocated to each generator in the post period had there been no reform.

I then compare the predicted production allocation with the generators' actual production in post periods to see how the capacity market reform contributes to changes in the production pattern and production cost.

The first step of this approach is to estimate the relationship between market demand and generation at the individual generator level. The estimating equation takes the following form:

$$Generation_{it} = \sum_{b}(\gamma_{bi} \cdot 1\{demand_t = b\}) + \beta_1 P_{it}^{coal} + \beta_2 P_{it}^{gas} + \beta_3 P_{it}^{oil} + \epsilon_{it}$$

The dependent variable is the actual power generation for generator i in hour t, measured in MWh. The main independent variables are a set of indicators for different levels of total demand for thermal generation (after subtracting nuclear and renewable generation, which are always scheduled before thermal units because of their near-zero marginal costs). I divided the total demand into bins with equal width, indexed by b. The bin width was 2000 MWh. The assigned production for each unit for a given system demand is mostly determined by the rank of the unit's bid price in the aggregate supply curve, as the PJM requires generators to produce in an increasing price order until total demand is met. However, actual production allocation could also differ from this supply in the cases where generators are scheduled to produce but experience outages in real time.

I also add fuel prices for coal, natural gas, and oil in the equation to control for the mechanical changes in the dispatch order among different fuel types due to the relative fuel price changes, rather than bidding behavior changes. Over the period of my study, the prices for coal, natural gas, and oil were relatively stable; thus, they are not likely to affect the dispatch order much. I further control hour-of-day, day-of-week, and month-of-year fixed effects in the regressions.

In the above equation, I estimated each generator's hourly production using pre-reform data from January 2015 to May 2016, and obtained a set of coefficients γ for each of 226 generators in PJM and 185 generators in MISO. Sample graphs of the coefficients from these pre-period generator-level regressions are shown in Figure 2.4. In particular, I show 6 example plants: 2 for gas-fired combined cycle plants, 2 for gas-fired combustion turbine plants, and 2 for coal-fired steam plants. As shown in the figure, the gas combined cycle plants reach capacity quickly, even at low levels of system demand. These plants are relatively new and efficient, especially after fracking greatly lowered the price of natural gas fuel after 2007. In contrast, gas combustion turbines and coal steam turbines are called on at higher levels of demand as they are generally old and inefficient.

For the second step of this approach, I use post-period data from June 2016 to May 2017, which are the first 12 months after the capacity market reform took effect. For each generator, I calculate the predicted production at each hour by maintaining the regression coefficients from the pre-period, while updating the actual system demand and fuel prices in the post-period. This is the counterfactual generation for each generator in the post-period had there been no reform. The "residuals"' between actual production in the post period and this predicted production reflects the effect of the reform on the production.

In the final step, I combine generators' marginal costs and the predicted/actual production allocations to calculate total product costs in the counterfactual and the post period. In this way, I quantify the effect of the reform on market production cost.

This approach utilizes a prediction model to estimate the ex-ante counterfactuals for the expected production in 2016 had the reform not been implemented. It requires no knowledge of an individual's bidding strategy or incentives, and thus relies on minimum structural assumptions. However, for the prediction of this approach to be useful for causal inference, some important assumptions need to be made. Essentially, I have to assume that the changes in the production allocation are to the result of changes in market fundamentals, but rather because of the changes in generators' behaviors. This means that, for example, the PJM method of dispatching generators had to be unchanged and the transmission grid had not undergone significant upgrades at the same time that the reform took effects. These

Figure 2.4: Examples of Generation Regressions by Individual Plant

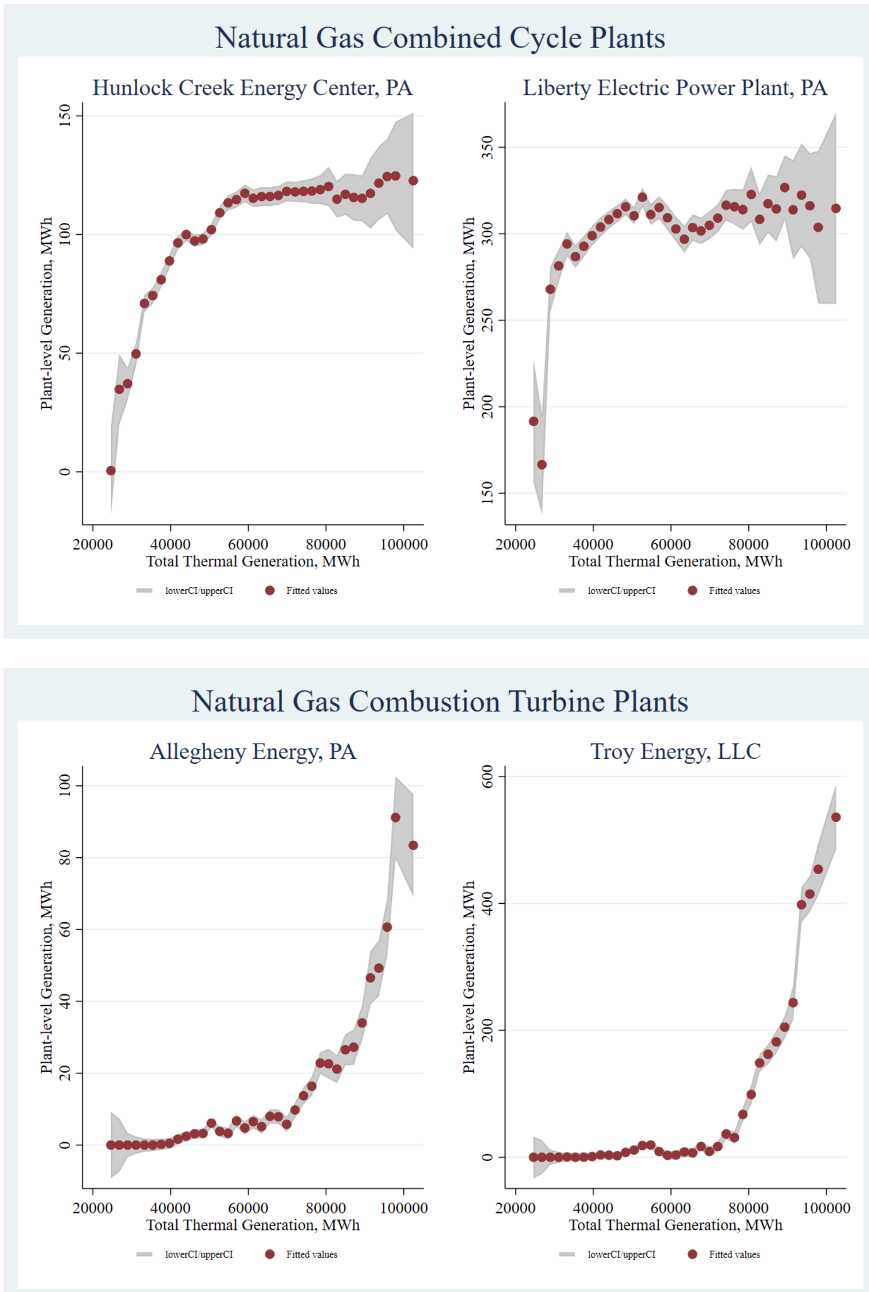
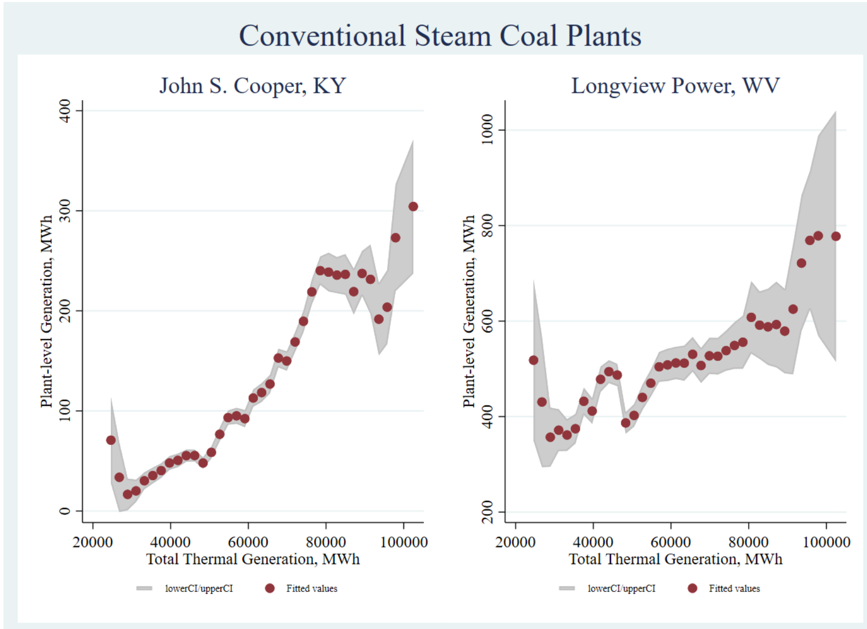


Figure 2.4: Examples of Generation Regressions by Individual Plant (Cont.)



concerns are allayed as I focused on the first 12 months as the post period. The transmission grid was unlikely to change significantly within such a short time. Moreover, I did not observe any proposed changes in market dispatch methods submitted by PJM to FERC during the period of my study.

2.6 Main Results

In this section, I report the results from the aforementioned two approaches and present the treatment effect estimates of the PJM capacity market reform on generators' bidding behavior and market production.

2.6.1 Impact of Reform on Producers' Bidding Behaviors

Difference-in-difference regressions estimate how PJM generators' bid prices change in response to the capacity market reform when compared to similar generators in MISO over time. Table 2.2 shows the results for both the standard DiD and matched DiD estimates. In

Table 2.2: DID Estimates of Capacity Reform Impact on Unit Bid Price

Daily Average Bid Price	*Standard DiD* (1) Levels	(2) Logs	*Matched DiD* (3) Levels	(4) Levels
Post×PJM	-17.51***	-0.11***	-16.76***	-15.65***
	(4.53)	(0.02)	(4.70)	(4.71)
Month-of-Year FE	X	X	X	X
Unit FE	X	X	X	X
Nearest Neighbor Matching			X	X
Threshold ($/MWh)			5	10
Generation units	1,102	1,102	1,052	1,068
N	988,572	985,599	934,503	952,038

Notes: Post×PJM is the treatment indicator (PJM generators) interacted with the post-reform time dummy. Matching criteria: (1) same fuel type (2) pre-period average bid price $||p_j - p_i||$ < threshold listed above. Standard errors clustered by generation unit in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

columns (1) and (2), the standard DiD estimates show that PJM generators lowered their bid price by $17.5/MWh or 11% after capacity market reform, compared to the bids from MISO generators. Figure 2.2 plots the movement of generators' bid prices in the PJM and MISO by month, after adjusting for fuel price, time/unit fixed effects, and system demand. This graph shows that the different trends in the two markets are mainly driven by PJM generators lowering their bids while the MISO generators' bids remained relatively stable. Figure 2.6 further plots the DiD estimates by month before and after the PJM reform. It shows a good parallel trend in bid prices for a 6-month period before the reform, and a sudden decrease in the bid price of the PJM generators, especially for the first 4 months of the capacity market reform implementation.

The nearest neighbor matching estimators in Table 2.2 columns (3) and (4) construct DiD estimates using control units in the MISO that most closely resemble the treated units in PJM with the same fuel type and similar bidding price before the reform. When n nearest neighbors are selected for each treated unit, they were assigned a weight equal to 1/n. Some

Figure 2.5: Monthly Trends in Generators Bid Prices in PJM and MISO

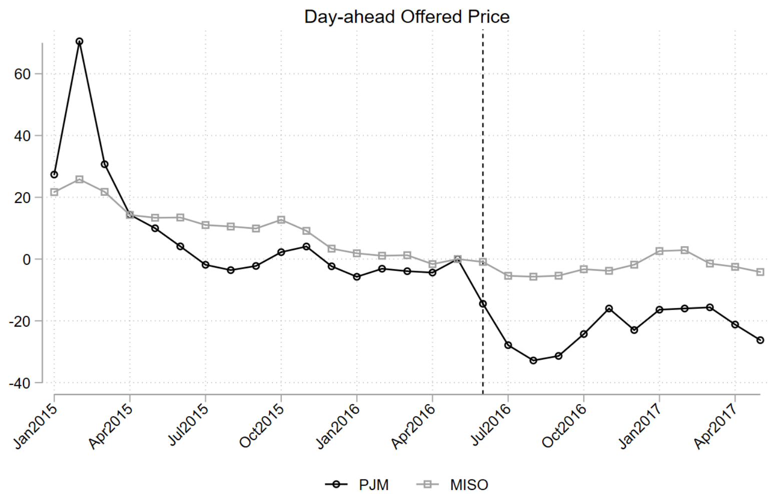


Figure 2.6: Monthly Trend of DiD Estimates

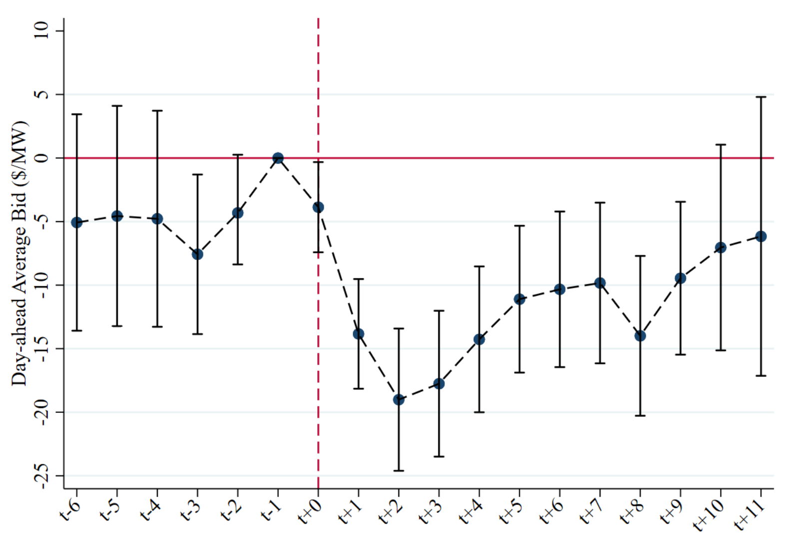
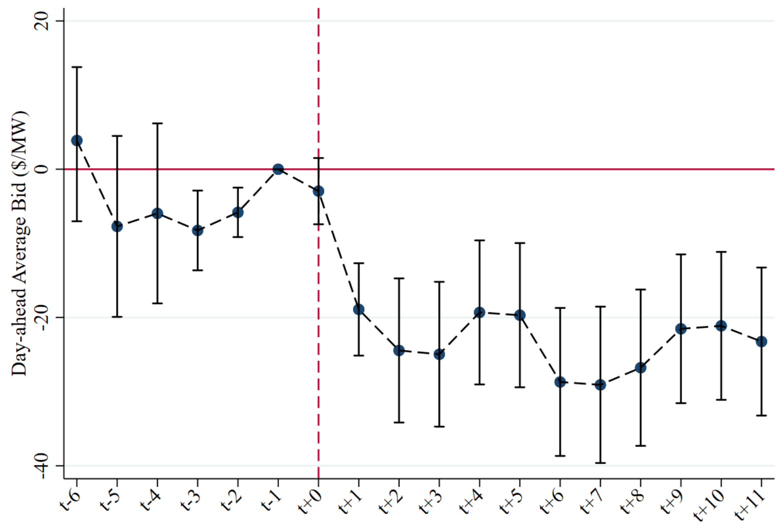


Figure 2.7: Monthly Trend of DiD Estimates for Gas-fired Units



control units were dropped from the regressions as they are not matched to any treated unit. The matched DiD results were very similar to the results of standard DiD, which confirmed that the estimated effect is not driven by different compositions of generator capacity in the PJM and MISO.

In addition, there is heterogeneity in the treatment effects on generators with different fuel types. As shown in Figure 2.7, 2.8 and 2.9, the treatment effect in the overall sample is mainly driven by gas-fired units, while oil units did not experience any change, and coal units' bid even increased during the winter of 2017. This is consistent with the expectation that the new performance-based reform reduced market power exercise, for which the marginal units (mostly gas-fired) have the strongest incentives. The infra-marginal units (coal-fired) and higher-cost units (oil-fired), on the other hand, are not significantly affected, because the ability to push up market price and exercise market power for an infra-marginal generator is much weaker.

Figure 2.8: Monthly Trend of DiD Estimates for Coal-fired Units

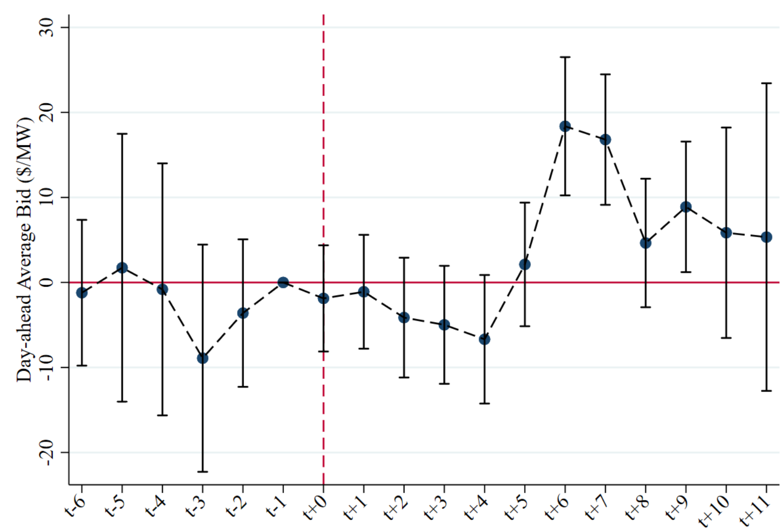
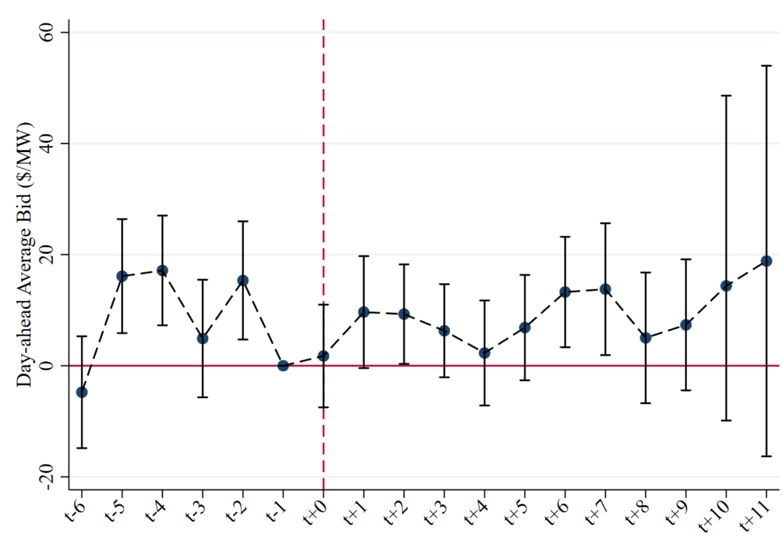


Figure 2.9: Monthly Trend of DiD Estimates for Oil-fired Units



2.6.2 Impact of Reform on Market Production Costs

I used the "generation regressions" approach and generator-level actual production data from CEMS to estimate the effect of the capacity market reform on market efficiency. Inefficiency arises in the electricity market when auction bidding does not result in least-cost production.[8] Herein, the market efficiency is measured by the total production cost, where lower production cost represents higher market efficiency. To measure the total generation cost at each hour, I first calculate the marginal cost for each generator using EIA data on heat rates, fuel types, and fuel prices, that is, $MC_{it} = heatrate_{it} \cdot fuelprice_{it}$. Thereafter, the market production cost at hour t can be measured by combining generator-level marginal cost and production, and then aggregating over all generators: $\sum_i (MC_{it} \times Generation_{it})$.

In Figure 2.10, I plot the distribution of hourly market production costs in the pre-reform period (January 2015-May 2016) and the distribution of predicted production cost from "generation regressions" in the PJM. We can see that the "generation regressions" model accurately predicts the market production costs across different hours in the pre-period, even though the model does not explicitly aim to match production cost, but rather the production dispatch for each generator.

Thereafter, I use the estimated coefficients in the "generation regressions" model to predict the market production outcomes had there been no reform in the 12-month post-period (June 2016-May 2017). In Figure 2.11, the distribution of the predicted production cost across each hour is plotted as a dashed red line, and the actual production cost distribution is plotted as a blue line. Comparing the two distributions, we can see that following the capacity market reform, production in the PJM market incurred lower costs than predicted, in terms of both the average cost and the right-tail of high-cost occurrences. This is consistent with the DiD results, but it might incorporate more than just the effect on generators' bidding behaviors, as discussed in the previous section.

8. Since most retail consumers do not directly respond to wholesale price variation, demand is inelastic in electricity market. So all inefficiencies in the electricity market are on the production side.

Figure 2.10: Predicted generation cost fits pre-period distribution reasonably well in PJM

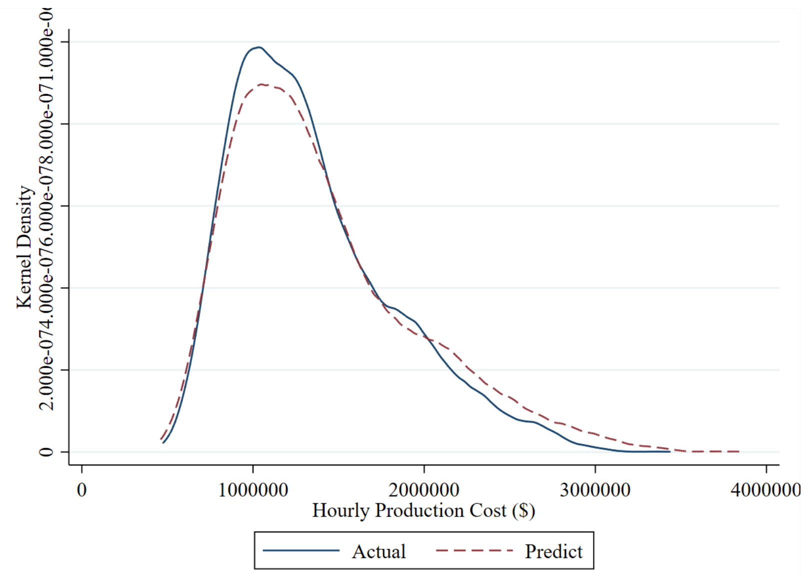


Figure 2.11: Post-period Production Cost Distribution in PJM: Predicted vs.Actual

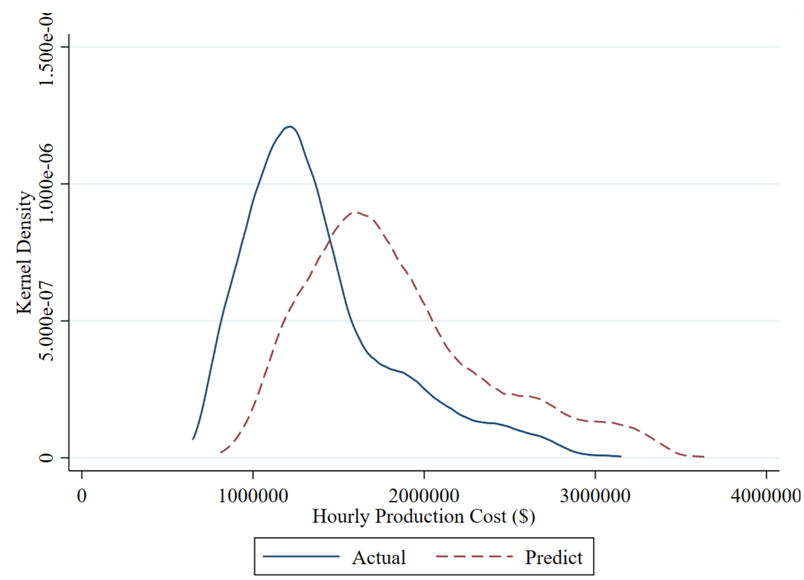
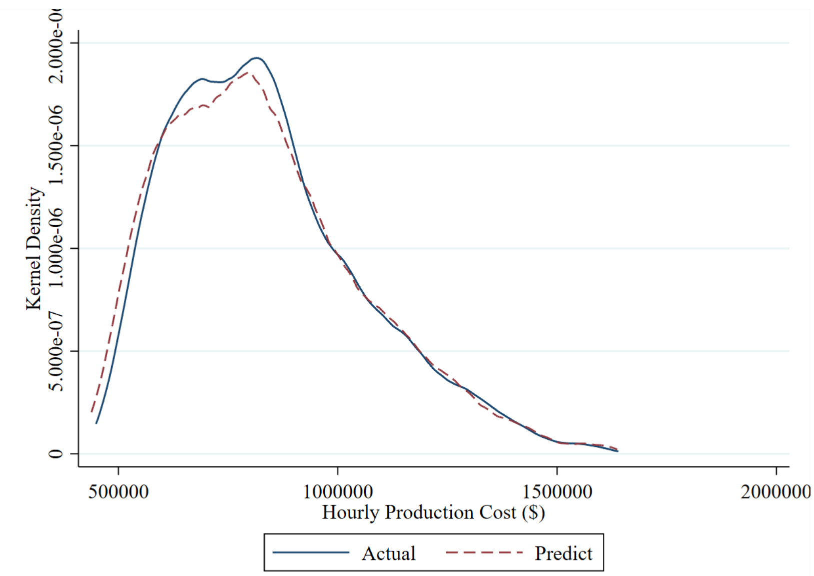


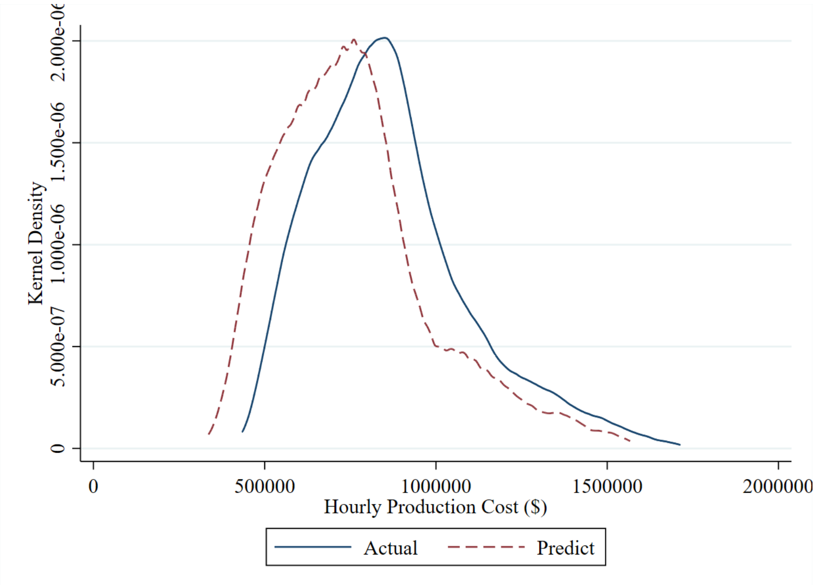
Figure 2.12: Pre-period Model Fit in MISO



For comparison, I apply the same method to the MISO market to compare the change in production cost before and after the PJM's reform. As shown in Figure 2.12, the "generation regressions" model accurately predicts the pre-period generation costs for the MISO market. Moreover, when combining the model with post-period demand and fuel price to predict the production cost after PJM's reform (Figure 2.13), the predictions continued to match the observed outcomes, with the actual production slightly higher than was predicted, which is the opposite to the PJM result. This comparison confirms that there is no common trend in the electricity market in 2016 that can explain the improvement in production efficiency in the PJM. Conversely, its neighboring market, MISO, experienced a negative change in its production efficiency. One possible reason for the higher than predicted actual cost in the MISO is that it had encountered a rapid expansion of renewable energy, especially wind power after 2015. Considering that transmission expansion lags behind such rapid growth of wind energy, the MISO market experienced more congestion; thus, the thermal production cannot be optimally dispatched, causing a higher total production cost.

I present the comparison between the predicted and actual production costs in the post-

Figure 2.13: Post-period Production Cost Distribution in MISO: Predicted vs.Actual



period for the PJM and MISO markets in Table 2.3. The average hourly production cost is shown for all hours (the upper panel), and for peak hours in the summer and winter months, defined by 1 pm to 8 pm in June–August and November–January (the lower panel). The results show large-scale savings in production costs in the PJM market that are attributed to the capacity market reform. Specifically, the cost savings are 0.44 million dollars on average for each hour, or equivalently, 25% when compared to the predicted costs. During summer and winter peak hours, such savings are even more notable, reaching 0.53 million dollars per hour. In contrast, the actual production cost is a little more than the predicted number in the MISO market, where the cost increase is about 0.1 million dollars per hour.

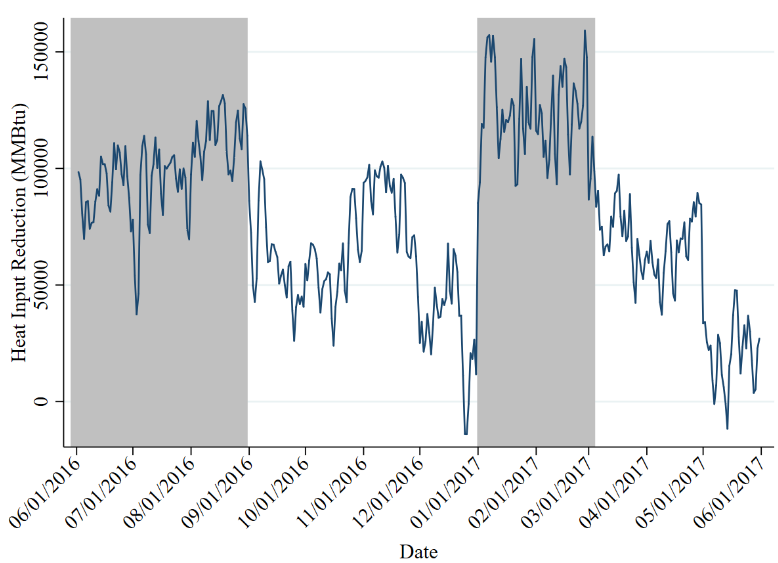
Lastly, Figure 2.14 displays the seasonal patterns in cost savings during the PJM post-reform period. This figure shows that production efficiency was predominantly improved during summer and winter months (shaded area), which is consistent with the fact that higher demand in summer is more attractive to market power exercise and severe whether/natural gas shortage in winter make capacity commitment more problematic.

Table 2.3: Post-period Hourly Production Cost Comparison, PJM and MISO

	Hourly Production Cost, After Reform	
	(1) PJM	(2) MISO
All Hours		
Actual($)	1,327,679	864,418
Predicted($)	1,770,734	760,770
Difference(%)	-25%	12%
Peak Hours		
Actual($)	1,718,633	1,278,825
Predicted($)	2,248,406	1,187,180
Difference(%)	-24%	7%
Number of Plants	226	185
Total Capacity (MW)	120,805	80,328

Notes: Actual hourly production cost is the hourly average cost of generation for the first 12 months of the reform. The predicted production cost is based on production predicted by "generation regressions" for the same period using actual demand and fuel prices. Generation costs are calculated based on marginal cost for each unit, not including capital costs or other fixed costs.

Figure 2.14: Generation Efficiency Improvement by Month



2.6.3 Welfare Implications of the PJM Capacity Market Reform

In evaluating the full cost-effectiveness of the PJM capacity market reform, it is necessary to consider its impacts on both energy market and capacity market. The social welfare is not necessarily improved if the cost reduction in providing electricity in the energy market is offset by the cost increase in providing generation capacity in the capacity market.

As the cost reduction in the energy market has been estimated using "generation regressions", the cost increase in the capacity market requires a closer look at generators' bids in the capacity market auction. Unfortunately, such data is confidential proprietary information, and therefore deriving an accurate measure of capacity market cost for the PJM's reform is beyond the scope of this paper. However, by calculating consumers' capacity payments using market clearing prices and quantities in capacity market auctions, it is possible to establish the upper limits of these costs.

Specifically, for 2016-2017 delivery year, PJM already held its capacity auction before the approval of its capacity market reform, thus subsequently after the approval held another auction for the same delivery year to register generators for the new design. This provides a rare opportunity to observe both old capacity auction prices and new auction prices for the same delivery year of 2016-2017. Under the old design, the PJM cleared the capacity auction at \$59.37/MW-day in its RTO region and at \$119.13/MW-day in the MAAC region. Under the new design, the capacity market clearing price is \$134/MW-day for all regions. Thus, combining each region's cleared capacity and its cleared price, the increase in capacity payment for the 2016-2017 delivery year due to the reform was estimated at 2.24 billion dollars.

According to my calculations, the estimated savings in energy production costs for the 2016-2017 delivery year is approximately 3.8 billion dollars. Thereby, the net benefit accrued from the capacity market reform would be 1.56 billion dollars for 2016-2017 year. Since this is an approximation based on the capacity payment cost, rather than the actual cost of maintaining generation capacity, it is likely to underestimate the net benefit. Nonetheless, this result shows a net benefit as a result of the PJM's reform in the capacity market design.

2.7 Conclusion

Performance-based capacity market reform is an innovative endeavor to integrate time-varying scarcity pricing with capacity market payment. PJM already initiated its transition to this new capacity market design in 2016, followed by New England ISO with a similar reform in its own capacity market in June 2018. Compared to the scarcity-pricing energy-only design implemented in the Texas ERCOT market, this new capacity market design could achieve the same goal of reliability , but with less price volatility; thus, its political feasibility has wider market appeal.

This paper is one of the first studies to empirically evaluate the effect of the reformed capacity market design on generators' bidding behaviors and market efficiency. The richness of the PJM market auction data enabled me to track each generator's bidding behaviors over time, and study how their bids changed before and after the reform took effect, especially when compared to similar generators in the neighboring MISO market that operated under the similar old design. The matched DiD results show that the capacity market reform contributed to a decrease in the average bid price of PJM generators by \$17/MWh, or approximately 10%. To capture the full impact of the reform on electricity market efficiency, I further exploited the unit-level hourly production data from EPA in a "generation regressions" approach to predict market production costs if there was no reform in 2016-2017 and compared the predictions with the actual results. This analysis reveals large savings in production costs as a result of capacity market reform. After accounting for both the savings in the energy market and the cost increase in the capacity market, the net benefit accrued from the reform was approximately 1.56 billion dollars for PJM in the 2016-2017 delivery year. This considerable benefit achieved by the implementation of the PJM capacity market reform is consistent with the theoretical expectation that by adjusting the capacity payment to reflect variations in the value of power plants' capacity we can effectively incentivize them to supply when they are most needed instead of withholding their capacity and exercising their market power.

As a consequence of the data limitations, there are important questions that cannot be answered in full in this paper. For example, how did producers perceive the uncertainties introduced by non-performance penalty? Did they over-estimate the risks of failing the new capacity obligations? Would they gradually learn the actual risks and adjust their behaviors over time? What would constitute a long-term equilibrium under the new capacity market design? A better understanding of these questions will be very informative for the discussion about the optimal design of the capacity market.

Chapter 3

Does Retail Deregulation Create Strategic Wholesale Buyers? Evidence from the U.S. Midwest Electricity Market

3.1 Introduction

Economists have long studied the relationship between the wholesale and retail markets, as they are very closely connected. For example, retail providers in the retail market are usually also the wholesale buyers in the wholesale market. Additionally, some firms in certain industries are vertically integrated, playing the roles of both upstream wholesalers and downstream retailers. The interaction between the two markets raises interesting empirical and theoretical questions in economics, including principal–agent problems, double marginalization, and price pass-through (e.g., Rey and Stiglitz, 1995; Shepard, 1993; Borenstein and Shepard, 1996).

After its widespread deregulation starting in the 1990s, the electricity industry has exhibited some new features in this interaction. Unlike the case of many other products, whose wholesale price is determined by contracts or delegation, deregulation in the electricity industry has created integrated wholesale markets, where the price is determined by a centralized auction. Regulated utility companies, along with deregulated competitive retailers, make demand bids in the wholesale market, operating with different incentives and purchase strategies.

In this study, I explore how retail market deregulation impacts the wholesale market by changing the retailers', that is, the wholesale buyers' incentives in demand bidding. Since the creation of wholesale markets, the issue of producer-side market power has become prominent in many regions and has been widely studied in the energy economics literature (e.g., Borenstein, Bushnell, and Wolak, 2002; McRae and Wolak, 2009). In the wholesale market, electricity demand and supply need to be strictly balanced every second of every hour while there is little response from the demand side as consumers do not directly respond to wholesale price variations. This market setting gives producers ability to drive electricity wholesale prices above their production costs, especially during high-demand hours. The California electricity crisis in 2000, when drought and market manipulation caused an 800% increase in wholesale prices[1], provides salient proof of this.

It is well understood in economics that the more elastic the demand is, the less market power (a lower price markup) can be exercised by producers. However, a demand-side response has rarely been found in previous studies on the electricity market, despite the severe market power exercised by the producers being observed. For example, most studies are conducted in regions with regulated retail markets (e.g., Borenstein et al., 2002, in California). Other places have deregulated markets but do not have sufficient retail competition during the time of the studies (e.g., Hortaçsu and Puller, 2008, in Texas; and Birge et al., 2014, in the Midwest).

In this study, I find that retail deregulation has important implications for introducing

1. https://en.wikipedia.org/wiki/California_electricity_crisis

demand-side response. One goal for retail deregulation is to increase retail competition by allowing deregulated retail companies to compete with traditional utility companies. The incentives of traditional utilities and competitive retailers are very different: most traditional utilities are under cost-of-service regulation and only keep fixed profits that are a predetermined proportion of their total costs. In contrast, competitive retailers in retail deregulated regions are profit-maximizing companies. In terms of wholesale market operations, although the utilities receive zero profit from a low purchase price, competitive retailers have incentives to be strategic in lowering their procurement costs.

In fact, the sequential market design in the wholesale market provides those buyers with an opportunity to be strategic. Most of the wholesale market consists of two sequential markets: a day-ahead (DA) market, which schedules production based on supply and demand bids one day before the operating day, and a real-time (RT) market, which allows for any adjustments in bids and schedules when operating hours are approaching. Previous studies find that the DA price is consistently higher than the RT price (e.g., Ito and Reguant, 2016, in the Spanish market; and Mercadal, 2018, in the U.S. Midwest market) and relate such DA price premium to the producers' exercising their market power in a sequential market setting. When facing DA price premiums consistently, it would be optimal for a wholesale buyer to divide its purchase between the day-ahead and real-time markets to minimize its purchase cost.

I find empirical evidence supporting the use of such a strategy by competitive retailers in the U.S. Midwest market (Midcontinent Independent System Operator or MISO). MISO covers all or parts of 15 states in the U.S. Midwest. Among them, Illinois is a retail-deregulated state with more than half of the electricity consumers served by competitive retailers[2]. The richness of hourly bidding data in MISO wholesale auctions allows me to compare demand bids in the day-ahead market with their final position in real-time and calculate how these wholesale buyers divide their purchase between the day-ahead and real-

2. https://www.pluginillinois.org/Suppliers.aspx

time markets.

Using an instrumental variables approach, I find that the competitive buyers in Illinois underbid their demand in the day-ahead market when the day-ahead price is higher than the spot price. In addition, they shift more demand to the spot market when the day-ahead price premium is higher, which is consistent with the strategic behaviors a cost-minimizing bidder should take in the sequential markets. Conversely, I do not find such strategic behaviors among the buyers in other retail-regulated areas. This finding confirms that retail deregulation changes buyers' incentives in the wholesale market and improves their bidding performance.

To further assess whether buyers' behavioral changes under retail deregulation indeed improve wholesale market efficiency, I employ a difference-in-differences (DiD) framework to estimate the changes in day-ahead market prices from 2010 to 2014 in Illinois, a retail-deregulated state, against Wisconsin, which is a neighboring regulated region that is comparable in many aspects. I exploit a policy change in the Illinois retail market in 2011, which facilitated a steep increase in the number of customers served by competitive retailers between 2011 and 2013. Aligning this with the timing of the large expansion in competitive retail consumption, I find that market prices in Illinois started to deviate from the similar path of the control state, Wisconsin after 2012, and kept decreasing. By 2014, the price in Illinois was already $6.1 lower compared to that in 2011 in Wisconsin, when the prices in the two states were almost the same. This reveals the effect of retail deregulation on wholesale market prices and efficiency.

This study contributes to the IO literature by studying the interaction between the wholesale and retail markets. Auction design in wholesale purchases is a peculiar feature in the deregulated electricity industry, and the analysis could provide insights into other markets with similar settings. For example, treasury bonds are issued through centralized auctions in many countries, and the buyers in the auctions are also the "retailers" in the secondary markets. Entities with different "retail" purposes could face different incentives that directly affect their bidding strategies (e.g. Hortaçsu and McAdams, 2010). This study is also related to the literature examining sequential market settings. The buyers' strategic underbid in the day-ahead market is similar to the "Coase conjecture" (Coase, 1972), where a monopoly seller of durable goods exercises market power by creating price differences in sequential markets but such market power could be mitigated if buyers are also strategic and willing to wait.

The results of this study have important policy implications for electricity deregulation. The empirical evidence shows that retail deregulation is one of the possible solutions to reducing producer-side market power as it motivates demand-side response in the wholesale market. Some other solutions have been discussed in previous literature, including vertical contracts (Bushnell, Mansur, and Saravia, 2008), financial traders (Jha and Wolak, 2015; Mercadal, 2016), and transmission expansion (Ryan, 2017). In addition, when competitive buyers are able to reduce their procurement costs in the wholesale market, this would benefit consumers in the retail market, which is directly related to the discussions in the electricity sector about providing "customer choice," or "retail choice" (Joskow, 2000; Borenstein and Bushnell, 2015).

This study is most closely related to Borenstein et al. (2008) and Ito and Reguant (2016). Borenstein et al. (2008) presented the first evidence of strategic behaviors from electricity buyers in the California electricity market. A special occasion emerged for a short period between 2000 and 2002, during which the three largest utilities were allowed to keep any profits from selling electricity to the customers in their service areas.[3] Therefore, they faced the same incentives as the deregulated retailers in my analysis and acted similarly to a strategic buyer in the wholesale market. Ito and Reguant (2016) studied the interaction between market power and limited arbitrage and used them to explain the price difference between the day-ahead and spot markets in the Spanish electricity market. They also found

3. This was done to compensate them for their capital loss due to the deregulation process, during which the generation assets were separated from these three utilities, so after deregulation, they transitioned to being only distributors and retailers.

that demand-side bids responded to changes in the day-ahead price premium. In this study, I show that the magnitude of the response is much larger in the context of the MISO market.

The remainder of this paper is organized as follows: Section 3.2 describes the institutional background of the U.S. Midwestern wholesale electricity market and the main data used in the analysis. In Section 3.3, I conduct empirical tests on how wholesale buyers/retailers from different regions bid under different incentives. In Section 3.4, I further estimate the effect of retail deregulation on wholesale market prices. Section 3.5 concludes.

3.2 Institutional Settings and Data

I begin by providing a background introduction about the U.S. electricity deregulation, particularly the deregulated retail market in Illinois. I then explain the features of sequential market design in the MISO wholesale market, which are the key to understanding buyers' strategies in the market. Finally, I describe the data used in the empirical analysis and present basic summary statistics.

3.2.1 Electricity Market Deregulation in the U.S. - Wholesale and Retail

Traditionally, electricity utilities are vertically integrated and responsible for generation, transmission, distribution, and retail services for the end-use consumers. Although they enjoyed relative autonomy over the grid operations within their service areas, they were under federal and state-level regulations. The cost-of-service regulation set the energy prices for the utilities on a cost basis, guaranteeing the recovery of their variable costs as well as a predetermined rate of return on their investment capital costs.

Major deregulations in the U.S. electricity industry started when the Federal Energy Regulatory Commission (FERC) implemented a series of major changes in the aforementioned structure in the 1990s. These changes required the separation of transmission system owners and power producers, open access for independent power generators to the electric grid, and transmission to be provided at regulated rates. FERC created regional transmission organizations (RTOs) and independent system operators (ISOs) to operate the transmission system independently and foster electricity generation competition.[4] ISOs/RTOs set up wholesale markets which use centralized auctions to determine the market price and ensure the economic dispatch of power production. Since then, many utilities across the country have joined an RTO or ISO and as of today, two-thirds of the electricity produced in the United States is sold via wholesale markets.

Although wholesale deregulations are subject to federal decisions, retail deregulations are subject to state decisions. As different states make different decisions about whether to deregulate their retail markets, this provides an opportunity for researchers to study a mix of deregulated and regulated states within the same wholesale market. I examine the midwest market, or MISO, in this study, where regulated utility companies and deregulated competitive retailers in different states make demand bids together in the market, facing different incentives and using different purchase strategies.

Regulated utility companies traditionally operate as monopolies or oligopolies in each state, providing transmission and distribution services at regulated rates. They also sell electricity to consumers as retailers. However, the cost-of-service regulation stipulates that they cannot keep the profits they make from the market except for a fixed amount that is proportional to their cost. This means that they do not have incentives to minimize their service costs[5], including their procurement costs in the wholesale market.

In retail-deregulated states, the utilities have become the "default" choice, with consumers allowed to switch to a competitive retailer. Competitive retailers face completely different

4. https://www.ferc.gov/market-oversight/mkt-electric/overview.asp

5. In fact, the state regulators have the right to not approve the recovery of any costs that are deemed "imprudent." However, this does not give the utilities incentives to minimize their procurement costs in the wholesale market. Bidding for all the demand in the day-ahead market is what buyers are expected to do to secure power delivery for their consumers the following day, even though the procurement cost is almost always not minimized.

incentives than the utilities. They are profit-maximizing companies and they compete with the utilities and other retailers for consumers. Most consumers are willing to sign long-term contracts at fixed retail prices, so they can avoid dealing with the significant price volatility in the wholesale market (Joskow, 2000). This indicates that for competitive retailers, minimizing the electricity procurement cost in the wholesale market is a major part of their profit maximization exercise.

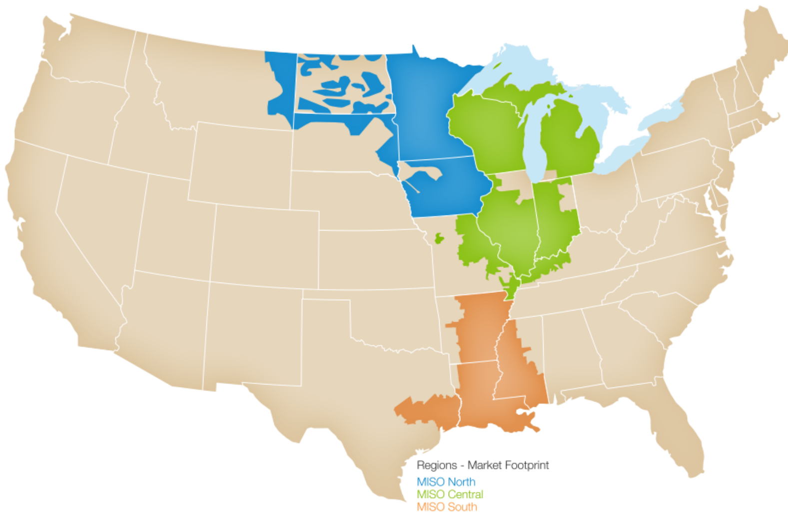
Heretofore, only 17 U.S. states and the District of Columbia have fully or partially deregulated their retail markets[6], in contrast to the widespread wholesale market deregulation. Even for these states, the retail deregulation might not be considered very successful. For example, the consumers' participation in the retail choice program in Michigan is capped at 10% of the incumbent utility's previous-year sales; California and several other states only provide retail choices for commercial and industrial consumers.

Illinois is a notable exception among these states. Although deregulation did not start off well in 2002, a policy change in the retail market in 2011 completely changed the situation. In 2011, an amendment to the Illinois Power Agency Act about "Municipal Electric Aggregation (MEA)" took effect, which allowed municipalities, counties, and townships to negotiate the purchase of electricity with alternative retailers on behalf of their residents. Between 2011 and 2013, opt-out MEA programs became extremely popular among municipalities, as many of them opted out of utilities contracts, and signed new bulk contracts with competitive retailers. The speed of expansion in competitive retail consumption was shocking: as of January 2014, more than 3 million customers were served by more than 50 competitive retailers in Illinois, 500 times more than the 6,199 customers served by several competitive retailers at the end of May 2011.

One additional note is that the MISO market I study does not include the entire Illinois state. Instead, it only controls central and southern Illinois, where the utility company

6. http://competitiveenergy.org/consumer-tools/state-by-state-links/

Figure 3.1: Map of MISO Control Regions



Source: 2015 Value Proposition, MISO Energy

Ameren delivers electricity.[7] The MISO-controlled part (or Ameren zones) has also been greatly affected by the MEA policy change, which I will exploit in Section 3.4. In June 2011, only 224 consumers were served by competitive retailers in the Ameren zones. This number was multiplied by 1,500 by the end of 2012 reaching 334,207. As of January 2014, 675,940 customers used electricity provided by more than 20 competitive retailers.

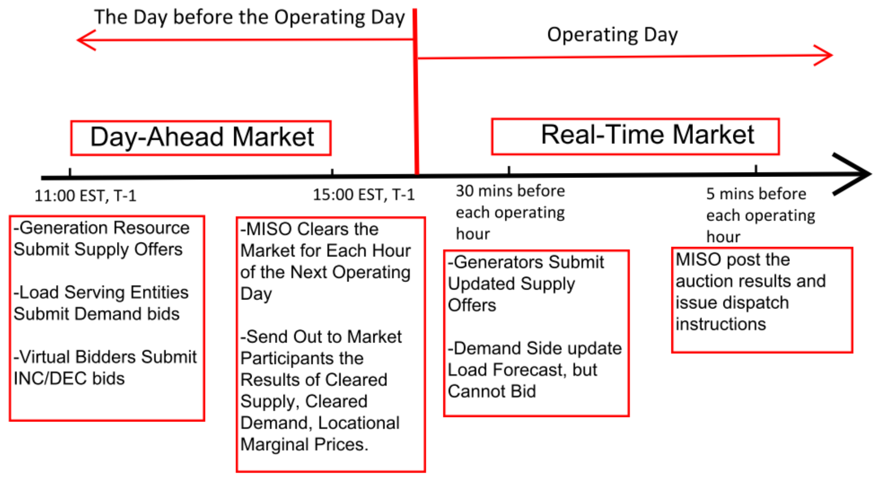
3.2.2 MISO Wholesale Electricity Market

Electricity market deregulation created ISOs as described above to manage the transmission system and administer the wholesale markets. In the U.S. Midwest, this role is played by MISO, which oversees all or parts of 15 U.S. states and the Canadian province of Manitoba (Figure 3.1).

MISO, like many deregulated markets in the United States and around the world, operates two sequential markets for wholesale trade: a DA forward market and an RT spot market. Most power is supposed to be bought and sold one day in advance (DA market), and any

7. The rest of Illinois is served by another utility company ComEd, and is part of the PJM RTO.

Figure 3.2: Timeline of the Sequential Markets: Day-ahead and Real-time



imbalance between day-ahead transactions and real-time demand is then cleared in the RT market. Each market uses uniform-price, multi-unit auctions to determine the market-clearing quantity and price.

Figure 3.2 summarizes how the two sequential markets work. One day before each operating day, the DA market begins at 11:00 a.m. EST, when producers and buyers submit their supply and demand bids for each hour of the following day. Qualified financial traders are also allowed to bid as a third party but their virtual bids for selling (purchasing) energy create an obligation to purchase (sell) an equal amount from the RT market. The DA auction closes at 3:00 p.m. EST. The ISO clears the market with the price and quantity at the intersection of the aggregate demand bidding curve and aggregate supply curve. Due to the capacity limits of the transmission lines, separate prices for each location in the grid are calculated by adjusting the energy price to the congestion and transmission loss. MISO then makes a dispatch plan for the next day, based on these auction results to ensure that the demand is met and the electricity is supplied at the lowest cost.

The RT market starts half an hour before midnight of the operating day, when producers submit bids and can update their final bids until 30 minutes before each operating hour. Buyers can also adjust their demand in the RT market. However, unlike the price-quantity bids they submit in the DA market, in this final stage of RT market, they can only update their demand quantity as price takers. For actual operations, each operating hour is divided into five-minute intervals. During every such interval, the system operator sends dispatch instructions to generators based on the auction results by balancing RT supply and demand bids and adjusting for transmission congestion and loss.

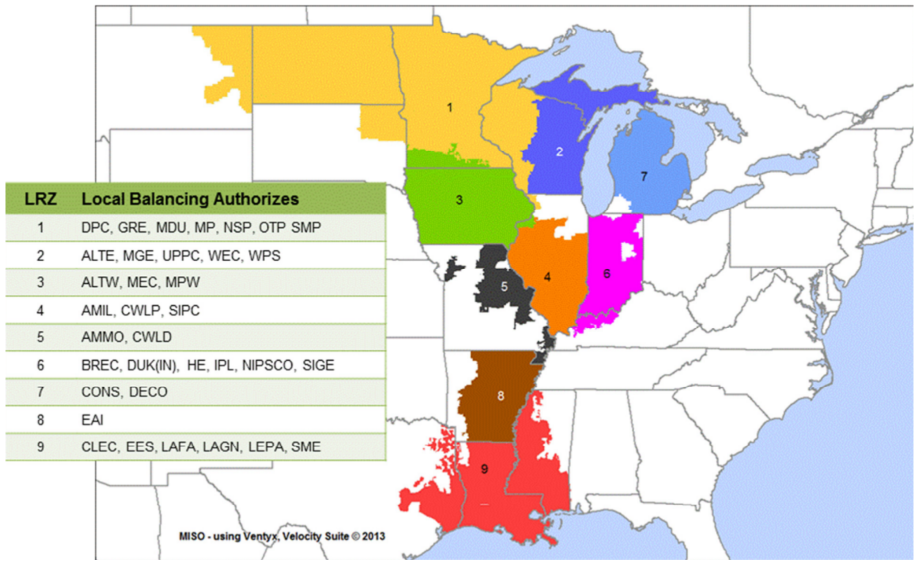
This sequential market setting gives buyers the flexibility to bid strategically. Although they have no control over the final quantities of end-use consumption, they do have discretion over the market in which they purchase electricity. For example, if the RT market price is lower and buyers shift some of their purchase from the DA market to the RT market, this would lower their total purchase cost as long as this shift does not significantly affect the price difference. In theory, we should be able to observe this kind of strategic behavior from competitive retailers who have incentives to manage their procurement costs, especially when the price difference between the two markets is large. In contrast, regulated utilities, which do not care about the price, are expected to buy most of their demand in the DA market, simply to secure the electricity delivery for the next day.

3.2.3 Data and Summary Statistics

Most of the data used in this study are from MISO's market reports on its website. For the analysis in Section 3.3, I use the following data reported hourly from 2014 to 2015: (1) each market participant's bidding data from the DA and RT market; (2) cleared quantity and locational marginal prices (LMPs)[8] data in the DA and RT markets at each node of the grid; and, (3) the demand forecast and actual demand at the local resource zone (LRZ) level. For the analysis in Section 3.4, I extend the study period from 2010 to 2014, for which

8. LMPs are the market-clearing prices at each generation or demand location, adjusted for congestion and transmission loss.

Figure 3.3: MISO Local Resource Zones (LRZ) Map



Source: 2014 Map of Local Resource Zone Boundaries, MISO Energy

I collect hourly LMP data reported at each node of the grid.

As shown in Figure 3.1, MISO divides its control area into three regions, for convenience in sending out dispatch instructions: central, north, and south. I will focus on MISO's central and north regions in this study, as the south region was only recently consolidated into MISO and is geographically independent, with very limited imports and exports from the rest of the grid. A finer division of MISO introduces LRZs (Figure 3.3), defined mainly by state boundaries and the electrical boundaries of the local grids. MISO creates LRZ divisions to address transmission congestion situations, during which LRZs are fully responsible for balancing supply and demand. Among the 7 zones in MISO's central and north, Illinois (the part under the Ameren's distribution service, as explained in Section 3.2.2), or LRZ4, is a retail-deregulated state.

For confidentiality reasons, MISO only makes LRZ-level demand data available to the public, instead of more detailed firm-level demand data. Therefore, in my study of how buyers divide their bids between the DA and RT markets, I focus on the state level, where the buyers' DA demand bids are aggregated and compared to the actual demands (RT bids) in each LRZ.

Table 3.1 provides summary statistics for 7 LRZs in MISO's central and north regions during 2014–2015. MISO's reported hourly demand is combined for LRZ2 and LRZ7, as well as for LRZ3 and LRZ5, again because of confidentiality concerns. There are 17,520 ($365 \times 2 \times 24$) hour-day observations for each zone, and Panel A shows the DA and RT market prices at the trading hub of each zone. On average, the DA price is higher than the RT price, so there is a DA price premium, varying from \$0.6/MWh to \$2.08/MWh across the zones. The medians of the DA price premiums show similar results.

Previous literature has provided theoretical foundation and empirical evidence that the DA price premium in sequential markets is a sign of market power exercised by the producers (e.g., Saravia, 2003; Borenstein et al., 2008; Ito and Reguant, 2016). To mitigate such market power, MISO introduced financial trades in 2005, intending to use their arbitrage to drive the price premium to zero. However, at the same time, MISO imposes some deviation charges on every trade made by virtual bidders and high qualifying standards for new virtual bidders to enter the market. These restrictions limited arbitrage activities from virtual traders, so the price differences and producers' market power still existed during my study period, as documented in recent studies on the same market (Birge et al., 2014; Mercadal, 2016).

Given the DA price premium and insufficient arbitrage to clear it away, how do buyers in each region respond to this market power exercise from producers? Panel B in Table 3.1 shows the average demand bids submitted by the buyers in each zone in the DA market auctions. Demand bids are allowed to be either fixed-quantity or price-sensitive so buyers can either specify a quantity that they are willing to buy at any price, or bid up to 9 quantity–price pairs, as a staircase demand function.

One thing is most noticeable in this panel. Comparing the quantity demanded and cleared in the DA market with the demand forecast (first two rows in Panel B), it seems that the DA market systematically clears less demand than that forecast. Conversations with MISO operation staff confirm that MISO does not have any regulations or offer advice

Table 3.1: Summary Statistics of MISO Local Resource Zones

	LRZ1	LRZ2_7	LRZ3_5	LRZ4	LRZ6
Panel A. Market Clear Prices					
Day-ahead Market Price ($/MWh)	27.46	36.76	29.13	31.85	34.22
	(16.23)	(24.98)	(14.04)	(17.36)	(20.44)
Real-time Market Price	26.70	34.68	28.53	30.23	32.99
	(23.99)	(30.53)	(24.72)	(27.21)	(28.54)
Day-ahead Price Premium					
Mean	0.76	2.08	0.60	1.62	1.24
	(20.98)	(29.09)	(21.48)	(25.92)	(26.18)
Median	0.82	2.06	0.87	1.64	1.71
Panel B. Day-ahead Demand Bids					
DA Cleared Demand (MWh)	10756	18120	10002	5381	10918
	(1603.3)	(2836.5)	(1709.7)	(887.1)	(1708.5)
DA Demand Forecast	11204	19137	10301	5708	11463
	(1645.5)	(2732.5)	(1771.5)	(955.0)	(1748.4)
Difference	-448	-1018	-299	-327	-545
	(218.9)	(638.1)	(244.2)	(271.9)	(220.3)
RT Actual Demand	11199	18819	10258	5683	11419
	(1648.2)	(2922.1)	(1744.2)	(962.8)	(1762.6)
DA Fixed Demand	10682	17779	9843	5073	10788
	(1586.4)	(2794.9)	(1686.9)	(854.4)	(1684.4)
DA Price-Sen Demand	82	450	184	312	135
	(68.52)	(192.7)	(54.69)	(77.83)	(77.80)
DA Underbid	521	1358	457	635	675
	(228.2)	(623.9)	(251.8)	(267.4)	(217.6)
Percent Underbid	0.047	0.072	0.044	0.110	0.059
	(0.0191)	(0.0353)	(0.0221)	(0.0401)	(0.0178)
N	17520	17520	17520	17520	17520

Notes: Standard deviations in parentheses. Summarized from hourly data between 2014 and 2015. Prices in Dollar/MWh. Bids in MWh. Prices in each zone are the average LMP from the zone-level trading hub.

on such bidding behaviors, so it reflects the market participants' own strategies. Moreover, if we compare the demand forecast to the actual demand reported in row 4, the forecast is very accurate on average, with a deviation of less than 50 MWh in a given hour across the zones. Therefore, this underbid cannot be explained by the possibility that buyers consistently under-forecast their demand in the DA market. However, this underbid behavior is consistent with a strategic buyer's response to the DA price premium. For cost-minimizing buyers, shifting some of the demand from the DA market to the spot market can lower their procurement cost and also possibly decrease the DA price. In Section 3.3, I formally discuss such a strategy for wholesale buyers.

In the following analysis, I define "underbid" as the difference between the demand forecast and DA demand bids, reflecting how much the buyers in each zone underbid their demand in the DA market compared to the demand forecast they have at the time of bidding. A quick comparison across the zones (last two rows in Panel B) shows that LRZ4, or Illinois, tends to underbid the most in terms of the percentage of its total demand.

3.3 Testing the Retail Deregulation Effect on Wholesale Buyers' Bidding

3.3.1 Model

I first develop a model to characterize how a cost-minimizing buyer strategically purchases electricity on the wholesale market. Since my main focus is on buyer-side strategic behaviors in sequential markets, I consider a simple framework where the buyer only needs to decide how to divide its total demand between the two markets. In MISO, although buyers can choose either fixed-quantity bids or price-sensitive bids, the two are essentially the same to buyers if we assume that they have perfect knowledge of the aggregate supply functions $S(p)$ in the market. They can either decide on an optimal quantity to buy in the DA market or equivalently, decide on a price p and choose any decreasing curve that passes through $(p, S(p))$. I further assume that there is no uncertainty and no risk aversion.

Let us denote each generator's supply function in the DA market, that is, the quantity generator i is willing to offer at price p in the DA market, as $s_i(p)$. Then, the aggregate supply function $S(p)$ is $S(p) = \sum_i s_i(p)$. Similarly, for the RT market, we have the RT aggregate supply function $T(p) = \sum_i t_i(p)$. $S(p)$ and $T(p)$ can be very different, even if producers only bid according to their marginal costs (without exercising market power). As discussed in Section 3.2.2, the DA production schedule is posted one day in advance, giving generators hours to prepare, but the RT schedule is only posted less than half an hour ahead, requiring the generators to adjust their production within a much shorter period. Thus, depending on the ramping ability of each generator, the marginal cost of providing the same MWh in the two markets could be very different. In addition, the supply functions are not necessarily the same as the generators' cost functions when the generators strategically adjust the price markups based on different demand elasticities in the two markets.

For convenience, let us denote the inverse supply functions as $P_{DA}(\cdot) = S^{-1}(\cdot)$ and $P_{RT}(\cdot) = T^{-1}(\cdot)$. Then, a buyer who has total demand Q to purchase and needs to optimally choose x, the quantity to buy in the DA market, solves the cost minimization problem as follows:

$$\min_x xP_{DA}(x) + (Q - x)P_{RT}(Q - x)$$

The first-order condition (FOC) for optimal purchases in the two markets is that the buyer equalizes the marginal purchase cost in the two markets:

$$\underbrace{P_{DA} + P'_{DA} \cdot Q_{DA}}_{MC\,of\,buying\,in\,DA} = \underbrace{P_{RT} + P'_{RT} \cdot Q_{RT}}_{MC\,of\,buying\,in\,RT}$$

It is reasonable to assume that both P'_{DA} and P'_{RT} are positive for any given quantity. When $P_{DA} > P_{RT}$, which is the most common case shown in Section 3.2.3, a buyer shifting 1 MWh from the DA market to the RT market would save the price difference $(P_{DA} - P_{RT})$

on that 1 MWh. At the same time, the buyer also saves on all the other MWhs it buys in the DA market because the DA price is lowered by P'_{DA}. However, this shift will increase the purchase cost of the amount it buys in the RT market ($P'_{RT} \cdot Q_{RT}$).

Since Q_{RT} is simply what buyers underbid in the DA market, that is, $Q_{RT} = Q - Q_{DA}$, the FOC can be rewritten, and we have:

$$underbid = Q_{RT} = [(P_{DA} - P_{RT}) + P'_{DA} \cdot Q]\frac{1}{(P'_{DA} + P'_{RT})}$$

This simple equation shows that holding everything else constant, the amount a strategic buyer underbids in the DA market increases when the DA price premium, $(P_{DA} - P_{RT})$, is higher. The underbid amount would also respond to P'_{DA}, which reflects the buyer's ability to decrease the DA price by underbidding. These two conclusions are tested in the following analysis.

3.3.2 Empirical Strategies

In this subsection, I focus on testing if the buyers' underbid is a response to the DA price premium, as predicted in the theoretical framework. In my baseline specification, the dependent variable is the hourly underbid amount ($underbid_{it}$) in the DA market by all buyers in hour t and zone i. $underbid_{it}$, as mentioned before, is defined as the difference between the demand forecast and the DA fixed-quantity demand, that is, $underbid_{it} = demand\ forecast_{it} - DA\,bids_{it}$. The main independent variable is the hourly DA price premium $premium_{it}$, defined as $DA\,price_{it} - RT\,price_{it}$. Thus, the main specification is as follows:

$$underbid_{it} = \beta_i premium_{it} + \alpha_i Q_{it} + \theta_{im} + \lambda_{ih} + \epsilon_{it}$$

This specification is run for each LRZ i separately, and β_i captures how buyers in each zone underbid in response to the change in the DA price premium. I further control for the demand forecast Q_{it}. The specification also includes the month-of-sample (θ_{im}) and hour-of-day fixed effects (λ_{ih}) to control for potential time trends and fluctuations.

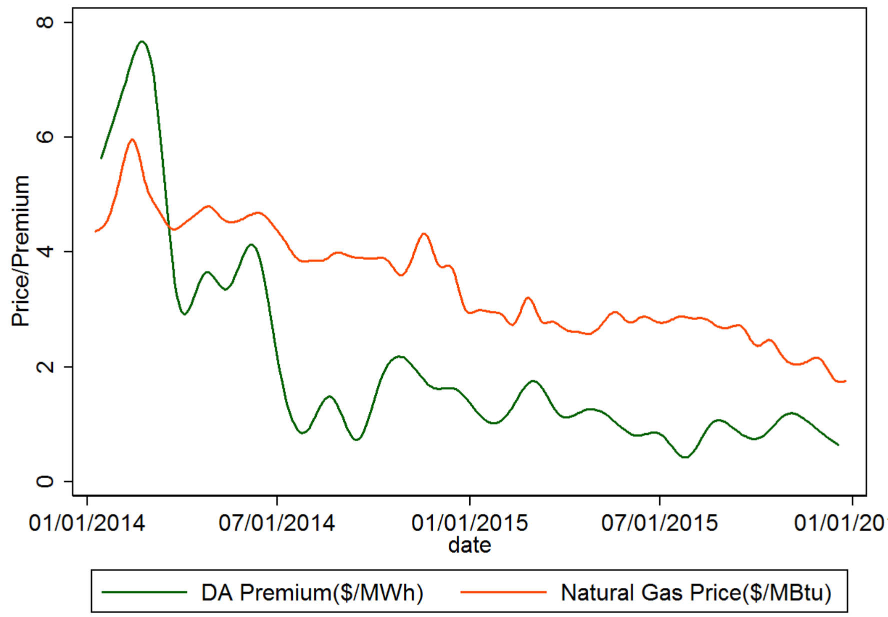
It is important to note that even after adding these controls, the DA price premium is likely to be endogenous. As an equilibrium outcome, the DA premium is affected by the buyers' demand, which is the dependent variable in the regression. To address this simultaneity bias, I use the price of natural gas as an instrument for the DA price premium.

The price of natural gas should be a valid instrument. First, natural gas price variations only change the fuel cost for the natural gas-fired generators so it works as a supply-side shifter and should not correlate with demand-side unobserved shocks ϵ_{it} in the buyers' underbid function. Second, it exhibits strong predictive power for the DA price premium, as shown in Figure 3.4. This is because, when the gas price is high, the differences between generators' marginal costs increase, which decreases competition at each level of demand and increases the generators' ability to exercise market power. As a consequence, the DA price premium increases.[9]

One concern about using the price of natural gas as an instrument is that some buyers could be vertically integrated utilities and could own coal-fired or gas-fired generators. Then, the price of natural gas could directly change their bidding behaviors since they may care more about their profits as producers, instead of their costs as buyers. There are three reasons why this is not likely to be a great concern. First, such cases would only be a real concern if such firms were net sellers in the market, which is not common for retail companies. Second, even for a vertically integrated corporation, it is common that its generation subsidiary and retail subsidiary operate separately as the creation of the wholesale market breaks the direct upstream-downstream links between them. Therefore, it is not necessarily true that they collude with each other in the wholesale market. Finally, Illinois, the retail-deregulated state I focus on, has no retailers that own generation resources, including the incumbent utilities

9. As shown in Ito and Reguant (2016), the argument why market power creates the DA price premium is similar to the dynamic monopoly price-discrimination model, leading to a declining price path.

Figure 3.4: Average Day-ahead Price Premium in MISO and Henry Hub Natural Gas Price



ComEd and Ameren. Therefore, the retailers in Illinois are all buyers in wholesale markets.

Given the above, I also run a robustness check using nuclear capacity generation as an instrument. Nuclear capacity experiences both planned and unplanned outages from time to time, related to refueling, maintenance, and safety. As nuclear generation usually constitutes a large share of the baseload in MISO, when an outage of nuclear capacity occurs, the competition among the generators is significantly reduced. Therefore, lower levels of nuclear generation can increase the generators' market power in the market and the DA price premium. This instrument would be better than the price of natural gas if vertically integrated utilities were the concern since only very few large companies own nuclear facilities (such as Exelon and Entergy) and most of them do not have retail subsidiaries. The drawback of this instrument, however, is that nuclear outages do not happen hourly but only every few weeks. Therefore, to gain enough statistical power, month fixed effect controls have to be relaxed in regressions.

Finally, I add the measure of P'_{DA} to the regression model and see whether the buyers' underbid also responds to their ability to affect the DA price as predicted in the model. P_{DA} is the inverse function of the DA aggregate supply function so P'_{DA} can be measured by the slope of the DA aggregate supply curve at the cleared quantity. Specifically, I sum the DA bids for all the suppliers in each hour and each region to form the aggregate DA supply curve. Then, I fit a linear curve to the local area around the cleared demand ($\pm$10% of the cleared price) to measure P'_{DA} as the slope of the curve. Using P'_{DA} as an independent variable creates the same endogeneity concern as that for the DA premium. Therefore, I use both the price of natural gas and nuclear generation as instruments when P'_{DA} is included in the model.

The price of natural gas and nuclear generation instruments should be able to provide independent exogenous variation for the DA price premium and P'_{DA}, respectively. The reason is that the price of natural gas and nuclear generation not only shift the prices that suppliers bid in the market but also the production orders (generators' orders in the aggregate supply curve). Therefore, even when holding the DA premium fixed, the slope of the supply curve at the cleared price P'_{DA} could still be different under different values of the instruments.

3.3.3 Results

Table 3.2 reports the wholesale buyers' underbid in response to the DA price premium. I run the regression for each LRZ separately, where Illinois (LRZ4) has competitive retailers that are also wholesale buyers whereas all the other states, including Minnesota, North Dakota, Wisconsin, Iowa, Missouri, and Indiana, are retail-regulated regions. Although Michigan also deregulated its retail section, the state's law places a 10% cap on the share of consumers served by competitive retailers. Therefore, I consider it as a regulated state since there is no actual competitive retail market operating in Michigan.

Columns 1 and 4 in each table present the first-stage results of 2-stage least squares (2SLS) regressions using the two instruments. Both instruments move the DA price premium

Table 3.2: Tests for Strategic Underbid from Wholesale Buyers in Day-ahead Markets

LRZ1: Minnesota, North Dakota

	First	Underbid	Underbid	First	Underbid	Underbid	Underbid
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gas price	0.286***						
	(0.079)						
DA premium		-0.120	-0.206		-0.004	0.126	0.766
		(0.093)	(0.159)		(0.068)	(0.225)	(4.492)
Nuclear Gen				-0.138			
				(0.077)			
P'_{DA}							0.913
							(5.201)
Constant	-2.077*	5.179***	4.305***	-0.193	5.275***	5.016***	-4.956
	(1.035)	(0.316)	(0.535)	(0.608)	(0.204)	(0.256)	(57.325)
Hour FE	✓		✓	✓		✓	✓
Month FE	✓		✓				
Year FE				✓		✓	✓
F statistic	13.00			3.21			
p-value	0.00			0.07			
N	11670	11670	11670	16750	16750	16750	11649

Notes: Sample from Jan 1, 2014 to Dec 31, 2015, with hourly observations. Henry Hub natural gas spot price in $ per Million Btu. Nuclear generation in GWh. Day-head premium in $ per MWh. Standard errors are clustered by date in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.2: Tests for Strategic Underbid from Wholesale Buyers in Day-ahead Markets (Cont.)

LRZ2&7: Wisconsin, Michigan

	First (1)	Underbid (2)	Underbid (3)	First (4)	Underbid (5)	Underbid (6)	Underbid (7)
Gas price	1.322***						
	(0.079)						
DA premium		0.035***	0.009		-0.035	0.010	0.031
		(0.010)	(0.009)		(0.018)	(0.016)	(0.019)
Nuclear Gen				-0.841***			
				(0.076)			
P'_{DA}							-2.304
							(4.207)
Constant	-1.667	7.416***	5.905***	0.631	6.867***	6.337***	7.081***
	(0.978)	(0.132)	(0.174)	(0.573)	(0.102)	(0.093)	(1.274)
Hour FE	✓		✓	✓		✓	✓
Month FE	✓		✓				
Year FE				✓		✓	✓
F statistic	279.25			121.69			
p-value	0.00			0.00			
N	11307	11307	11307	16347	16347	16347	11285

Notes: Sample from Jan 1, 2014 to Dec 31, 2015, with hourly observations. Henry Hub natural gas spot price in $ per Million Btu. Nuclear generation in GWh. Day-head premium in $ per MWh. Standard errors are clustered by date in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.2: Tests for Strategic Underbid from Wholesale Buyers in Day-ahead Markets (Cont.)

LRZ3&5: Iowa, Missouri

	First (1)	Underbid (2)	Underbid (3)	First (4)	Underbid (5)	Underbid (6)	Underbid (7)
Gas price	0.923***						
	(0.070)						
DA premium		0.075**	0.062*		0.069**	0.081**	-0.200
		(0.023)	(0.025)		(0.024)	(0.028)	(2.567)
Nuclear Gen				-0.868***			
				(0.071)			
P'_{DA}							-1.977
							(18.921)
Constant	-3.143***	5.140***	4.193***	0.137	4.882***	4.603***	18.566
	(0.750)	(0.149)	(0.220)	(0.546)	(0.128)	(0.175)	(130.501)
Hour FE	✓		✓	✓		✓	✓
Month FE	✓		✓				
Year FE				✓		✓	✓
F statistic	174.56			151.42			
p-value	0.00			0.00			
N	11599	11599	11599	16618	16618	16618	11577

Notes: Sample from Jan 1, 2014 to Dec 31, 2015, with hourly observations. Henry Hub natural gas spot price in $ per Million Btu. Nuclear generation in GWh. Day-head premium in $ per MWh. Standard errors are clustered by date in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.2: Tests for Strategic Underbid from Wholesale Buyers in Day-ahead Markets (Cont.)

LRZ4: Illinois (Ameren Service Area)

	First	Underbid	Underbid	First	Underbid	Underbid	Underbid
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gas price	0.646***						
	(0.080)						
DA premium		0.135***	0.133**		0.093***	0.108***	0.080***
		(0.041)	(0.049)		(0.021)	(0.026)	(0.021)
Nuclear Gen				-1.060***			
				(0.078)			
P'_{DA}							1.793
							(4.378)
Constant	-5.690***	5.778***	5.386***	1.747**	5.356***	5.161***	4.893***
	(0.858)	(0.255)	(0.347)	(0.547)	(0.146)	(0.163)	(0.964)
Hour FE	✓		✓	✓		✓	✓
Month FE	✓		✓				
Year FE				✓		✓	✓
F statistic	64.51			183.80			
p-value	0.00			0.00			
N	11489	11489	11489	16647	16647	16647	11466

Notes: Sample from Jan 1, 2014 to Dec 31, 2015, with hourly observations. Henry Hub natural gas spot price in $ per Million Btu. Nuclear generation in GWh. Day-head premium in $ per MWh. Standard errors are clustered by date in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.2: Tests for Strategic Underbid from Wholesale Buyers in Day-ahead Markets (Cont.)

LRZ6: Indiana

	First (1)	Underbid (2)	Underbid (3)	First (4)	Underbid (5)	Underbid (6)	Underbid (7)
Gas price	0.751^{***}						
	(0.072)						
DA premium		-0.014	-0.006		0.042^{*}	0.051^{*}	0.020
		(0.013)	(0.016)		(0.019)	(0.023)	(0.025)
Nuclear Gen				-0.659^{***}			
				(0.069)			
P'_{DA}							3.921
							(5.542)
Constant	-1.329	5.709^{***}	5.641^{***}	-0.405	5.929^{***}	5.873^{***}	4.919^{***}
	(0.837)	(0.090)	(0.125)	(0.570)	(0.119)	(0.118)	(1.425)
Hour FE	✓		✓	✓		✓	✓
Month FE	✓		✓				
Year FE				✓		✓	✓
F statistic	107.85			92.28			
p-value	0.00			0.00			
N	11626	11626	11626	16818	16818	16818	11603

Notes: Sample from Jan 1, 2014 to Dec 31, 2015, with hourly observations. Henry Hub natural gas spot price in \$ per Million Btu. Nuclear generation in GWh. Day-head premium in \$ per MWh. Standard errors are clustered by date in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

in directions consistent with the discussions above. Specifically, a higher gas price induces a higher DA price premium, and higher levels of nuclear generation reduce the premium. The F statistics and p values show that both instruments have strong predictive power for the DA price premium.[10]

Columns 2 and 3 present the main regression results using the price of natural gas as an instrument. Because the levels of demand vary greatly by region, to compare percentage changes across regions, I take the logarithm of the underbid amount. Among all five zones, the retail-deregulated buyers in Illinois (LRZ4) show the largest response to the DA price premium. As shown in Column 3 in the LRZ4 table, a 1 $/MWh increase in the DA price premium makes Illinois buyers underbid 13.3 percentage points more in the DA market. This is consistent with my model of the competitive retailers' cost minimization. A similar result is reported by Ito and Reguant (2016), who find that in the Spanish market, firms with a small demand also tend to respond to a higher premium by withholding more demand in the DA market. Their coefficients range from 0.7 to 2.6 percentage points, which are much smaller than what I find in MISO. In contrast, as regards the regulated buyers in the other regions, their underbid response to DA price premium either is small in magnitude, statistically nonsignificant, or exhibits a sign opposite to what is expected. This provides evidence that retail deregulation creates more strategic buyers in the wholesale market.

Columns 5–7 in each table present robustness checks for the main results. Columns 5 and 6 repeat the tests replacing natural gas price with nuclear generation as the instrument. The main conclusions remain the same, as 1 dollar/MWh increase in DA price premium in Illinois is associated with DA underbid of 10.8 percentage points. The responses in other zones are still small and statistically nonsignificant.

Finally, I include the measure of buyers' ability to move the DA price, P'_{DA}, in the regression model and use both instruments for the DA price premium and P'_{DA}. The results are shown in Column 7. Competitive retailers' responses to the DA premium do not

10. The only exception is in LRZ1's first stage when using nuclear generation as an instrument.

substantially decrease because of the inclusion of P'_{DA}. Moreover, it seems that competitive retailers also underbid by a greater amount when their ability to reduce DA prices is greater, although the estimate is not statistically significant. This is consistent with the model. When their ability to reduce the DA price is higher, competitive retailers are more likely to do it by shifting more demand to the RT market. This strategy leads to a lower DA price and a lower total purchase cost for them.

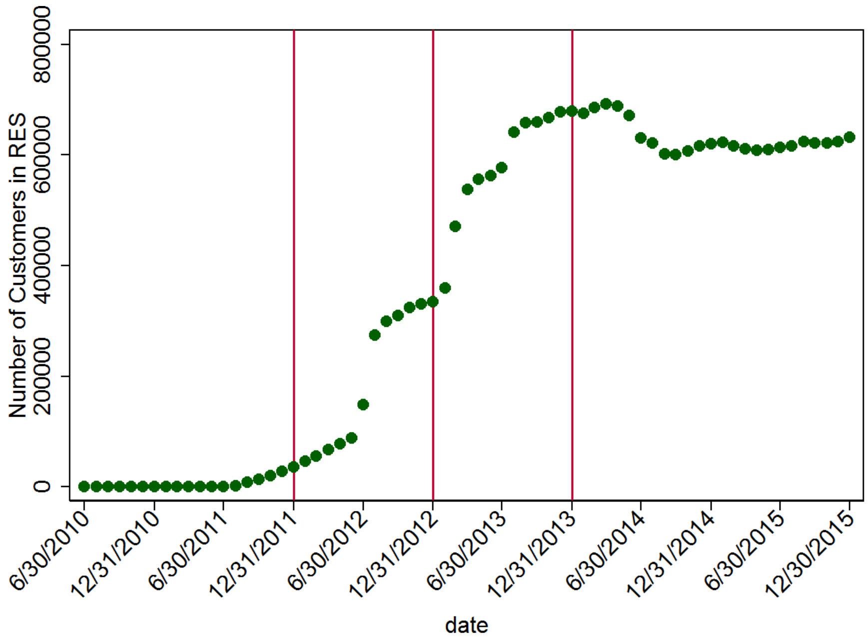
3.4 Estimating the Retail Deregulation Effect on Wholesale Price

In Section 3.3, I found evidence that buyers from a retail-deregulated state (Illinois) bid more strategically in the wholesale market than those from regulated regions. A natural question for the next step is whether this strategic behavior leads to price and cost reductions in the wholesale market for the buyers. In this section, I exploit a regulation change in Illinois in 2012, which greatly intensified the retail competition there, and test whether, as a result, the increased retail competition decreases the local market price in Illinois.

3.4.1 Policy Changes in Illinois and Difference-in-Difference Framework

As discussed in Section 3.2.1, a prominent feature of the policy change in Illinois Power Agency Act is that it allows municipalities and counties to opt out of the incumbent utility's program and negotiate the purchase of electricity on behalf of their residential/commercial customers with competitive retailers. This has completely activated the electricity retail market in Illinois. Although competitive retail consumers were almost nonexistent in the middle of 2011, the number of customers served by retail electric suppliers (RES) increased 1,500-fold in 2012 (Figure 3.5). Moreover, there was another large jump in the number

Figure 3.5: Number of Customers Served by Competitive Retails in Illinois Ameren Zones



Source: Plug In Illinois website, Illinois Commerce Commission

of RES customers in 2013, which increased the total customer number to 680,000. This immense and nearly vertical jump was due to more than 500 communities taking advantage of the opt-out opportunity and joining the competitive retailers' services at approximately the same time after the policy change. This dramatically increased the number of competitive retailers in the market and the amount of demand they serve, which induced more strategic demand-side bidding in the wholesale market.

As regards examining whether these incentives have reduced wholesale market prices, a direct comparison between the market prices before and after the policy change might not be that helpful. Electricity prices are well known for their high volatility as the demand and supply change dramatically from hour to hour. They are susceptible to many factors, and buyers' strategic behaviors would only be one of the many factors that move the prices. To overcome this identification difficulty, I employ a DiD estimator to compare the local market prices in Illinois and those in a region that has not experienced a buyer-side policy change but is similar to Illinois in all other aspects. Thus, I select Wisconsin (labeled as LRZ2 in

MISO data) as the control group in this DiD estimation.

Wisconsin is an ideal control group for Illinois. First, as both states are geographically neighbors and both follow dispatch commands from MISO in the central region, many changes or impacts experienced by Illinois would also affect Wisconsin, including weather variation, fuel cost fluctuation, and different operation rules implemented by MISO central. This helps isolate the impact of retail competition in the DiD design. Second, the competitive buyers' strategies induced by the retail policy change in Illinois are not likely to affect Wisconsin much, due to the nodal pricing and LRZ design in MISO. Under an ideal scenario, the wholesale market is cleared by a uniform price across all locations. However, due to transmission constraints and congestion, the electricity dispatch cannot be implemented at a uniform price very often. The nodal pricing mechanism allows each location across the grid to have different prices, based on the local transmission and demand situation. During congestion hours, each LRZ has full responsibility for balancing the supply and demand locally when a unified dispatch does not work. Thus, in many cases, Illinois and Wisconsin clear their local market independently, with different prices reflecting the local demand/supply. Thus, if buyers in Illinois become more strategic, we are likely to see such strategies moving local market prices in Illinois more often than in Wisconsin, hence allowing us to identify the impact of retail deregulation on local market prices.

Table 3.3 presents the summary statistics for some important variables in the two states in 2014. It shows that the two states have very similar weather conditions, demand, and generation capacity. The import limits imposed by MISO are also very similar. In the following subsections, I fully exploit the richness of the electricity market data and study how hourly DA prices change at 136 buyer locations in Illinois and 47 buyer locations in Wisconsin from 2010 to 2014.

Table 3.3: Summary Statistics in LRZ2 (Wisconsin) and LRZ4 (Illinois) in 2014

	LRZ2	LRZ4	Difference
Mean Temperature ($^\circ F$)	45	48	-3
Max Temperature ($^\circ F$)	80	84	-4
Min Temperature ($^\circ F$)	-8	-9	1
Average Wind Speed (mph)	10	10	0
Annual Metered Load (GWh)	65,113	50,332	14,781
Summer Peak Demand (MW)	11,730	9,563	2,167
Winter Peak Demand (MW)	10,113	8,262	1,851
Installed Capacity (MW)	15,029	10,746	4,283
Capacity Import Limit (MW)	3,083	3,025	58

Source: 2015 MISO Independent Load Forecast, MISO 2015; and Planning Year 2014 LOLE Study Report, MISO 2014. Temperature and wind speed measures are compared between Milwaukee, WI and Chicago, IL.

3.4.2 Graphical Illustration

Figures 3.6 and 3.7 provide an illustration of the wholesale price trends in Illinois and Wisconsin over time. In the graphs, the hourly DA market prices across different locations are aggregated into monthly median prices for each state. As Figure 3.6 shows, the monthly DA prices in the two states tracked each other closely before 2012, with no clear difference between them. Then, coincidentally with Illinois's MEA policy taking effect, which fostered more competitive retailers, a price difference between the two states began to appear in 2012, with Illinois's prices deviating downward from those of Wisconsin. By the end of 2012, the price difference became very clear. The difference became even wider in 2013, as the DA prices in Illinois became consistently lower than those in Wisconsin, coinciding with another large jump in the number of competitive consumers in Illinois.

Figure 3.7 takes the difference between Illinois's and Wisconsin's monthly prices, and shows a similar pattern as described above. Before 2012, the price differences simply fluctuated around 0, consistent with the volatile nature of electricity prices but there was no clear upward or downward trend observed. After 2012, the price difference began to increase, and this increase continued until 2014. The two graphs present a strong correlation between the increasing retail competition in Illinois and the increasing wholesale price difference. This lends preliminary support to the prediction that the intense retail competition induced more strategic demand bids in Illinois, thus suppressing local wholesale prices.

3.4.3 Regression Specifications and Results

Here, I conduct formal tests under the DiD framework. The main specifications are as follows:

Figure 3.6: Day-ahead Price Trends in Wisconsin and Illinois

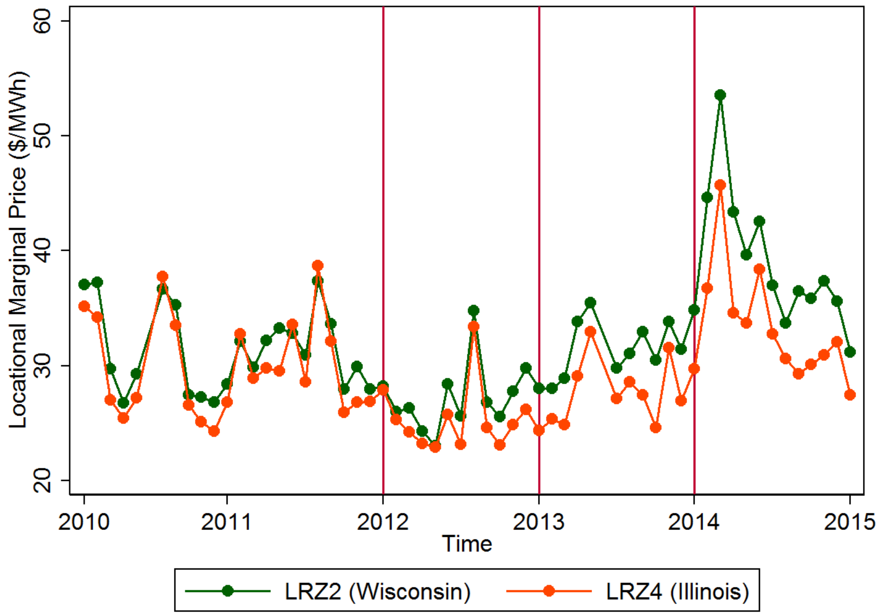
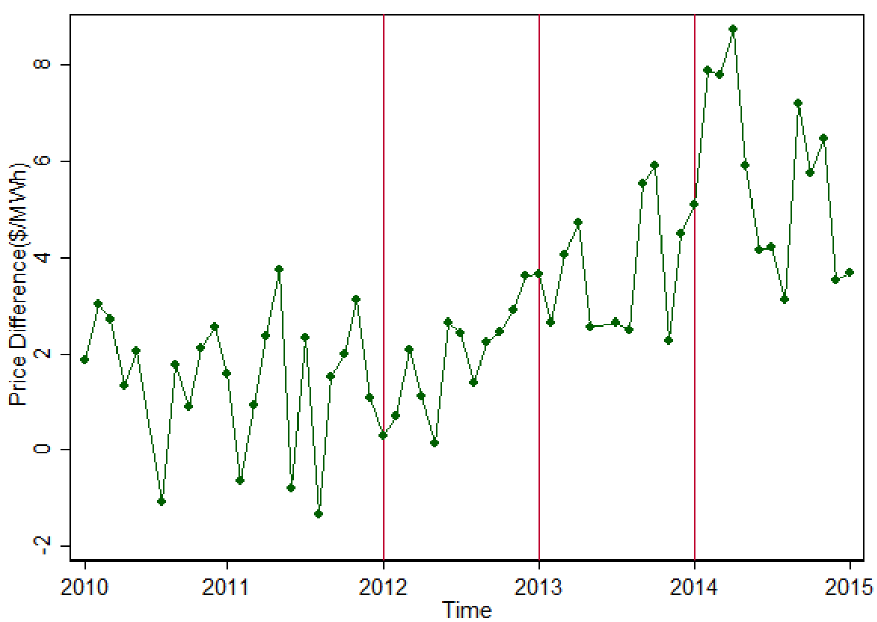


Figure 3.7: Day-ahead Price Difference in Wisconsin and Illinois



$$
\begin{aligned}
LMP_{it} = \alpha_0 &+ \alpha_1 \cdot I(t \geq 2011) + \alpha_2 \cdot I(t \geq 2012) + \alpha_3 \cdot I(t \geq 2013) + \alpha_4 \cdot I(t \geq 2014) \\
&+ \beta_1 \cdot I(t \geq 2011) \cdot IL_{it} + \beta_2 \cdot I(t \geq 2012) \cdot IL_{it} + \beta_3 \cdot I(t \geq 2013) \cdot IL_{it} \\
&+ \beta_4 \cdot I(t \geq 2014) \cdot IL_{it} + \gamma_1 IL_{it} + \boldsymbol{X}_{it} + \boldsymbol{\theta}_t + \boldsymbol{\theta}_t \cdot IL_{it}
\end{aligned}
$$

$I(t \geq y)$ are time indexes taking the value 1 if year t is after year y, where y=2011, 2012, 2013, and 2014 (2010 is treated as the base year here). By incorporating these five terms, I can account for the general time trends of each year. IL_{it} equals 1 if the buyer's pricing location is in Illinois, which accounts for any time-invariant difference between the two states. $\boldsymbol{X}_{it}$ include other controls added to the specification, including temperature, wind speed, and the price of natural gas. $\boldsymbol{\theta}_t$ are the month-of-year and hour-of-day fixed effects. I also add $\boldsymbol{\theta}_t \cdot IL_{it}$ to allow the two states to have their own separate monthly/hourly trends.

β_1 through β_4 are the DiD estimators of interest. β_1 represents the difference between Illinois and Wisconsin in terms of their price change in 2011 compared to the base year, or equivalently, $\beta_1 = \Delta LMP^{IL}_{2011} - \Delta LMP^{WI}_{2011}$, where $\Delta LMP_{2011} = LMP_{2011} - LMP_{2010}$ in each state, as 2010 is the base year. β_2 through β_4 are similarly defined, representing such a difference in 2012, 2013, or 2014.

Table 3.4 reports the regression results. The estimates for β_1 through β_4 are presented in rows "$I(2011) \times IL$" through "$I(2014) \times IL$," respectively. Column (1) shows the baseline result, with no fixed effects. In Column (2), I control for yearly, monthly, and hourly fixed effects, and in column (3), I include more flexible forms of the time effects, allowing the two states to have different trends. In Column (4), I further control for weather conditions, and in column (5), I add the price of natural gas into the estimation to account for the changes in electricity price induced by fuel cost fluctuations.

The results are consistent across all the specifications. The estimate of β_1 is small and

Table 3.4: Effects of Retail Deregulation on Day-ahead Price

	LMP (1)	LMP (2)	LMP (3)	LMP (4)	LMP (5)
I(2011)	-0.329	-10.340***	-10.370***	-2.543	-5.774***
	(0.479)	(0.578)	(0.576)	(1.423)	(1.634)
I(2012)	-3.898***	-7.279***	-7.268***	-1.525	23.518***
	(0.426)	(0.554)	(0.565)	(1.166)	(2.249)
I(2013)	4.762***	3.587***	3.607***	3.350***	-2.740**
	(0.428)	(0.562)	(0.571)	(0.662)	(0.959)
I(2014)	9.208***	8.234***	8.227***	-0.107	-4.045**
	(1.102)	(0.707)	(0.694)	(1.189)	(1.418)
I(2011)×IL	0.157	0.215	0.250	0.191	0.169
	(0.275)	(0.275)	(0.252)	(0.440)	(0.472)
I(2012)×IL	-1.571***	-1.565***	-1.570***	-1.981***	-2.578***
	(0.261)	(0.260)	(0.253)	(0.361)	(0.420)
I(2013)×IL	-1.128***	-1.293***	-1.307***	-1.193**	-0.884*
	(0.256)	(0.255)	(0.248)	(0.411)	(0.436)
I(2014)×IL	-2.882***	-2.832***	-2.829***	-2.043***	-2.844***
	(0.385)	(0.384)	(0.362)	(0.479)	(0.545)
IL Dummy	-0.908***	-0.925***	-3.811	3.510*	4.715*
	(0.187)	(0.186)	(2.385)	(1.652)	(2.394)
Temperature				-1.675***	-1.469***
				(0.207)	(0.241)
Temperature Squared				0.016***	0.015***
				(0.002)	(0.002)
Avg_wind_speed				-0.021	-0.018
				(0.043)	(0.047)
Gas Price					6.912***
					(0.917)
Year FE		✓	✓	✓	✓
Month & Hour FE		✓			
Month×IL & Hour×IL FE			✓	✓	✓
N	5350632	5350632	5350632	5231496	3611184

Note: Standard errors are clustered by date in parentheses. Temperature and wind speed data from Milwaukee, WI and Springfield, IL are from National Oceanic and Atmospheric Administration. Henry Hub natural gas spot prices are from Energy Information Administration. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

statistically nonsignificant, implying that Illinois and Wisconsin had a similar price trend in 2011. This result supports the common trend assumption required for the DiD design. Then, β_2, β_3, and β_4 are negative and statistically significant, which indicates that starting in 2012, the wholesale prices in Illinois became \$1/MWh–\$3/MWh lower than the prices in Wisconsin. Adding β_1 to β_4, we obtain an average price difference of \$6.1/MWh between Wisconsin and Illinois by 2014. This indicates that the demand-side responses had a large and significant effect on the wholesale market prices. Since a high day-ahead wholesale price is correlated with producers' exercising market power, this drop in price shows the benefit of more strategic demand bids, which improve the efficiency of the wholesale market.

A potential concern about the DiD strategy and these results is whether some other changes have affected Illinois and Wisconsin separately, which can explain the price path difference. Although such unobserved factors might exist, for them to confound the estimates, they would have to come into play during the timeline of Illinois's retail policy change. Again, since both Illinois and Wisconsin follow orders from the MISO central region, any changes in market regulation or dispatch rules should have affected both states and could not have created such different price paths. The Annual electric generator report data from the Energy Information Administration Form 860 further prove that no large-scale generation capacity was added in Illinois or Wisconsin between 2012 and 2014. Therefore, no significant change in the producer side could explain the price difference after 2012. In summary, these arguments allow me to interpret the DiD results as evidence of the impact of retail deregulation on mitigating producers' market power and lowering wholesale electricity prices.

3.5 Conclusion

Electricity wholesale buyers are traditionally thought to be non-strategic and inelastic, which has prompted producers to exercise their market power and has made consumers pay higher prices. In this study, I provide empirical evidence that deregulations in electricity retail market bring competitive retailers to compete with the utilities. When they act as buyers in the wholesale market, they have strong incentives to be strategic and are more likely to underbid in the DA market in response to the higher DA price premium. By doing so, they minimize their purchase costs in the wholesale market and mitigate some of the producers' market power that created the DA price premium in the first place. By contrast, I did not find such strategic behaviors in the regions that only have regulated utility buyers.

I also find direct evidence from a policy change that greatly increased electricity demand served by competitive retailers in Illinois that, increased demand-side responses from competitive retailers indeed contribute to lower wholesale prices in the local region. The lower market price reflects an improvement in wholesale market efficiency and also implies welfare gains for consumers as competitive retailers pass the lowered wholesale prices through to retail prices and benefit the electricity consumers.

These findings suggest that electricity retail deregulation has likely improved wholesale market efficiency and consumer welfare by inducing more response from the demand side. Hence, although there are still political concerns and consumer-side inertia that prevent the retail deregulation to be widely implemented in many other states, the potential benefit documented here needs to be seriously considered among different approaches for reforming electricity markets.

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