Gone with the Wind: Consumer Surplus from Renewable Generation*

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Abstract

I show horizontally integrated electricity generators competing in wholesale electricity markets can internalize the benefits of low cost renewable generation by strategically withholding output from their conventional resources when their own wind turbines are generating electricity. This strategic response attenuates the impact of low cost renewable generation on the price of electricity, reducing consumer benefit from renewable generation. Using data on one of the largest wholesale electricity markets in the US, I show renewable generation is associated with physical withholding, implying 30% of wind generation replaces withheld units, decreasing consumer surplus by $3.3 billion from 2014 to 2016.

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1 Introduction

Whoever benefits from a low cost technology depends largely on how firms compete in a market. This basic notion of economic pass-through under imperfect competition, most recently explicated by Weyl and Fabinger (2013), states a firm with market power has a greater ability to internalize the benefits of a low cost technology by adjusting their competitive strategies. In wholesale electricity markets there has been a rapid deployment of a new low cost technology, namely renewable generation in the form of utility scale wind turbines. This technology, coupled with solar generation, accounts for over half of new electricity generation capacity in the US since 2008 (EIA, 2017) and has created immense value because it doesn't require fuel to generate electricity. The value associated with the low marginal cost attribute of renewable generation can be just as large if not larger than the public benefit of avoided pollution externalities (Callaway, Fowlie, and McCormick, 2018; Ovaere and Gillingham, 2019). In these wholesale electricity markets, constructed as multi-unit uniform price auctions, inelastic demand and capacity constraints allows market participants some degree of market power. Without explicitly taking into account the competitive conduct of existing electricity generators, our understanding of how renewable generation impacts the price of electricity in wholesale electricity markets is incomplete.

In this paper I evaluate the competitive effects of more renewable generation in wholesale electricity markets, and quantify the consumer surplus associated with the lower operating cost of renewable generation taking into account how market participants will strategically respond to renewable generation. I first use an equilibrium framework to derive a quantity pass-through equation, showing how more renewable generation should impact the price of electricity taking into account firm conduct. Then, modifying Klemperer and Meyer's (1989) Supply Function Equilibrium framework, I show that diverse market participants, those that own wind turbines and other assets, have an incentive to withhold their other assets when their own wind turbines are generating electricity.[1] This physical withholding[2] attenuates the consumer benefit associated with renewable generation, and showcases how firms can exert market power to internalize the benefits of a low cost technology.

Leveraging hourly data on ex-ante generator-specific strategies from one of the largest wholesale electricity market in the United States, I show direct evidence of strategic withholding by diverse market participants. Identification comes from variation in the cleared quantity offered by a market participant, to the wholesale market operator, at a given price within a year-month-hour (e.g. June, 2016, 4pm). While my empirical strategy is most similar to Fabra and Reguant's (2014) analysis of emission cost pass-through, the use of within offer price variation is novel. I find the market participants that own more wind capacity withhold their output more in response to renewable generation, and they withhold their output more in response to their own wind generation relative to wind generation from wind turbines they do not own. This is robust to concerns regarding congestion constraints and net imports. With the detailed data on supply and demand for every hour, I am able to make rare and credible claims regarding consumer surplus from renewable generation by re-constructing the market equilibrium and calculating an expression for the price reduction from renewable generation taking into account the strategic response by traditional electricity generators.

I find that the potential consumer surplus from the low cost of renewable generation is large. In the Midcontinent Independent System Operator's wholesale electricity market from 2014 to 2016, I find a potential consumer benefit of $69 per person per year associated with the low operating cost of renewable generation. However, how horizontally integrated electricity generators respond to renewable generation is important for determining the realized consumer surplus from renewable generation. If electricity generators were to act as profit maximizers in a supply function equilibrium, the realized consumer surplus would have been only $19 per person per year. Conversely,

[1] Throughout, I use the term *diverse* to define horizontally integrated market participants that own wind turbines and conventional electricity generators and the word *conventional* to describe electricity generators that are not wind turbines or solar panels.

[2] Physical withholding is a reduction in the quantity offered to the market, at a given price, with the intent to influence the market price. This is in comparison to economic withholding, which involves bidding a generator's quantity at a higher price.

estimated parameters of firm level withholding, that do not place any structure on the firm's incentives, suggest \$47 per person per year of consumer benefit is realized. During the entire sample period, this suggests physical withholding associated with renewable generation reduced consumer surplus by over 3 billion US dollars.

With this paper I am making three contributions. First, I show that understanding the incentives of the firm is a key to calculating welfare effects of renewable-generation electricity. Many papers have evaluated the integration of renewable generation in electricity markets, uncovering a "merit order effect" where renewable generation displaces high cost generation and lowers the market price, idealized in Figure 1.[3] The results are location specific, often determined by the fuel mix and fuel prices, and are large.[4] Overwhelmingly, these empirical papers do not consider how the increase in renewable generation might change the strategies of electricity generators, but instead assume a perfectly competitive market or an economic dispatch of resources. This is despite theoretical importance of competitive conduct in how renewable generation can impact the price, as shown by Ben-Moshe and Rubin (2015) and Acemoglu, Kakhbod, and Ozdaglar (2017).

In this paper I focus on the consumer surplus component of total welfare for two reasons.[5] For one, the impact renewable generation on the price of electricity is frequently cited as one of the reasons to enact policies supporting renewable generation.[6] For example, a report from the American Wind Energy Association identifying the merits or wind energy in the Mid-Western United States points to a simulation that finds "wind has been shown to reduce overall energy costs for consumers saving ratepayers \$63 to \$147 per year (assuming a 20 GW scenario in 2020)"

[3]These papers either consider a simulation model (Sensfuß, Ragwitz, and Genoese 2008; McConnell et al. 2013), or estimate the reduced form change in price due to renewable generation (Woo et al. 2011; Cludius et al. 2014; Clò, Cataldi, and Zoppoli 2015; Woo et al. 2015, 2016).

[4]For example, Woo et al. (2016) find that a one gigawatt hour (GWh) increase of wind generation in California lowers the wholesale market price by \$1.5 to \$11.4 per megawatt hour. This implies average hourly wind generation can lower total market revenue by millions of dollars per day assuming the average hourly wind generation in California during 2017 was around 1.5 GWh and the average hourly load is 24 GWh. If 1.5 GWh of wind generation reduces the price by 9.75 \$/MWh, for 24 GWh in a hour, for twenty-four hours, total market revenue declines by 5.6 million USD that day.

[5]The consumer in a wholesale electricity market is not always the end consumer of electricity. Often it is a regulated distribution utility. However, consumer surplus in wholesale markets can broadly represent consumer surplus as long as the wholesale price is passed onto the retail, commercial, or industrial price of electricity.

[6]The primary reason for policies supporting renewable energy is the public benefits of avoided pollution. Despite this, the cost component is often brought up in public policy debates.

(AWEA, 2014). Public policies implemented with the intent of providing consumers this benefit will under-deliver if ignore the strategic response of existing electricity generators. Second, increasing consumer surplus is one of the primary goals of wholesale electricity markets.[7]

My second contribution it to provide direct evidence of strategic bidding in multi-unit auctions using exogenous variation in wind production. Wholesale electricity markets are multi-unit auctions where the uniform price is set by the marginal unit. In such markets there is a known incentive for market participants to withhold output to increase their own revenue (Ausubel et al., 2014). This incentive increases in proportion to the infra-marginal market share of the electricity generator (Wolfram, 1998). For the firms that own renewable resources, increased renewable generation is a large short-run increase in their infra-marginal market share, intensifying their incentive to withhold their generation. Because wind generation is determined predominately by weather patterns, this variation is as good as random.

While a number of papers have looked at strategic bidding in multi-unit auctions (Hortaçsu, Kastl, and Zhang, 2018; Doraszelski et al., 2017; List and Lucking-Reiley, 2002), and even in wholesale electricity markets (Hortaçsu and Puller, 2008; Wolfram, 1998; Borenstein, Bushnell, and Wolak, 2002; Reguant, 2014; Ito and Reguant, 2016), they typically rely on structural models trying to uncover price-cost margins or underlying valuations. The exogenous nature of wind generation, in combination with the rich data on generator-specific strategies, allows me to substitute structural assumptions on firm conduct with parsimonious estimating equations that identify parameters of a firm's underlying strategy. With these parameters, and the quantity pass-through equation, it is straight forward to make claims regarding consumer surplus in the spirit of Chetty (2009).

Finally, this paper provides an status update on competition in wholesale electricity markets. Ever since the California electricity crisis in the early 2000s, regulators and market monitors have worked to ensure that wholesale electricity markets approximate the competitive outcome. As a result, wholesale electricity markets in the US are currently perceived as competitive by economic

[7] See Borenstein and Bushnell (2015) for the historical, political, and economic rational for wholesale electricity markets.

researchers (Bushnell, Mansur, and Novan, 2017), regulators (FERC, 2011), and independent market monitors (Potomac Economics, 2018). This is partly because of long term forward contracts, a forward wholesale market, and vertical commitments between producers and consumers of wholesale electricity. Despite this, there is mounting evidence that the market participants in wholesale electricity markets still have the ability and incentive to exercise market power (Woerman, 2019; McDermott, 2019; McRae and Wolak, 2019). As the electricity grid transitions towards more renewable generation, it is important to consider the ways in which a firm's ability and incentive to exert market power might change, and to develop tools to characterize and diagnose imperfectly competitive behavior.[8] An immediate policy implication of this paper is better market monitoring for physical withholding of capacity. This can be accomplished using the methods outlined within this paper.

The paper proceeds as follows, section 2 outlines a general framework for understanding how renewable generation, in particular wind, impacts the price of electricity in wholesale markets. Section 3 provides context by describing key details on the market I study including an introduction to the data. Section 4 turns to micro-data on firm strategies, showing evidence of physical withholding during windy hours. Section 5 summarizes the implications of withholding for consumer surplus in wholesale markets, section 6 concludes with a discussion.

2 Wind Generation in Wholesale Electricity Markets

The high fixed costs of electricity generation, transmission, and distribution lends itself to a model of natural monopoly and has historically been served by vertically integrated investor, or municipality, owned utilities operating under cost of service regulation. Since the 1980s the electricity industry has undergone deregulation and restructuring at the state and federal level largely motivated by the success seen in other industries (such as rail and natural gas), and analysis showing

[8]Overall, Independent Market Monitors do a good job identifying and mitigating blatant exertion of market power in wholesale electricity markets. In Appendix B I outline exactly how this is done for the market I study, as well as characterize the market in terms of forward contracts and vertical commitments.

the potential for increased efficiency (for example Joskow and Schmalensee (1983)).[9] Restructured wholesale electricity markets emerged, where competitive supply and demand bids are submitted to a centralized and impartial Independent System Operator, who then decides which units to dispatch and the price they receive. As of 2012, these markets cover 60% of generation capacity within the US and they are effective in reducing production cost by reallocating output within and between power control areas (Cicala, 2017).

The following is intended to model a wholesale electricity market operating as a multi-unit uniform price auction that allows for diverse market participants and a degree of low variable cost renewable generation. This illustrative model is based off-of Klemperer and Meyer (1989) and motivated by the "supply function" nature of the data, however the testable predictions I present can be derived from a general model of imperfect competition as done in Acemoglu, Kakhbod, and Ozdaglar (2017). Demand for electricity is determined by Load Serving Entities, predominately utilities, that charge customers a rate for electricity in the retail market.[10] These Load Serving Entities submit demand bids for each hour that can be price sensitive, but are overwhelmingly inelastic with respect to price. I model demand in the wholesale market at time t as $D_t(p) = d_t(p) + \varepsilon_t$ where $d_t(p)$ is the deterministic component of demand as a function of price that can be forecasted and ε_t is a random variable representing fluctuations in the quantity demanded. I model ε_t to be an $i.i.d.$ random variable with expectation equal to zero.

Supply in the wholesale electricity market is provided by market participants, which I denote by the subscript o, who own multiple electricity generating assets including coal, gas, nuclear, or hydrological based resources. Each conventional unit owned by market participant o, denoted by the subscripts $k \in K_o$, submits a unit-specific supply curve as a function of price, $s_{kt}(p)$. This offer curve represents the quantity the market participant o is willing to produce from unit k at

[9] Public Utilities Regulatory Policy Act (PURPA) of 1978 encouraged alternative fuels and introduced independent power producers (IPPs). Federal Energy Regulatory Commission (FERC) orders 888 and 889 in 1996 laid the ground work for competitive wholesale electricity markets. FERC order 2000, promulgated in 1999, encouraged the formation of Regional Transmission Organizations to serve as planning bodies over a larger geographic area. State policies have introduced retail competition and forced divestiture of vertically integrated assets.

[10] Load Serving Entities in wholesale markets can also be generators of electricity if they are vertically integrated. The commercial and retail rate of electricity is typically a time-invariant rate or increasing block pricing. Industrial consumers typically have peak demand charges as well.

time t for price p. I consider the market participant's aggregate supply sans wind generation as $S_{ot}(p) = \sum_{k \in K_o} s_{kt}(p)$. When the uniform market clearing price is $\hat{p}$, the market participant will produce $S_{ot}(\hat{p}) = \sum_{k \in K_o} s_{kt}(\hat{p})$ with costs $C_{ot}(S_{ot}(\hat{p}))$ and revenue $\hat{p} S_{ot}(\hat{p})$. In what follows I assume that costs are weakly increasing and convex, $C''_{ot}(S_{ot}(\hat{p})) \geq 0$, $C'_{ot}(S_{ot}(\hat{p})) \geq 0$.

The quantity of electricity generated by wind turbines at time t is modeled by an aggregate quantity, W_t. The aggregate quantity, W_t, is common knowledge to all market participants and perfectly forecast-able. The comparative statics below do not change in a meaningful way by introducing a random component to total wind generation, as highlight by Acemoglu, Kakhbod, and Ozdaglar (2017).[11] The proportion of wind that is owned by market participant o at time t is denoted by $\theta_{ot} \in [0,1]$, with $\sum_o \theta_{ot} = 1$. This implies the amount of wind generated by market participant o at time t is $\theta_{ot} W_t$. In this model I assume that wind generation always clears at the equilibrium because of its low variable cost.[12]

Wholesale electricity markets typically have a hourly day-ahead forward market in addition to the real-time market. The forward market is a purely financial market that allows electricity generators to commit to production ahead of time. Any shortfall of a market participant's day-ahead commitment must be resolved with electricity purchased in real-time. This forward commitment effectively forces each market participant to act as a Stackelberg leader (Allaz and Vila, 1993). Although this is an important component of wholesale electricity markets, I do not include it in what follows because it will not change the strategic response of electricity generators to more wind generation in the real-time market, as shown by Acemoglu, Kakhbod, and Ozdaglar (2017).

The price concept most common in U.S. wholesale electricity markets is a Locational Marginal Price (LMP). This price represents the marginal cost of increasing energy production at any given moment and at any given location within the market, and therefore varies by location (at different

[11] Acemoglu, Kakhbod, and Ozdaglar (2017) shows the general incentives to withhold output remain when wind generation is a random value, is private information, and correlated across wind turbines.

[12] I assume the variable cost of production for wind turbines is zero as it does not require fuel. There are other variable operation and management cost associated with wind turbines, but the Federal Renewable Energy Production Tax Credit is larger than these costs. It is possible that wind generation can be curtailed manually, however the market I study, MISO, has incorporated wind generation as part of the economic dispatch since 2011, resulting in a curtailment rate of less that 1%.

pricing nodes) and by time (typically at 5 minute intervals). The LMP can be decomposed into three distinct components: the Marginal Energy Component (MEC) determined as the price where supply equals demand at a load-weighted reference node, marginal congestion cost associated with the shadow price of system transmission constraints and out of merit dispatch, and marginal losses associated with transmitting the electricity over long distances. At any given moment, the MEC is the same at every location within the market while the losses and congestion components vary by node.[13] Analytically, I consider the price p to represent the MEC of the LMP.[14] For most hours, the MEC is the largest component of the LMP.

2.1 Market Equilibrium and the Analytical Merit Order Effect

Moving forward, I will suppress the time subscript. The market operator takes the supply offers as given, observes the realized demand shock, ε, to solve for the dispatch quantity for each firm and the price received in accordance with a security constrained dispatch algorithm.[15] Outside of security constraints and reliability concerns, we can think of the market clearing as follows:

$$\underbrace{d(p)+\varepsilon}_{\text{demand } D(p)} = \underbrace{\sum_o S_o(p)}_{\text{conventional supply}} + \underbrace{W}_{\text{wind}} \tag{1}$$

Implicitly differentiating the market clearing condition with respect to total wind generation, W, gives the equilibrium effect of increased renewable generation on wholesale market price.[16]

$$\frac{dp}{dW} = -\frac{1+\sum_o \frac{\partial S_o(p)}{\partial W}}{\sum S_o'(p) - d'(p)} \tag{2}$$

[13] Some markets are known for very high and negative prices at times, this is typically because of the congestion and loss components.

[14] This is in contrast to Mercadal (2015), who explicitly uses the cross-sectional variance in transmission cost and losses to cluster MISO into multiple smaller markets.

[15] The algorithm is

[16] I assume that the quantity of electricity demanded in the wholesale market by load serving entities does not depend on the quantity of electricity generated by wind turbines at a given moment in time, that is $\frac{\partial D(p)}{\partial W} = 0$. If this assumption is violated Equation 2 becomes $\frac{dp}{dW} = -\frac{1+\sum_o \frac{\partial S_o(p)}{\partial W} - \frac{\partial D(p)}{\partial W}}{\sum S_o'(p) - d'(p)}$.

Where $'$ denotes the partial derivative with respect to the function's main argument. Equation 2 is the rate at which an increase in renewable generation impacts the equilibrium price, what I am calling the analytical merit order effect. This value depends on the supply function slope, demand slope, and the strategic response by market participants. The intuition of Equation 2, when the slope of demand and $\frac{\partial S_o(p)}{\partial W}$ are equal to zero, is shown in Figure 1 where the change in the price of electricity is determined by the difference in price submitted for the marginal unit, $-\frac{1}{\sum_o S'(p)}$.

This can be thought of as the pass-through of increased renewable generation. This is related to, but different from, the conventional pass-through rate of a cost shock or tax. To show this, consider the market equilibrium with a unit tax, $d(p) = \sum S_o(p-t)$, under perfect competition. Implicitly differentiating the market equilibrium with respect to t uncovers the well-known pass-through formula $\frac{dp}{dt} = \frac{\sum S'_o}{\sum S'_o - d'} = \frac{1}{1+\frac{\varepsilon_D}{\varepsilon_S}}$ where ε_D and ε_S denote the own-price and market supply elasticities respectively. The denominators of Equation 2 and the unsimplified traditional pass-through equation are identical, representing a marginal deviation from the market equilibrium. The numerator is different because the shock impacts supply differently. An increase in wind generation impacts the total quantity supplied, while the tax impacts the cost of production.[17]

Electricity markets are often considered to be imperfectly competitive because of capacity and transmission constraints, a degree of market power, as well as vertical and horizontal relations. I incorporate competitive conduct into Equation 2 with the inclusion of $\frac{\partial S_o(p)}{\partial W}$ in the numerator. Without placing structure on the market or market participants' incentives it is impossible to sign this value. The sign of this term suggests the extent to which increased renewable generation has a pro- or un- competitive effect on market participants' behavior. If the term is positive the market participant offers more generation quantity to the market at any given price in response to increased renewable generation. This pro-competitive outcome arises if the firm is trying to ensure their generation clears in the market, and is not displaced by the increased renewable generation.[18] The

[17]This is related to the concept exogenous quantity pass-through described by Weyl and Fabinger (2013). It differs in that wind generation is an increase in the aggregate market quantity, while Weyl and Fabinger (2013) model the exogenous quantity as a firm specific quantity, identical across firms.

[18]Ciarreta, Espinosa, and Pizarro-Irizar (2017) finds evidence of this in the Spanish electricity market by looking at the difference in the offer curves over long periods of time.

implication is that renewable generation would decrease the price by more than the change in cost of the marginal unit. Conversely, when the term is negative, the supplier is offering less quantity from conventional generators to the market at any given price. This un-competitive outcome could be an attempt by the firm to offset the merit order effect of increased renewable generation.

2.2 Market Participants' Strategy and Testable Predictions

A firm with market power can internalize the benefits associated with increased renewable generation. Figure 2 provides the intuition. When a market participant with market power is considering the incentives to withhold, they are comparing a higher price and smaller quantity to a lower price and larger quantity. When this market participant owns a wind turbine that is also generating electricity, they receive additional benefit of increasing the price directly proportional to the quantity of electricity generated by their wind turbine. This is because they receive revenue from the inframarginal wind turbine but do not incur any cost. This is consistent with the idea of bid shading in multi-unit uniform price auctions presented by Ausubel et al. (2014).

The strategies employed by market participants in wholesale electricity markets can be characterized by Klemperer and Meyer's (1989) Supply Function Equilibrium framework. Market participants with some degree of market power will choose the supply function $S_o(p)$ that maximizes their expected profit, with the expectation taken over the uncertainty in price due to demand shocks. Appendix A shows the optimal strategy of market participant o with conventional assets and wind turbines can be characterized by

$$p - C_o'(S_o(p)) = -\frac{S_o(p) + \theta_o W}{RD_o'(p)} \tag{3}$$

where $RD_o'(p) \equiv d'(p) - \sum_o S_{j\neq o}'(p)$ is the slope of residual demand for market participant o. This general first order condition relates to the inverse elasticity pricing rule and is commonly used in the application to wholesale electricity markets.[19] Evaluating how the best response function

[19] See Green and Newbery (1992); Wolak (2001, 2007); McRae and Wolak (2009); Hortaçsu and Puller (2008); Ryan (2017); Reguant (2014); Ito and Reguant (2016); Mercadal (2015).

changes when there is more wind generation in a given hour provides the following[20]

$$\frac{\partial S_o(p)}{\partial W} = -\frac{\theta_o}{1 - RD'(p)C''_o(S_o(p))}. \tag{4}$$

Because residual demand is non-positive, $RD'(p) \leq 0$, and costs are assumed to be weakly convex, $C''_o(S_o(p)) \geq 0$, this expression is non-positive, $\frac{\partial S_o(p)}{\partial W} \leq 0$ implying there is an un-competitive effect associated with more renewable generation in the form of physical withholding. If marginal costs are constant,[21] $C''_o(S_o(p)) = 0$, and residual demand is finite,[22] $RD'(p) < -\infty$, Equation 4 equals $-\theta_o$; a market participant will withhold their conventional generation by the quantity of wind generated, one for one. In this case the market participant would be generating the same electricity across all of their assets, however replacing their higher cost conventional generation with lower cost renewable generation.

Before presenting the testable predictions, it is important to discuss how Equation 3 and Equation 4 would differ if there were a forward market. The optimal strategy by each market participant would be a supply function net of the quantity sold in the forward market.[23] However, the change in the optimal strategy in response to more wind generation would be identical. Further, the incentives to reduce the quantity offered in response to more wind generation would extend to the day-ahead market. This is exactly the case in the Cournot-Nash equilibrium presented by Acemoglu, Kakhbod, and Ozdaglar (2017). More wind generation will reduce forward precommitments because it reduces the real-time price. However, more diverse ownership increases forward precommitments because that increases the real-time price. Together, the incentives to response strategically that exist in the real time market are identical to the incentives in the forward market.

[20]For simplicity I assume the more wind generation doesn't change the slope of the optimal strategy, and as a result, doesn't change the slope of the residual demand. That, is I assume $\frac{\partial S'_o(p)}{\partial W} = 0$. Violating this assumption would have no meaningful impact on the general notion of testable predictions presented below.

[21]This is a common assumption, for example see Woerman (2019)

[22]That is to say, the firm has some market power.

[23]If firm o has the forward quantity contract Q^f, the first order condition would become

$$p - C'_o(S_o(p)) = -\frac{S_o(p) + \theta_o W - Q^f}{RD'_o(p)}$$

From this we have the following testable predictions:

Testable Predictions

(i) *Only market participants that own wind turbines will reduce their quantity offered in response to more wind generation. Market participants that do not own wind turbines will not change their offer curve in response to more wind generation. For these firms $\theta_o = 0$ at all times implying $\frac{\partial S_o(p)}{\partial W} = 0$ always.*

(ii) *Market participants that generate a larger share of the total wind generation will reduce the quantity offered by a larger amount in response to more wind generation so long as they have some market power. This follows from $\frac{\partial^2 S_o(p)}{\partial W \partial \theta_o} = -\frac{1}{1-RD'(p)C_o''(S_o(p))} < 0$ when $RD'(p) > -\infty$.*

(iii) *Market participants will only change their offer curve in response to their own wind generation, not in response to the wind generation of other market participants. This can be seen by noting that only the market participant's own wind generation, $\theta_o W$, appears in Equation 3. Their optimal strategy does not directly depend on $\sum_{j\neq o} \theta_j W$.*

It is worth while discussing how this comparative static would be different in a perfectly competitive scenario. Here the market participants are price takers and residual demand is flat, $RD'(p) = -\infty$. As a result Equation 4 would be $\frac{\partial S_o(p)}{\partial W} = 0$ and more renewable generation would not be associated with any physical withholding.

3 The Midcontinent Independent System Operator and Data

The Midcontinent Independent System Operator (MISO) was formed in 1998 and approved as the first Regional Transmission Organization in the US by the Federal Energy Regulatory Commission in 2001.[24] The operator serves as a non-profit organization managing transmission and dispatch of electricity generating units within its footprint through a variety of market operations, focusing

[24] MISO was formerly known as the Midwest Independent System Operator up until 2013.

on reliability, efficiency, and the development of electricity resources. Since the incorporation of the Southern Region in 2013, MISO has become one of the largest wholesale electricity market in the United States with a total of 180 gigawatts of generation capacity, and conducts market operations from Montana to Michigan to Louisiana as shown in Figure 3. The distribution of wind turbines and conventional electricity generating assets within MISO is shown in Figure 4. The largest concentration of wind turbines in the United States is in the Great Plains, extending from Iowa to Texas. MISO operates a number of markets in combination with planning and oversight to achieve its goals in distribution and reliability including a day ahead and real time wholesale electricity market similar to the model described in section 2. These markets capture almost all electricity generation and transmission activities within MISO's footprint that are not part of bilateral contracts.

Two institution details complicate the incentives outlined in section 2. First, not all states within MISO's footprint passed legislation forcing vertically integrated utilities to divest there generation assets, so some of the generators in the market are owned by utilities that are also load serving entities. This vertical relation decreases the incentives for firms to manipulate the market price so long as they are net buyers from the wholesale market (Bushnell, Mansur, and Saravia, 2008). If they are net sellers, these utilities keep any excess revenue received from the wholesale market and still have an incentive to increase the wholesale price. Although the data on utility purchases and sales into wholesale markets are limited, Appendix B uses information from the EIA to show a number of the large horizontally integrated utilities in MISO that own wind turbine capacity are net sellers over the course of the year. Second, wind turbines in the U.S. are typically financed by long term purchasing power agreements, so utilities do no benefit from higher than average prices in wholesale markets.[25] In appendix B I use data from the America Wind Energy Association to show that MISO is unique in that over half of all wind turbine capacity was built in part by utilities for their own use and so are not financed with a long-run purchasing power agreement at a fixed price per MWh.

[25] Public utilities that are tax exempt also have limited interest in wind turbines because they can not claim the production or investment tax credit.

MISO publishes data regarding their market operations on their website as Market Reports. The primary data I use are the daily real time generation offers by cleared generation units from January of 2014 to December of 2016.[26] I focus on the real time market because there are no purely financial players in the real time market, increasing the benefits from withholding output.[27] These data provide a time consistent unit and owner identification code, the generating unit type (steam, combustion, wind turbine, hydro), the ex-post quantity generated and LMP received at five minute intervals, as well as details on the generating unit's supply bid.[28] Unit-level data on the hourly LMP received and the quantity generated for all units are summarized in Table 1. The sample average unit LMP is $27.42/MWh with wind turbines receiving a lower than average LMP and combustion turbines receiving the highest LMP on average. This is because the LMP is lower when wind turbines generate electricity, while the combustion turbines only generate electricity when the LMP is high. In terms of unit level generation, steam turbines and combined cycle units produce the most electricity per hour. To give context to the units, households in the United States consume approximately 1 MWh of electricity in a month on average. Overall I observe a total of 1,324 units during the sample, of which 211 are wind turbines.

As show by Equation 4, the impact of renewable generation on the price of electricity can depend on who owns the wind turbines so it is important to know the portfolio of unit types owned by every market participant. I take advantage of the time-invariant owner code associated with the generating units in the supply offer data to characterize the size and content of market participants' portfolios, as all units with the same owner code are owned by the same market participant. I consider the maximum quantity generated by a unit during the sample period as a measure of its capacity, Figure 5 shows the portfolio for the thirty largest market participants and their corresponding owner code. It is evident that almost all of these market participants have diverse assets, and that some of the largest market participants own a sizable amount of wind generation capacity.

[26]The start date is a few months after when the Southern Region was integrated into MISO. The end date is when MISO stopped reporting unit specific identification numbers to preserve the privacy of the asset owners.

[27]Evaluating strategic behavior in the day-ahead market should present similar results.

[28]It is important to note that I observe the unit type, but not the fuel type, which is necessary for analysis on generation costs or emissions.

In addition to the micro-data on unit level offers, MISO's market reports include hourly market level information on average LMP, the marginal energy component (MEC) of the LMP, the hourly fuel mix, the number of binding transmission constraints, the shadow price of relieving the binding constraints, wind forecasts, and net imports. I supplement these data with daily weather measures from the National Oceanic and Atmospheric Administration averaged across all states in MISO, as well as daily day-ahead natural gas prices at Henry Hub from the Intercontinental Exchange. Panel A in Table 2 summarizes these data. This market is large, clearing 71 GWh in a hour on average. A little more than half this is provided by coal based generators, and a fourth by natural gas. Wind generation provides almost 5 GWh on average, with a maximum of 13.7 GWh. While wind generation is a small portion of the market overall, there are moments when wind turbines produce more electricity than all the nuclear plants within MISO, and wind can meet up to 20% of load during periods of low demand.

Hourly unit level supply offer data include up to ten price-quantity pairs that outline the quantity each unit is willing to produce at a given market price. Additional data include minimum and maximum generation quantities, a flag if the unit 'must run', and a flag if the offer curve is a piece-wise linear or step function. I reconstruct unit specific supply curves for the hour by interpolating the price-quantity pairs on a common support (e.g. from -10 dollars to 100 dollars at an interval of 1 dollar). When appropriate, I extrapolate or truncate the quantity offered using the maximum and minimum quantity available. To ensure the function is everywhere differentiable and monotonic I smooth the offer curve using a normal kernel following Wolak (2001). For a set of price and quantity pairs, (p_{ikt}, q_{ikt}), $i = 1 \ldots N$, for unit k at time t, the smoothed supply function is

$$\hat{s}_{kt}(p) = \sum_i q_{ikt} \Phi \left(\frac{p - p_{ikt}}{h} \right)$$

where Φ is the standard normal cumulative distribution function and h is smoothing parameter.[29] I aggregate these unit level supply functions by market participant. Because I only observe the

[29] I use a bandwidth of three dollars, as does Kim (2017). It is important to note that changing the bandwidth will impact the consumer surplus calculation, but not the estimation results. Changing the bandwidth does not alter the consumer surplus calculations significantly.

supply functions of cleared units, this implicitly assume the bid from the not cleared units was zero at all prices. Figure 6 shows all offer curves of two sample market participants for all days in a month at the same time of day.

With the detailed data on supply and demand for every hour I calculate an expression for the analytical merit order effect, Equation 2, for two different assumptions on competitive conduct. One is for when market participants are acting as if they are in a competitive market, with $\frac{\partial S_o(p)}{\partial W} = 0$. This could be because the market participants have no ability to exercise market power, or because they have the ability to exercise market power but choose not to practice physical withholding. As a result the analytical merit order effect is

$$\frac{dp_{comp}}{dW} = -\frac{1}{\sum S_o'(p) - d'(p)} \tag{5}$$

The second analytical merit order effect I consider is when firm's residual demand slope is finite and have they zero marginal cost of production up until the capacity constraint. This is the other extreme of firm behavior in which they'll withhold output from their conventional units exactly equal to the amount of electricity generated from their wind turbines, $\frac{\partial S_o(p)}{\partial W} = -\theta_o$, making the analytical merit order effect

$$\frac{dp_{SFE}}{dW} = -\left(1 - \sum_{o \in V} \theta_o\right) \frac{1}{\sum S_o'(p) - d'(p)} \tag{6}$$

where V is the set of diverse market participants.

To find the slopes at equilibrium, I aggregate all of the generating unit supply curves within MISO to obtain a market supply curve.[30] To find the market equilibrium, I find the price where supply is equal to demand as shown in Figure 7.[31] At this equilibrium I calculate the local slope of supply and demand as the difference in the quantity, along the curve, for a one step increase in

[30]Here I define the entire MISO region as a single market. I've considered other market definitions including subregions within MISO and price clusters similar to Mercadal (2015).

[31]Because I am interested in the impact of wind on the price of electricity, I define the equilibrium without using the supply bids by the wind generating units. In addition I use generation within the market instead of market demand, as this is a measure of demand net of imports.

price. The equilibrium prices and slopes are summarized in Panel B of Table 2. This price should correspond to the Marginal Energy Component of the LMP.

I use the slope of supply and demand, summarized in Panel B of Table 2 to calculate an exact expression of Equation 5 for every hour in my sample. I do the same for Equation 6 where I use the fraction of wind owned by diverse market participants in that hour for the value of $\sum_{o \in V} \theta_o$. Table 2 shows that on average the proportion of wind owned by diverse market participants is 72%. The resulting values are summarized as "Analytical Merit Order Effect, Competitive" and "Analytical Merit Order Effect, SFE" respectively in Table 3. For a one GWh increase in wind generation for a given hour, we'd expect the price to decrease by \$0.65/MWh if market participants were acting competitively, and \$0.19/MWh if market participants were withholding according to their incentives in a Supply Function Equilibrium. For context, the same increase in wind has been associated with a 3.18% price decline in Spain (Böckers, Giessing, and Rösch, 2013), 0.8 to 2.3 €/Mwh price decline in Germany (Cludius et al., 2014), 1.5 to 11.4 \$/Mwh price decline in California (Woo et al., 2016), and 3.9 to 15.2\$/Mwh price decline in Texas (Woo et al., 2011).[32]

To find the total price effect, I take the analytical merit order effect for an hour and multiply this by the quantity of electricity generated by wind for that hour. This provides values of dp_{comp} and dp_{SFE}. The total price effect is \$3.7/MWh in a perfectly competitive market and around \$1/MWh according to the supply function equilibrium framework. These values vary tremendously, ranging from near zero to over \$100/MWh. This is consistent with the wholesale market where prices fluctuate greatly and can reach over \$1,000/MWh.

4 Evidence of Strategic Withholding

The difference between the total price effect under perfect competition and complete withholding, presented in Table 3 as dp_{comp} and dp_{sfe}, highlights the importance of the firm's strategy in

[32]It is important to note these numbers include the impact on wind generation on congestion and transmission. Which in part explains why the estimates are different. In addition, the fuel mix in MISO is more coal heavy than in the other regions.

how renewable generation impacts the price of electricity. However, these calculations rely on assumptions on how firms are competing in the wholesale market and responding to more renewable generation. In this section, I use detailed data on the strategies of all market participants to directly estimate how firms are responding to more renewable generation, and as a result side-step structural assumptions on how the firm's are competing. This approach is valuable in wholesale electricity markets, where there is convincing evidence that market participants are not always acting in a way that is fully rational (Hortaçsu and Puller, 2008; Hortaçsu et al., 2017).

I begin by aggregating the conventional unit supply curves, similar to has described in section 3, by owner code for every hour.[33] This gives me a hourly supply curve of the conventional assets for every market participant on a common support. For computational purposes, I limit the prices to be every \$3 interval between 0 and 60 dollars. These curves are defined by a set of $b = 1 \ldots 21$ price quantity pairs, (p_b, q_{otb}), for owner o at time t. The set of p_b are the same for all market participants, for all hours, only the quantities offered at these prices change.

Because I only observe the bids for cleared units, this approach implicitly assumes the not cleared units submitted an offer of zero MW at all prices. It is possible the not cleared units (1) did not submit a bid because they changed their status to unavailable or not participating, (2) submitted a bid that did not clear because it was strategically uneconomic,[34] or (3) submitted a bid that was uneconomic due to other market conditions. Explanations (1) and (2) are consistent with the testable predictions derived in section 2. Explanation (3) has the potential to bias my results. In particular, I would incorrectly ascribe not cleared units to acting strategically if more wind generation forces units not to clear, and a market participant's own wind turbine inordinately impacts their own conventional assets. Because my estimates are robust to periods with limited or no transmission constraints, and so wind turbines influence all electricity equally, it is unlikely explanation (3) fully explains the pattern of the estimates presented below.

[33] I do not include bids from wind turbine units. I don't apply the smoothing function of Wolak (2001) here because I don't care about the slope of the offer curve for estimating the strategic response.

[34] In speaking with the market monitor, this can be accomplished by increasing the required start cost, incremental cost, energy cost, required start time, required notification time, minimum down time, or reducing their maximum daily starts, or dispatch maximum

To directly test for strategic physical withholding, I see how the quantity offered at a given price changes in response to increased renewable generation. The general estimating equation of interest is

$$q_{otb} = \delta WindGWh_t + X\beta + \eta_{op_bymh} + \varepsilon_{otb} \tag{7}$$

where q_{otb} is the quantity offered, in MW, by market participant o at time t and price bin p_b. X represents other determinants of a market participant's strategy including hourly cleared GWh in MISO, hourly net imports, daily temperature measures and daily natural gas prices. Identification comes from owner specific, month-of-sample by hour, fixed effects for every price bin, η_{op_bymh}. This captures the average quantity offered by market participant o at price p_b within a month-of-sample hour (e.g. September 2014, 4pm). Therefore the coefficient δ is identified off the deviation from the market participants month-of-sample hour average supply curve. To ensure I am looking only at relevant bid prices, I discard any observations where the market price is more than the price bin plus three, $p_b + 3$.[35]

Because these data represent the ex-ante strategy of economic units owned by the firm, withholding the quantity offered at a given price would imply that $\delta < 0$. The supply function equilibrium theory presented in section 2 suggests the coefficient of δ should be (i) negative only for diverse market participants that own both wind turbines and conventional assets, (ii) increasing in the share of total wind owned by the diverse market participant, and (iii) negative only in response to a market participants own wind generation.

Table 4 shows the estimate of δ in Equation 7 is negative. Overall, a 1 GWh increase in wind generation in an hour is associated with a 2.8 MW reduction it the quantity offered at a given price on average across all market participants. In column (2), I interact $WindGWh_t$ with an indicator variable for if a market participant owns wind turbines and conventional assets. This shows that diverse market participants reduce the quantity offered by 13 MW on average, while the

[35] I add three to the price bin because the price bins are at three dollar intervals. Using the full sample provides a similar result to what follows.

independent market participants only reduce the quantity offered by 1.3 MW, differing by a factor of ten. Finally, in column (3) I decompose $WindGWh_t$ into the quantity of electricity generated by independent wind turbines and the quantity of electricity generated by wind turbines owned by diverse market participants. This shows that the quantity offered by diverse market participants is reduced the most in response to diverse wind generation, and that market participants that do not own wind turbines respond much less overall. Further, the asymmetry between one additional market GWh generated, and one additional GWh of diverse wind generation, suggests that unit are not clearing for strategic reasons instead of economic ones.

The estimates presented in Table 4 are the average effects for all market participants, or at best separated by if a market participant owns wind turbines. I expect there to be substantial heterogeneity in how market participants respond to increased renewable generations because they vary in the portfolio of wind based generation and their bidding sophistication. I interact $WindGWh_t$ in Equation 7 with the owner code of every market participant to get a unit specific estimate of δ_o. In particular, I estimate the parameters in the following equation

$$q_{otb} = \delta_o WindGWh_t \cdot OwnerCode_o + X\beta + \eta_{op_bymh} + \varepsilon_{otb} \tag{8}$$

Figure 8 presents the density of all owner-specific point estimates separated by whether or not the market participant owns wind turbines. This shows the coefficients for the market participants that do not own wind generation are near zero, whereas the density for diverse market participants has an obvious left skew and is centered below zero. Table 5 presents the point estimates from Equation 8 for all 23 diverse market participants. Most importantly, the sum of all market participant specific coefficients at the bottom of the table represents the aggregate response to a 1 GWh increase in wind generation.

As shown in section 2, a firm's incentive to withhold increases with the amount of electricity they generate from wind turbines. I match the estimates for owner-specific withholding coefficients for diverse market participants, $\hat{\delta}_o$, with the total capacity of all wind turbines owned by each market participant. Figure 9 shows how there are a few market participants that are withholding the most in response to wind generation, and these market participants also own the most wind turbine capacity.

Finally, we expect market participants to only withhold their output when their own wind turbines are generating wind. This is because they are withholding output to increase the revenue received by their wind turbines and not to prevent price suppression on the conventional assets. To show evidence for this I estimate the parameters from the following equation

$$q_{otb} = \delta_{op_b} OwnWindGWh_t \cdot p_b + \chi_{op_b} OtherWindGWh_t \cdot p_b + X\boldsymbol{\beta_0} + \eta_{p_b ymh} + \varepsilon_{tb} \tag{9}$$

where δ_{op_b} represents how owner o changes the quantity offered at price p_b in response to electricity generated from their own wind turbines, and χ_{op_b} is how a market participant o changes the quantity offered in response to electricity generated by all other wind turbines. This is estimated separately for each market participant because it is computational intensive. Figure 10 shows these estimates for four market participants that own a large share of total and wind generation. It is clear that these market participants are responding more so to their own wind generation than the electricity generated form other wind turbines.

One concern might be that market participants are withholding output when they know constraints within the transmission system would make their unit un-economic because of wind generation. I show these results are robust to concerns regarding transmission congestion by re-estimating Equation 7 on the subsample of hours when (1) the largest losses and congestion price within MISO is below the 10th percentile of all hours, and (2) when there is one or less binding constraints within MISO. This also gets at the issue of market segmentation. MISO is operating the most like a singular market with a uniform price for these subsamples. Table 6 shows the results do not change in a meaningful way, although some of the estimates become underpowered. Most importantly, the sum of point estimates, at the bottom of Table 6, remains economically meaningful and statistically significant.

5 Implications for Consumer Surplus

Using the analytical merit order effect for the expected price change due to increased renewable generation it is possible to make claims regarding consumer surplus in the wholesale electricity market. This calculation is for the consumers in the wholesale market, typically a distribution utility or electricity retailer. The change in surplus for ultimate electricity consumers is likely to be different, as utilities don't always pass-on wholesale savings (Hausman, 2018) and have complex rate structures. In which case, this is an upper-bound on the change in surplus for ultimate consumers, representing the maximum available possible benefits. It is important to note, this is not a total welfare calculation as I don't quantify the dead weight loss associated with strategic withholding.

I model consumer surplus from electricity during hour t at market price p as

$$CS_t(p) = \int_p^\infty D_t(x)dx$$

where $D_t(x)$ is the demand for electricity at time t and price x. To see how consumer surplus changes due to an increase in the quantity of wind, W_t, I take the total derivative to get

$$\frac{dCS_t}{dW_t} = -D_t(p)\frac{dp}{dW}_t$$

implying the change in consumer surplus during the entire sample period would be[36]

$$\Delta CS = -\sum_t D_t(p)\frac{dp}{dW}_t dW_t. \tag{10}$$

When calculating consumer surplus, I consider three alternative values for $\frac{dp}{dW}$. One is the prediction under the assumption of price taking behavior, where $\frac{dp_{comp}}{dW}_t = -\frac{1}{\sum_o S_o'(p) - d'(p)}$. For the second, I assume diverse firms are withholding perfectly to offset more wind generation, con-

[36]This is using a local approximation for how wind generation impacts consumer surplus. The total change in consumer surplus is driven entirely by changes in the market price, no quantity effects. This is reasonable given the inelasticity of demand in the wholesale market.

sistent with the supply function equilibrium framework and constant marginal costs, $\frac{dp_{sfe}}{dW}_t = -\left[1-\sum_{o\in V}\theta_o\right]\frac{1}{\sum_o S_o'(p)-d'(p)}$ where $\sum_{o\in V}\theta_o$ is the proportion of wind owned by diverse market participants. Third, I use the estimates of physical withholding for diverse market participants from Equation 8 as an estimate of $\frac{\partial S_o}{\partial W}$. Table 5 shows $\hat{\delta}_o$ for all diverse market participants. The sum of these estimates, presented in the bottom of Table 5, suggests that over 30% of wind generation is replacing withheld offers by diverse market participants.

All together this provides me with three separate estimates of consumer surplus, all varying in the degree to which market participants withhold their generation offer

$$\Delta CS_{comp} = \sum_t D_t(p)\frac{1}{\sum_o S_{ot}'(p)-d_t'(p)}dW_t \tag{11}$$

$$\Delta CS_{SFE} = \sum_t D_t(p)\frac{1-\sum_{o\in V}\theta_{ot}}{\sum_o S_{ot}'(p)-d_t'(p)}dW_t \tag{12}$$

$$\Delta CS_{obs} = \sum_t D_t(p)\frac{1-\sum_{o\in V}\hat{\delta}_o}{\sum_o S_{ot}'(p)-d_t'(p)}dW_t \tag{13}$$

Table 7 presents all estimates of the total change in consumer surplus, as well as market revenue over the sample period. I normalized these totals to a value per person per year assuming 50 million people live within MISO's footprint.[37] The potential consumer surplus from increased renewable generation, according to Equation 11, is seven to ten billion USD over three years, equivalent to 50 to 69 USD per person per year. This number is greatly diminished if diverse market participants withhold perfectly, as calculate by Equation 12. The total consumer surplus would be only 2 to 2.8 billion USD, or 14 to 19 USD per person per year. Using the observed withholding coefficients to calculate consumer surplus, as in Equation 13, the surplus per person per year is 34 to 47 USD, suggesting that observed withholding by diverse market participants reduces consumer surplus by 15 to 21 USD per person per year.[38]

[37]This population estimate is my best guess given that 61 million individuals live in the states of Arkansas, Illinois, Indiana, Iowa, Louisiana, Michigan, Minnesota, Mississippi, Missouri, North Dakota, Wisconsin according to the 2016 US Census Bureau estimates.

[38]Instead of normalizing the consumer surplus per person per year, it's possible to normalize it by the total MWh of wind generation. This presents ΔCS_{comp} between 57 and 79 \$/MWh per MWh wind, ΔCS_{obs} between 39 and 54 \$/MWh per MWh wind, ΔCS_{sfe} between 16 and 21 \$/MWh per MWh wind.

The potential consumer benefit is large relative to the existing subsidy payments for renewable generation. For example, during the sample period the United States government spent a total of 6.6 billion dollars on subsidizing wind production for the entire United States (Sherlock, 2014).[39] Finally, it is important emphasize that this loss in consumer surplus is not dead-weight loss. Likely there is some dead weight loss from higher cost units replacing withheld units, however a majority of the loss in consumer surplus is a transfer from producers to consumers.[40] If the producers were to take the captured revenue and directly invest it into more renewable generation, the observed withholding estimates suggests this would add approximately 3 GW of wind turbine capacity, increasing capacity of wind turbines in MISO by more than 20%.[41]

6 Discussion

The increase in renewable generation capacity within the United States has created immense value by providing low marginal cost electricity. However, the incidence of this value depends largely on how horizontally integrated market participants, owning wind turbines, compete in wholesale electricity markets. I first derive an analytical expression for how increased renewable generation should impact the price of electricity. I show the strategic response of conventional electricity generators to increased wind generation is an important factor to consider in price formation. In particular, a supply function equilibrium model with horizontally integrated generating units predicts that diverse market participants will reduce their generation offer in response to an increase of their own wind generation. Using detailed data on supply and demand from 2014 to 2016 in MISO's wholesale electricity market, I quantify the expected price reduction under a model of perfect competition and a supply function equilibrium model with withholding.

I directly test for evidence of physical withholding by diverse market participants using month-

[39] This estimate is for the Federal production tax credit and doesn't include the federal investment tax credit or implicit subsidies from state policies like renewable portfolio standards or PURPA.

[40] Uncovering the identity of each unit would allow a calculation of dead weight loss using information on fuel type and heat rate.

[41] A generous estimate for new wind turbine capacity is \$1 billion per GW of capacity (US-DOE, 2017).

of-sample by hour, price, owner fixed effects. Indeed, it is the diverse market participants that reduce the quantity offered, and they do it more in response to their own wind generation. This has important implications for consumer surplus and overall economic efficiency if this withholding leads to less efficient units having merit in the dispatch order. The analytical merit order effect I calculate and withholding coefficients I estimate imply increased renewable generation has the potential to increase consumer surplus by 50 to 69 USD per person per year, however observed withholding by diverse market participants reduces consumer surplus by 15 to 21 USD per person per year. This has implications for the market monitor in these wholesale electricity markets, as increased renewable generation might be associated with un-competitive behavior.

There are several policy implications that come from these results as well as avenues for future research. For one, the ownership of the renewable generation assets is not neutral to the incidence of consumer and producer surplus. Wind turbines and solar panels owned by diverse market participants in wholesale markets will not reduce the price of electricity by as much as the same assets owned by independent market participants or assets compensated by purchasing power agreements. If the policy goal is to use renewable generation to reduce the price paid by consumers, policy makers should pay attention to which type of resources they are subsidizing.

This incentive structure is interesting in a dynamic sense. The ability of horizontally integrated market participants to capture the benefits of low marginal cost generation through strategic withholding increases their incentive to invest in renewable generation. Because renewable generation reduces emission externalities associated with electricity generation, additional investment in this technology can be good from a social planner's perspective. As a result, the short run exercise of market power might be offset by the long run investment incentives in more renewable generation capacity and one possible way to increase renewable generation capacity is to allow diverse market participants to exercise market power when their own wind turbines are generating electricity.

This research shows that more renewable generation isn't always displacing the most expensive generating units because of profit motives. There might be technical reasons for this in addition to the economic incentives shown here. Better understanding why this might be the case can increase the value derived from renewable generation. Further, characterizing the emissions of the withheld units as well as the units replacing the withheld units can be used to comment on the emission implications of strategic behavior.

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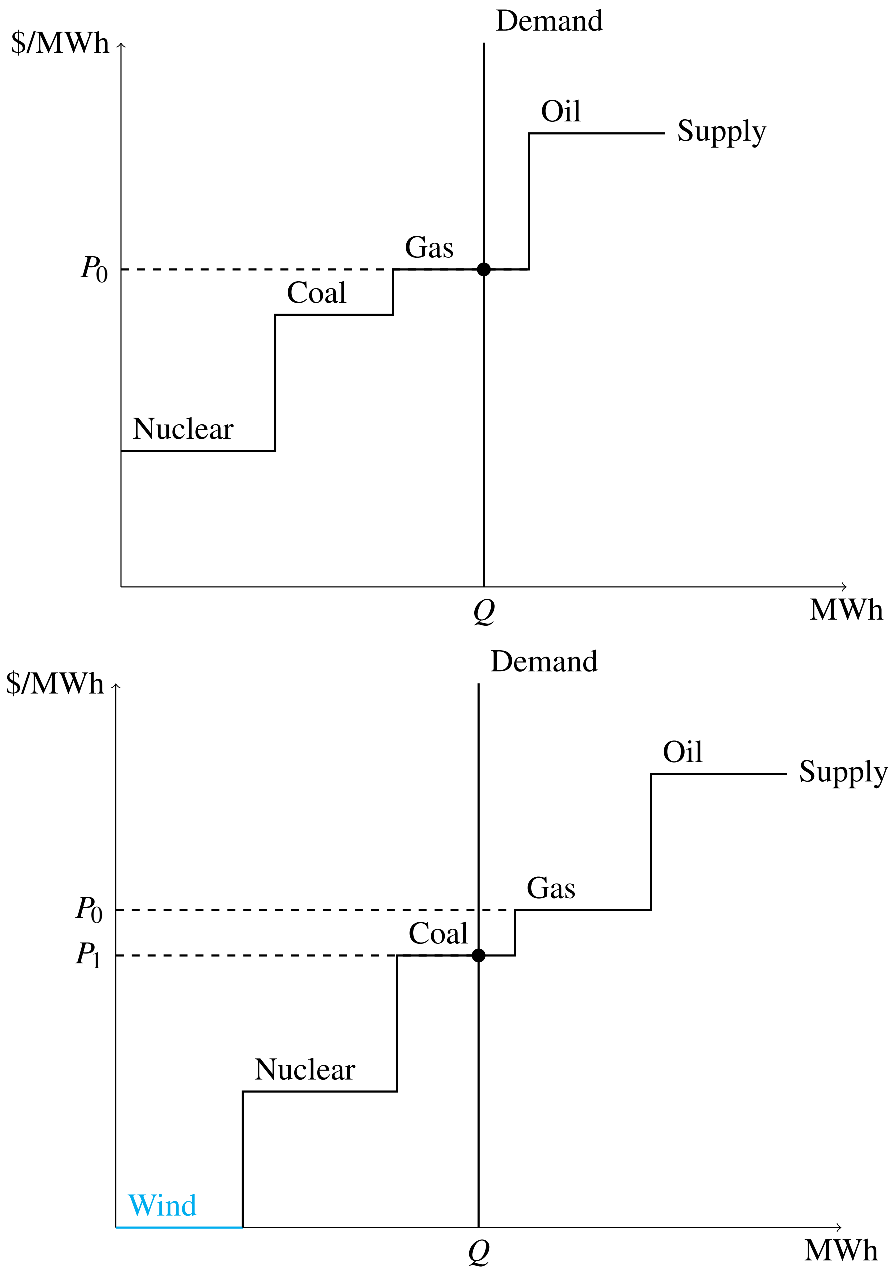
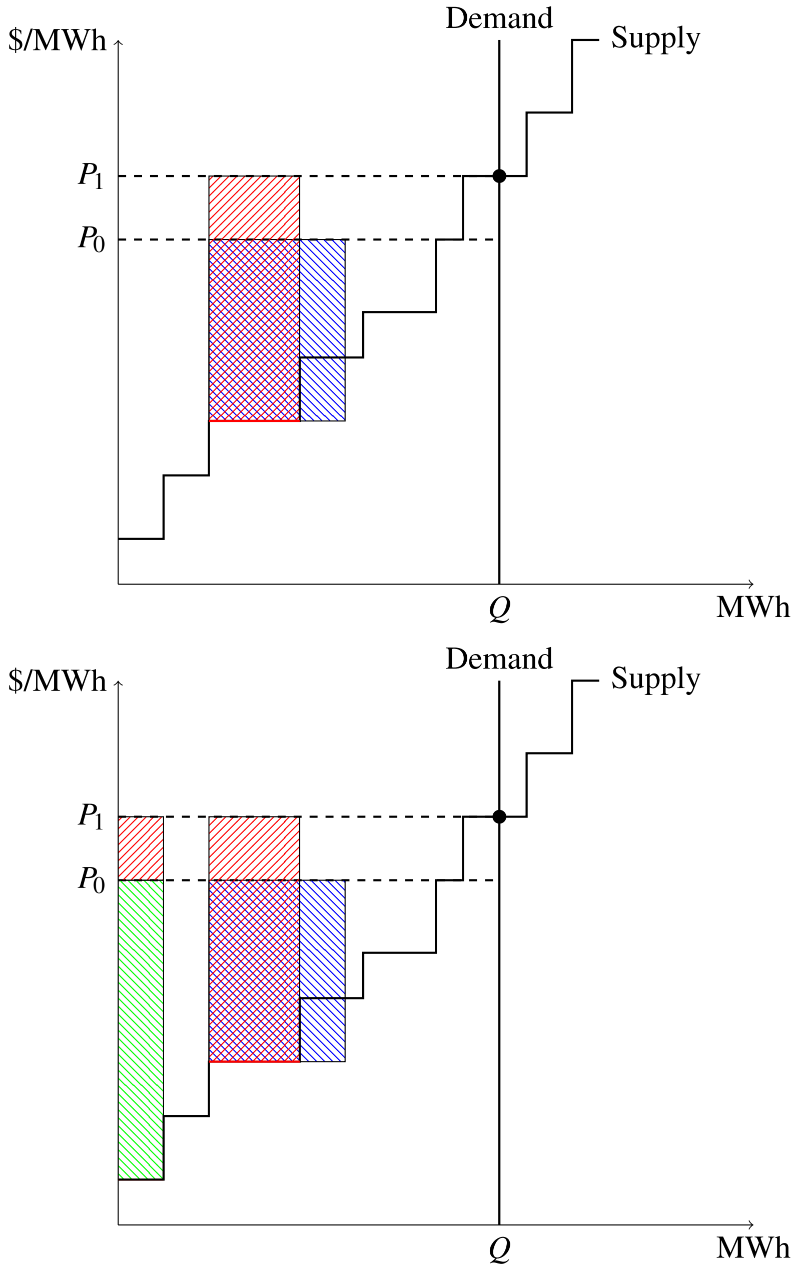
Tables and Figures

Figure 1: The Merit Order Effect of Renewable Generation.



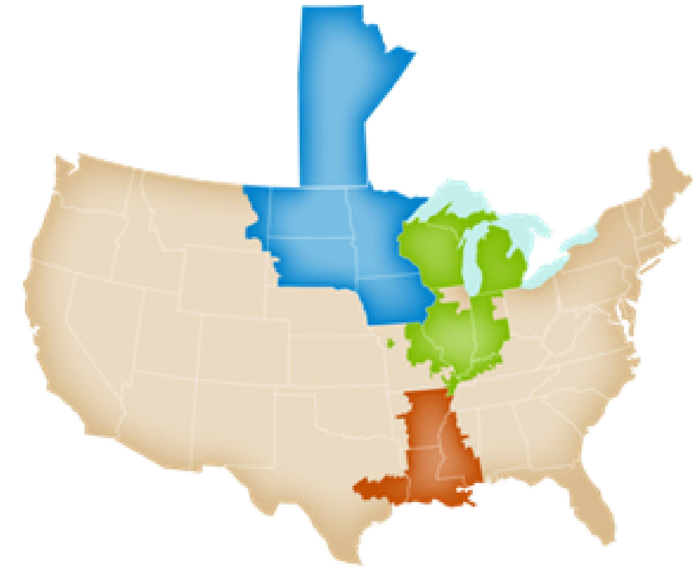
Electricity markets are conceived as a Merit Order, where the lowest cost resources have merit and are dispatched first. When wind turbines generate electricity, it is believed they displace higher cost units as wind generation shift the supply curve to the right. As a result of the supply shift, the equilibrium price of electricity decreases, from P_0 to P_1, displacing higher cost electricity generating units. This simplified model does not consider how increased wind generation might impact the incentive's of conventional electricity generators.

Figure 2: Incentive for Diverse Market Participants to Withhold Output.



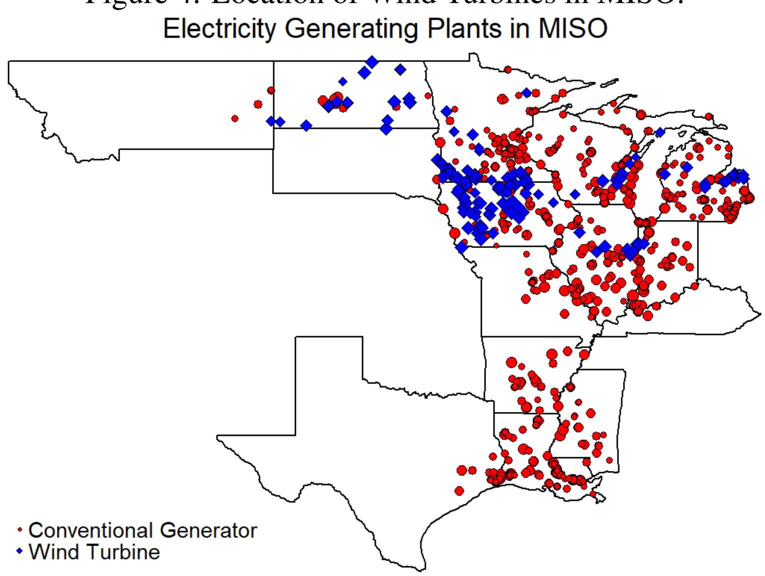
When a firm with market power considers the incentives to withhold their output they trade off a lower price and a larger quantity with a higher price and a smaller quantity. This trade off is represented in the top figure, for the firm that submits a bid corresponding to the red step, by the area of the only blue cross hatch and the only red cross hatch rectangles. When the market participant is diverse, owning wind turbines and conventional generators, they receive additional revenue from a higher price on their wind based assets. In the bottom panel, the green cross hatch represents the revenue from the wind turbine if the firm does not withhold and the additional red only cross hatch rectangle shows the revenue received from the wind based asset if they withhold their output.

Figure 3: MISO's Footprint



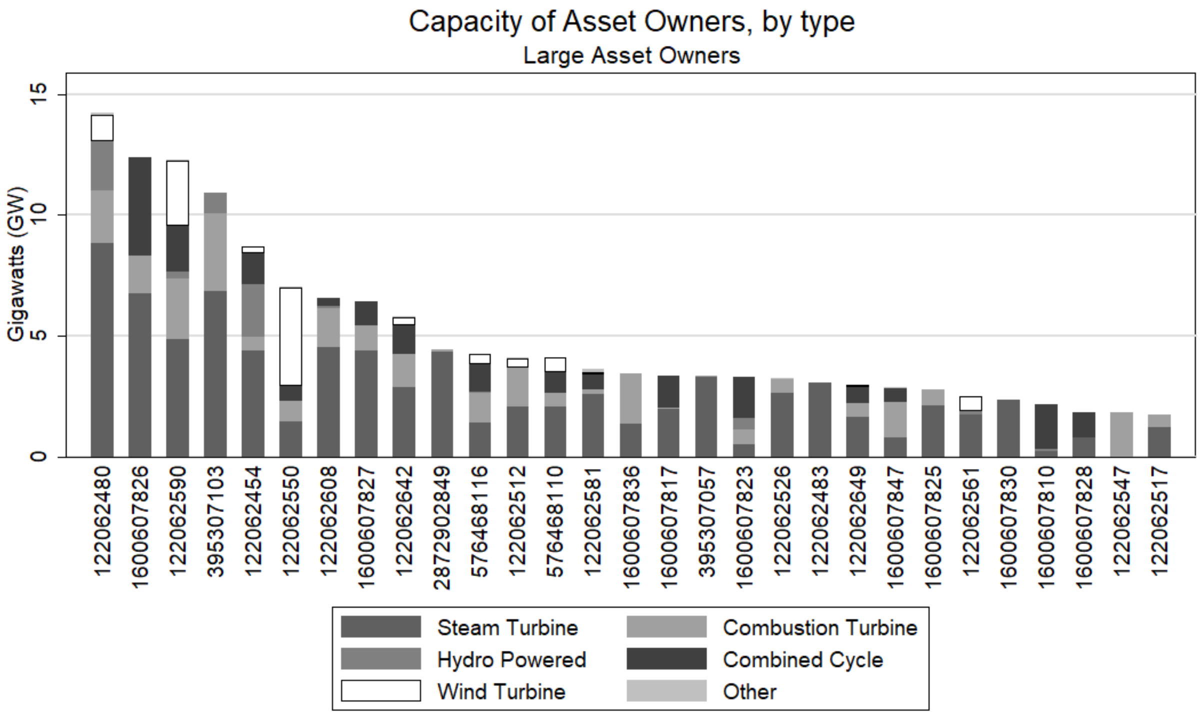
Source: misoenergy.org.

Figure 4: Location of Wind Turbines in MISO.



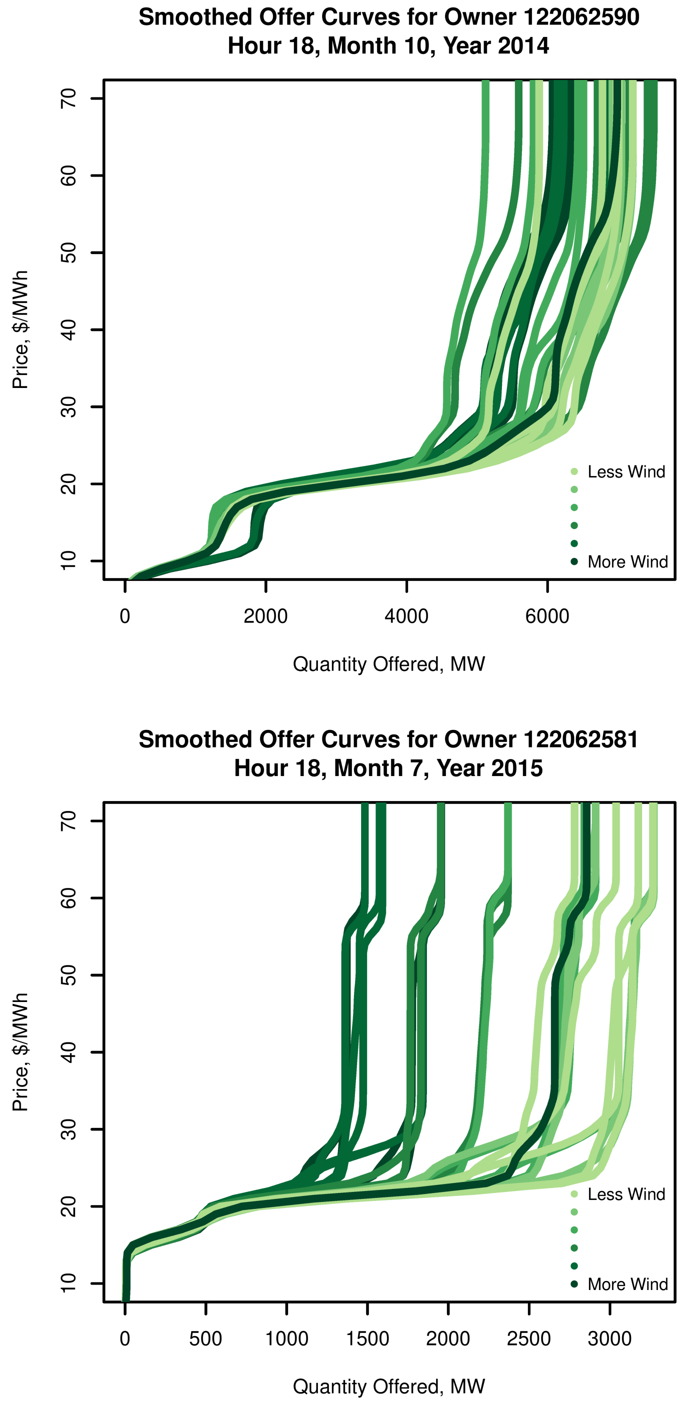
The locations of all electricity generating units in MISO according to the Energy Information Agency form 860 for the year 2016. Wind turbines are blue diamonds while conventional generators are red circles. The size of the point is proportional to the log of the generating unit's capacity.

Figure 5: Capacity and Portfolio of Market Participants in MISO.



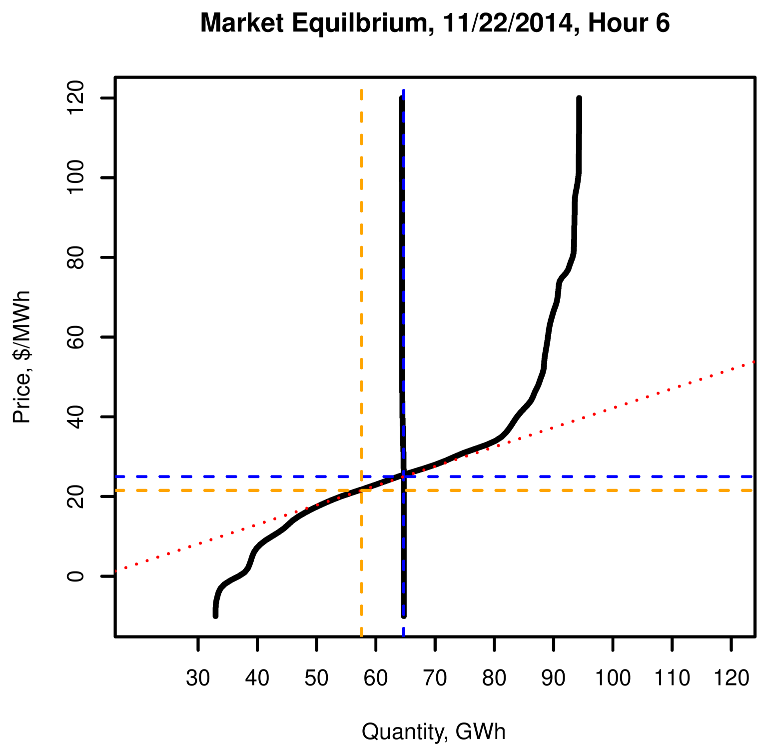
The capacity and portfolio of the thirty largest market participants in MISO. Capacity is measured as the maximum MWh produced by a unit during the entire sample period. The bar labels are the Market Participant's coded identification number. This shows large market participants own wind generation and conventional assets. There are approximately 220 smaller market participants that appear during the sample period.

Figure 6: Sample Offer Curves.



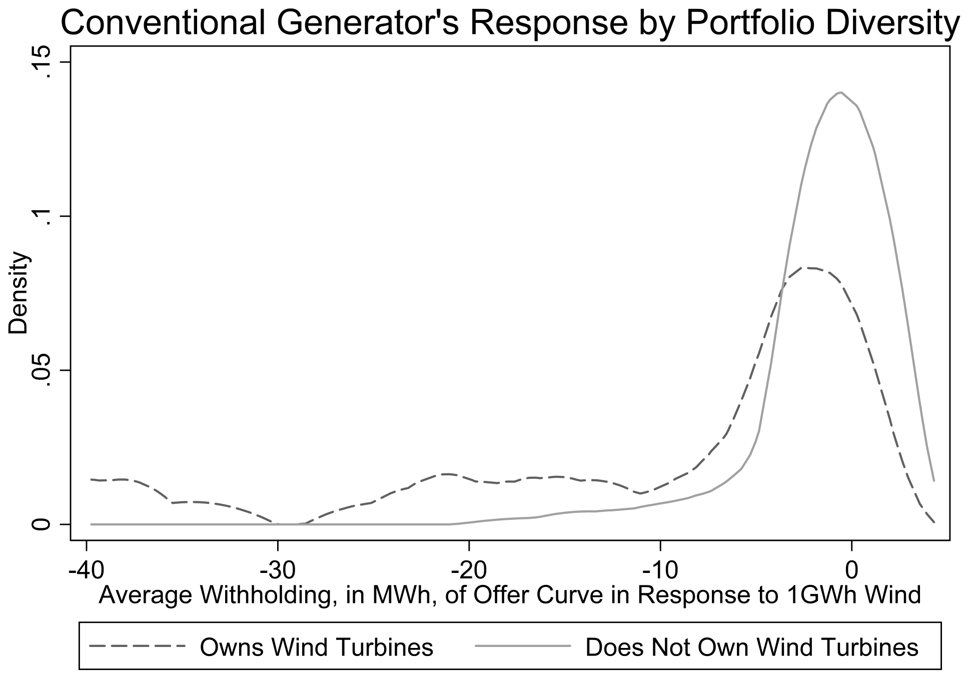
Set of all cleared offer curves by two market participants in a single year-month-hour. A cleared offer curve is the hourly supply curve offered by the market participant for a given hour, this represents the ex-ante quantity they are willing to produce across all units for a given market price. This also showcases the type of variation used in the bid level regression that include year-month-hour fixed effects. Darker lines are associated with windier hours.

Figure 7: Reconstructed Equilibrium.



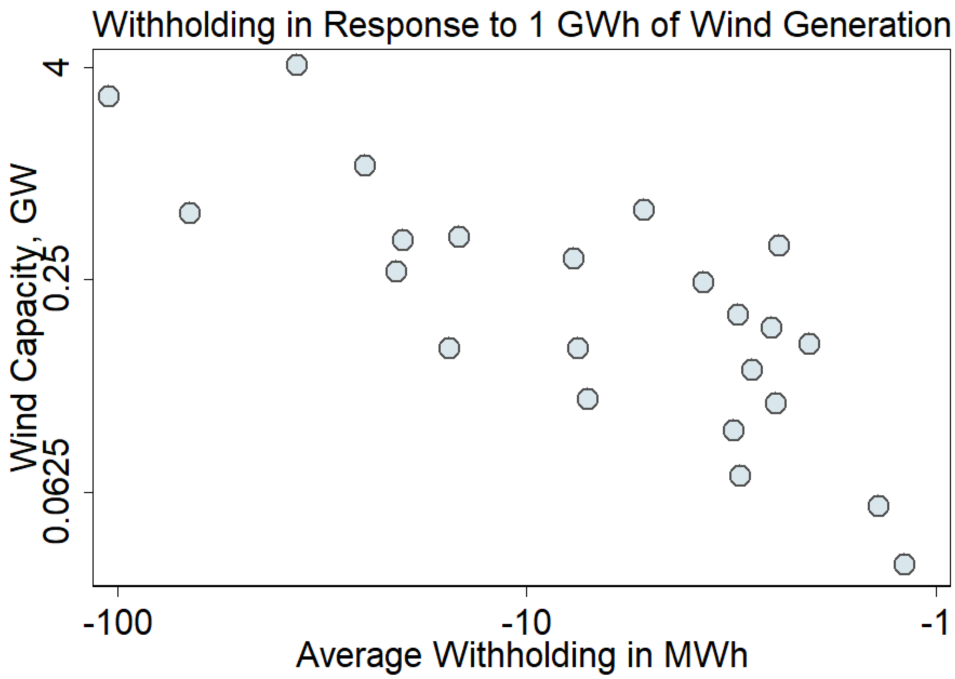
The reconstructed market supply and demand curves, in black, for a sample hour form the equilibrium price. The equilibrium is denoted by the dashed blue lines. The calculated merit order effect for a one unit increase is shown by the dashed red line. Walking down the merit order effect from the equilibrium shows the expected price reduction with the yellow dashed lines.

Figure 8: Density of Withholding Coefficients.



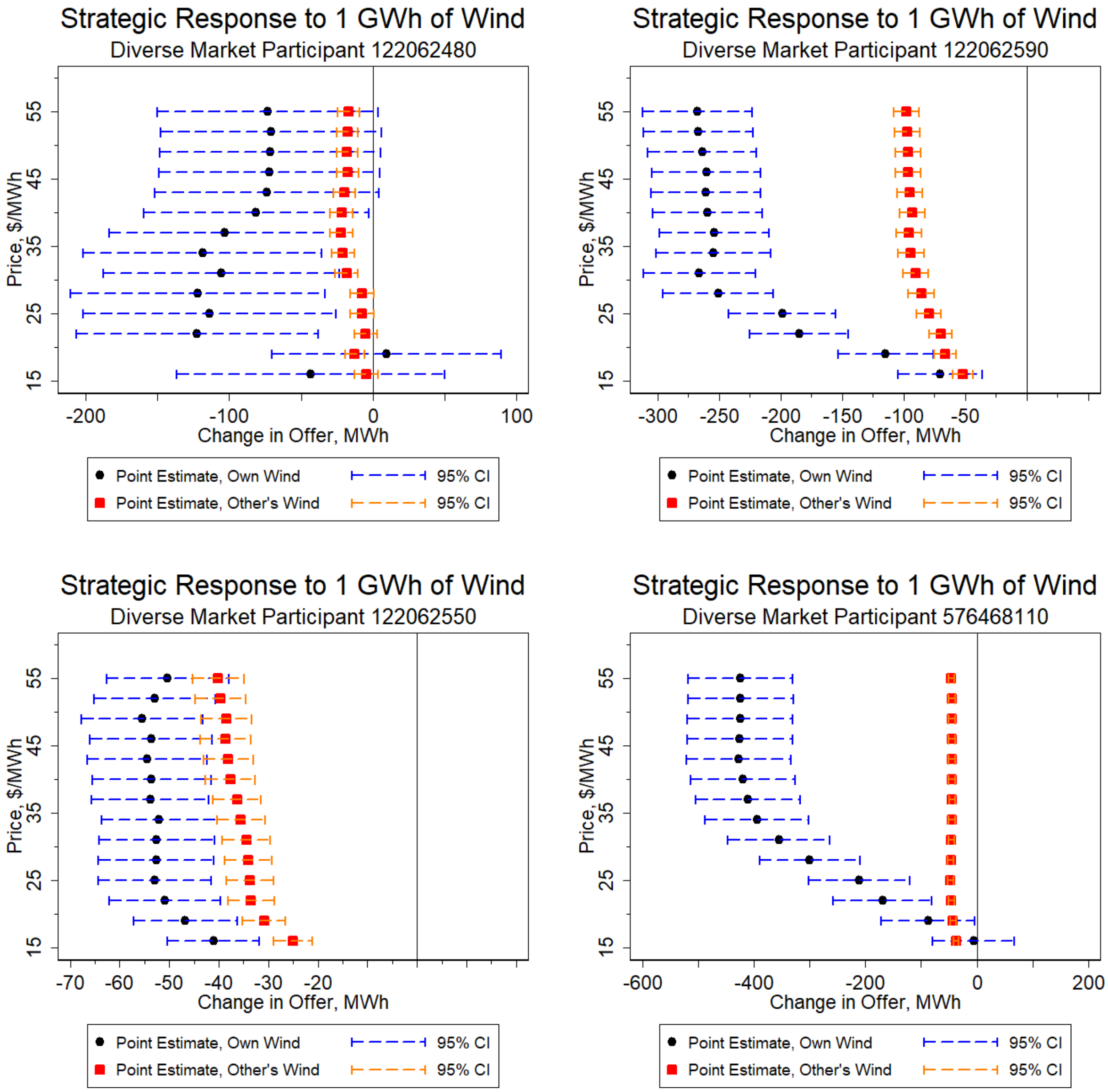
Kernel density of withholding coefficients for ever market participant separated by the market participant's portfolio diversity. Withholding coefficients are how the market participants offer curve changes in response to increased wind generation controlling for the month/year/hour/price/owner average quantity. Both densities use a Epanechnikov Kernal with a bandwidth of two dollars. Values below -40 MW/GWh are truncated.

Figure 9: Withholding Coefficients and Owner Wind Turbine Capacity.



Owner specific withholding coefficient and owner total wind turbine capacity for diverse market participants. Withholding coefficients are estimates from Equation 8, turbine capacity is the sum of each turbine's maximum output in the sample period. Note the horizontal axis is in $\log_{10}$ and the vertical axis is $\log_2$.

Figure 10: Owner Specific Withholding.



Withholding coefficients at every price bin for a select number of large and diverse market participants. Estimates come from estimating Equation 7 with flexible price bins interacted with WindGWh, separately for each market participant. Confidence interval uses robust standard errors.

Table 1: Unit Level Summary Statistics.

	Unit-Hour LMP		Unit-Hour MWh			
	Mean	Std. Dev.	Mean	Std. Dev.	Num. Units	Unit-Hour Obs.
Steam Turbine	28.55	29.01	224.14	235.98	411	6,072,029
Combustion Turbine	34.91	46.19	148.07	157.24	441	981,114
Hydro Powered	29.87	33.06	23.08	45.06	83	1,252,130
Combined Cycle	29.55	28.91	299.35	146.04	76	672,407
Wind Turbine	22.97	26.80	28.75	39.44	211	4,504,944
Other	31.97	39.91	33.66	65.56	102	292,701
Total	27.42	30.73	136.17	194.97	1,324	13,775,325

Notes: Unit-Hour observations come from MISO Real Time Cleared Offers Market Report From January 1, 2014 to December, 24, 2016. The sample includes all electricity generating units that produced positive output. LMP stands for location marginal price and is given is USD per MWh. The MWh produced and price received are reported at 5 minute intervals within a single hour. The Unit-Hour observations are the hourly average of these values.

Table 2: Market Level Summary Statistics.

	Mean	Std. Dev.	Min	Median	Max	Obs.
Panel A						
Market LMP, USD/MWh	27	20.8	-26.8	23.7	1,571	26,117
Market MEC, USD/MWh	29.9	22.7	-28.7	25.8	1,806	26,117
Market GWh Generated	71.4	12.6	42.1	70.4	116	26,117
Coal GWh	36.8	8.46	16.5	36.6	56.8	26,117
Gas GWh	15.9	6.21	4.57	15.3	43.4	26,117
Hydro GWh	.988	.5	.305	.843	3.29	26,117
Nuclear GWh	11.4	1.23	6.1	11.7	13.3	26,117
Other GWh	1.35	.852	.295	1.07	7.74	26,117
Wind GWh	4.96	2.79	.132	4.61	13.7	26,117
Wind GWh, Diverse	3.58	2.1	.0551	3.29	10.2	26,117
Wind GWh, Independent	1.37	.722	.0693	1.3	3.61	26,117
Shadow Price of Constraints	-.947	1.28	-17.3	-.506	0	26,117
Number of Binding Constraints	3.79	2.65	0	3.17	19.2	26,117
Max Daily Temperature, C	17.6	10.4	-11.7	19.5	33.4	26,117
Natural Gas Price, USD/MMBtu	3.13	1.01	1.49	2.84	7.88	26,117
Net Exports GWh	4.41	1.99	-1.77	4.27	11.6	26,117
Wind Forecast Error, GWh	-.00594	.965	-4.13	.00101	4.32	26,093
Panel B						
Equilibrium Price, USD/MWh	28.8	8.47	17	26	118	26,117
Supply Slope, $\Delta MWh/\Delta\frac{USD}{MWh}$	2,627	1,512	17.5	2,307	7,432	26,117
Demand Slope, $\Delta MWh/\Delta\frac{USD}{MWh}$	-4.98	7.49	-67.7	-1.25	0	26,117

Notes: Market-Hour observations from January 1, 2014 to December, 24, 2016. Market LMP, from the Nodal LMP Market Report, is taken as the average of all LMPs with an hour. The MEC is found by subtracting the Loss and Congestion Component from the LMP for each hour. Generation quantity in GWh comes from the Fuel Mix Market Report. The decomposition of Wind into Diverse and Independent Owners comes from the Cleared Offers Market Report. Diverse is defined as wind generation that is owned by a market participant that owns assets other than wind turbines. Independent wind comes from market participants that own only wind based resources. Shadow Price, in thousand USD, and Number of Binding Constraints comes from MISO's Real Time Binding Constraint Market Report. Temperature data is an average of all temperature readings within MISO's footprint from the Global Historical Climatology Network operated by NOAA. Wind Forecast Error and day ahead Henry Hub natural gas price and comes from Yes Energy. The wind data is missing one day of data from June of 2015. Equilibrium Price, Supply Slope, and Demand Slope are recovered from the offer supply and demand curves. The equilibrium is where the offered supply net of wind equals the demand less of net imports.

Table 3: Analytical Merit Order Effect.

	Mean	Std. Dev.	Min	Max	Obs
Analytical Merit Order Effect, Competitive	-0.65	1.05	-57.10	-0.13	26,117
Analytical Merit Order Effect, SFE	-0.19	0.29	-15.64	-0.03	26,117
dp_{comp}, USD	-3.73	8.87	-477.07	-0.04	26,117
dp_{sfe}, USD	-1.02	2.36	-130.66	-0.02	26,117

Notes: Analytical Merit Order Effect comes from the theoretical prediction of the impact of 1 GWh of wind on the price of electricity with the corresponding assumptions on the price of electricity. Competition corresponds to Equation 5, the supply function equilibrium (sfe) corresponds to Equation 6. The values of $dp_{comp,sfe}$ come from multiplying the analytical merit order effect by the GWh of wind based electricity. The slopes of supply and demand come from the equilibrium without wind bids and demand less of net imports. The value of $\sum_{o \in V} \theta_o$ is set equal to the proportion of wind that is generated by diverse market participants in a hour.

Table 4: Withholding of Offer Curve in Response to Wind Generation.

	(1)	(2)	(3)
Market GWh Generated	3.345***	3.345***	3.347***
	(0.536)	(0.536)	(0.535)
Wind GWh	-2.787***		
	(0.736)		
Not Diverse Owner × Wind GWh		-1.256***	
		(0.258)	
Diverse Owner × Wind GWh		-13.23**	
		(4.665)	
Not Diverse Owner × Wind GWh, Indpendent			-2.653
			(1.586)
Diverse Owner × Wind GWh, Indpendent			-8.437
			(12.26)
Not Diverse Owner × Wind GWh, Diverse			-0.778
			(0.631)
Diverse Owner × Wind GWh, Diverse			-14.85*
			(6.283)
Owner-Price-Year-Month-Hour Fixed Effects	Yes	Yes	Yes
Observations	28,777,140	28,777,140	28,777,140
R-squared	0.97	0.97	0.97

Notes: Data comes from MISO Real Time Offer Market Reports January 1, 2014 to December 24, 2016. This sample is all offers by market participants during peak hours, defined as 3pm to 8pm inclusive. Offer curves are are interpolated and defined at 3$ intervals between 0 and 60 USD. All unit level offers are aggregated to the market participant. One observation is the quantity offered by all units owned by the same market participant at a given price for that hour. Diverse market participants own wind turbines and conventional electricity generating assets. Wind Based GWh, Independent, is wind based electricity generated by market participants that own only wind turbines. Likewise, Wind Based GWh, Diverse is wind based electricity generated by diverse market participants. All specifications include fixed effects for the average quantity offered by the market participant at the price for a given month-hour. Other controls include hourly net imports, daily temperature, daily natural gas price. Standard errors, in parenthesis, are clustered by month of sample and owner. *, **, *** denote p-value less than 0.1, 0.05, and 0.01 respectively for each hypothesis test.

Table 5: Owner Specific Withholding of Diverse Market Participants.

	Quantity Offered, MWh			
	(1)		(2)	
Owner Code=122062454 × Wind GWh	-15.04***	(2.805)	-20.84***	(3.220)
Owner Code=122062463 × Wind GWh	0.235	(1.095)	-1.194	(1.313)
Owner Code=122062474 × Wind GWh	-1.798	(1.120)	-3.010*	(1.302)
Owner Code=122062480 × Wind GWh	-19.03***	(3.394)	-24.87***	(3.317)
Owner Code=122062486 × Wind GWh	-2.111	(1.529)	-3.115	(1.673)
Owner Code=122062512 × Wind GWh	-13.64***	(1.627)	-20.05***	(1.855)
Owner Code=122062521 × Wind GWh	-1.291	(1.048)	-2.459	(1.228)
Owner Code=122062548 × Wind GWh	-1.809	(1.221)	-3.042	(1.509)
Owner Code=122062550 × Wind GWh	-33.76***	(1.912)	-36.44***	(2.050)
Owner Code=122062561 × Wind GWh	-3.642*	(1.535)	-5.146**	(1.643)
Owner Code=122062564 × Wind GWh	0.162	(1.131)	-1.375	(1.347)
Owner Code=122062581 × Wind GWh	-6.737***	(1.765)	-7.468**	(2.122)
Owner Code=122062590 × Wind GWh	-97.41***	(3.234)	-104.9***	(3.870)
Owner Code=122062603 × Wind GWh	-1.814	(1.364)	-3.690*	(1.628)
Owner Code=122062624 × Wind GWh	-1.824	(1.048)	-2.815	(1.361)
Owner Code=122062627 × Wind GWh	-0.524	(1.116)	-2.029	(1.401)
Owner Code=122062642 × Wind GWh	-8.172**	(2.851)	-7.649*	(3.136)
Owner Code=122062646 × Wind GWh	-1.437	(1.090)	-2.513	(1.405)
Owner Code=122062647 × Wind GWh	-3.649***	(0.688)	-7.097***	(0.954)
Owner Code=122062649 × Wind GWh	-14.39***	(1.660)	-15.40***	(1.603)
Owner Code=125767546 × Wind GWh	-1.519	(1.417)	-2.416	(1.570)
Owner Code=576468110 × Wind GWh	-62.20***	(2.516)	-66.40***	(2.737)
Owner Code=576468116 × Wind GWh	-11.70***	(2.082)	-14.57***	(1.771)
Owner-Price-Year-Month-Hour Fixed Effects	Yes		Yes	
Controls for Demand	Yes		Yes	
Peak	No		Yes	
Sum of Coefficients	-303.10		-351.40	
Standard Error of Sum	14.36		17.10	
Observations	9,532,246		2,596,242	
R-squared	0.97		0.97	

Notes: Data comes from MISO Real Time Offer Market Reports January 1, 2014 to December 24, 2016. This sample is all offers by diverse market participants. Column (1) uses the full sample, while column (2) is only for peak hours, defined as 3pm to 8pm inclusive. Offer curves are are interpolated and defined at $3 intervals between 0 and 60 USD. All unit level offers are aggregated to the market participant. One observation is the quantity offered by all unit owned by the same market participant at a given price for the hour. Sample includes all diverse market participants. All specifications include a fixed effect for the average quantity offered by the market participant at the price for a given month-hour, and control for hourly demand. Other controls include hourly net imports, daily temperature, daily natural gas price. Standard errors, in parenthesis, are clustered by month of sample and owner. *, **, *** denote p-value less than 0.1, 0.05, and 0.01 respectively for each hypothesis test.

Table 6: Robust to congestion concerns.

	(1)		(2)	
Owner Code=122062454 × Wind GWh	-20.71***	(2.290)	-50.41*	(18.69)
Owner Code=122062463 × Wind GWh	0.199	(2.021)	-2.812	(4.387)
Owner Code=122062474 × Wind GWh	-1.391	(2.249)	-9.427	(8.171)
Owner Code=122062480 × Wind GWh	-22.14***	(4.310)	-7.496	(11.94)
Owner Code=122062486 × Wind GWh	-3.115	(2.153)	-8.406	(7.919)
Owner Code=122062512 × Wind GWh	-19.90***	(4.274)	-12.77	(7.787)
Owner Code=122062521 × Wind GWh	1.480	(2.276)	-1.273	(3.975)
Owner Code=122062548 × Wind GWh	-5.777	(2.897)	-4.105	(4.605)
Owner Code=122062550 × Wind GWh	-44.77***	(5.385)	-12.22*	(5.165)
Owner Code=122062561 × Wind GWh	-1.603	(3.496)	-13.18**	(4.295)
Owner Code=122062564 × Wind GWh	-5.668*	(2.571)	-4.233	(4.532)
Owner Code=122062581 × Wind GWh	-11.41**	(3.514)	21.08	(14.42)
Owner Code=122062590 × Wind GWh	-92.59***	(4.754)	-130.9***	(10.54)
Owner Code=122062603 × Wind GWh	-4.210	(3.750)	-5.769	(4.139)
Owner Code=122062624 × Wind GWh	-2.285	(2.227)	-10.56	(8.373)
Owner Code=122062627 × Wind GWh	-2.274	(2.386)	-3.243	(4.779)
Owner Code=122062642 × Wind GWh	-9.654*	(3.816)	-24.61	(14.56)
Owner Code=122062646 × Wind GWh	-1.822	(2.465)	-4.245	(4.658)
Owner Code=122062647 × Wind GWh	-6.656***	(1.153)	-9.012*	(4.126)
Owner Code=122062649 × Wind GWh	-17.88***	(2.511)	-1.937	(8.170)
Owner Code=125767546 × Wind GWh	5.367	(4.383)	-4.290	(5.333)
Owner Code=576468110 × Wind GWh	-73.30***	(4.069)	-54.27***	(5.076)
Owner Code=576468116 × Wind GWh	-9.955***	(2.421)	-35.99***	(4.848)
Owner-Price-Year-Month-Hour Fixed Effects	Yes		Yes	
Controls for Demand	Yes		Yes	
Peak	Yes		Yes	
Sum of Coefficients	-343.40		-381.03	
Standard Error of Sum	30.16		39.74	
Observations	889,025		143,362	
R-squared	0.97		0.98	

Notes: Data comes from MISO Real Time Offer Market Reports January 1, 2014 to December 24, 2016. This sample is offers by diverse market participants during peak hours, comparable to column (2) of Table 5. Column (1) is restricted to the 10% of sample hours with lowest hourly maximum congestion and loss price. Column (2) is restricted to the sample hours with on or fewer system wide binding constraints. Offer curves are are interpolated and defined at \$3 intervals between 0 and 60 USD. One observation is the quantity offered by all unit owned by the same market participant at a given price for the hour. Sample includes all diverse market participants. All specifications include a fixed effect for the average quantity offered by the market participant at the price for a given month-hour, and control for hourly demand. Other controls include hourly net imports, daily temperature, daily natural gas price. Standard errors, in parenthesis, are clustered by month of sample and owner. *, **, *** denote p-value less than 0.1, 0.05, and 0.01 respectively for each hypothesis test.

Table 7: Impact of Withholding on Consumer Surplus.

	Net Demand		MISO Demand	
	Total, Bil.USD	Annual USD/person	Total, Bil.USD	Annual USD/person
Revenue	58.70	393.93	55.33	371.34
ΔCS_{comp}, no curtail	7.38	49.51	10.22	68.62
ΔCS_{obs}, observed	5.08	34.09	7.04	47.25
ΔCS_{sfe}, full curtail	2.03	13.61	2.78	18.66
$\Delta CS_{comp} - \Delta CS_{obs}$	2.30	15.42	3.18	21.37
$\Delta CS_{comp} - \Delta CS_{sfe}$	5.35	35.90	7.44	49.96

Notes: Time period of interest is from January 1st, 2014 to December 24th, 2016. All calculations come from Equation 11, Equation 12, Equation 13. Revenue is the sum of Market MEC and market generation quantity in MWh for all hours. "Net Demand" uses the analytical merit order effect and production quantity at the equilibrium where supply net of wind equals demand less net imports. "MISO Demand" uses the equilibrium where supply net of wind equals total demand within MISO. Bil. stands for billion. Annual per person calculations divides the total quantity by 2.98 years and 50 million people. This number is the authors best guess for the population within MISO's footprint based on the cumulative population of 61 million in the states of Arkansas, Illinois, Indiana, Iowa, Louisiana, Michigan, Minnesota, Mississippi, Missouri, North Dakota, Wisconsin according to the 2016 US Census Bureau estimates. All numbers are in nominal US dollars.

Appendices

A Firm's incentives

Given the notation presented in 2, market participant o's profit at time t is characterized by

$$\Pi_o(S_o(p)) = p[S_o(p) + \theta_o W] - C_o(S_o(p)) \tag{14}$$

Where p is the market price, $\theta_o \in [0,1]$ is the fraction of total wind generation produced by market participant o, W is the perfectly forecast-able quantity of electricity generated by wind turbines, and $C_o(S_o(p))$ is the cost of producing $S_o(p)$.[42] All market participants have perfect information on the cost of production of all other market participants.

Demand is composed of a forecast-able quantity and a random forecast error, $D(p) = d(p) + \varepsilon$, where ε is an $i.i.d.$ random variable with expectation equal to zero.[43] Taking the strategies of the other market participants as given, all uncertainty in the market participant's payoff is from the demand forecast error, ε. Market participants choose a supply function mapping the ex-post market price to the quantity they want to produce. The Nash-equilibrium is defined by all market participants choosing the supply function that maximizes their expected profits, taking the other (profit-maximizing) supply functions as given. Because the equilibrium in this model is defined by a system of differential equations with considerable asymmetry, I only consider the firm's best response.

To characterize the equilibrium, I show that every realization of ε is associated with one price-quantity pair which outlines the optimal supply function for that firm, following Klemperer and Meyer (1989). If we first assume the profit maximizing price-quantity pairs *can be* characterized by a supply function $q_o = S_o(p)$, the profit maximizing price associated with a realization of ε will tell us the optimal quantity profit maximizing. Also noting that the quantity produced by market participant is defined by the residual demand $RD(p,\varepsilon) = d(p) + \varepsilon - \sum_{j \neq o} S_j(p) - W$, we can write

[42] Cost are strictly increase and weakly convex in $S_o(p)$

[43] Demand is strictly decreasing in price.

the market participants profit function as

$$p[RD(p,\varepsilon)+\theta_o W]-C_o(RD(p,\varepsilon)) \tag{15}$$

with the first order condition with respect to price provides

$$p-C'(RD(p,\varepsilon))=-\frac{RD(p,\varepsilon)+\theta_o W}{RD_p(p,\varepsilon)} \tag{16}$$

where $RD_p(p,\varepsilon)$ is the slope of the residual demand with respect to price $(d'(p)-\sum_{j\neq o}S'_j(p))$.

This implicitly defines the optimal price as a function of the demand shock ε, $p^*_o(\varepsilon)$, taking forecast-able demand, the strategy of other players, and the forecast-able wind generation as given. The corresponding profit maximizing quantity is $RD(p^*_o(\varepsilon),\varepsilon)\equiv q^*_o(\varepsilon)$, providing a locus of parametrized profit maximizing price-quantity pairs: $p^*_o(\varepsilon),q^*_o(\varepsilon)$. As long as there is a one to one mapping between ε and p^*_o, we have that $p^*_o(\varepsilon)$ is invertible and the optimal supply function is $S_o(p)=q_o((p^*_o)^{-1}(p))$.

Finally, substituting $S_o(p)$ for $RD(p^*_o(\varepsilon),\varepsilon)\equiv q^*_o(\varepsilon)$ and $d'(p)-\sum_{j\neq o}S'_j(p)$ for $RD_p(p,\varepsilon)$ in Equation 16 we have

$$p-C'(S_o(p))=-\frac{S_o(p)+\theta_o W}{d'(p)-\sum_{j\neq o}S'_j(p)} \tag{17}$$

B Institutional Details on MISO

B.1 Markets in MISO

Markets in MISO include a day ahead and real time wholesale electricity market to balance generation supply and load demand, a market for financial transmission rights to manage the risk of congestion, a market for ancillary services that ensure reliability through frequency regulation, and an annual capacity market. Other important components of MISO include revenue sufficiency guarantee charges to those that are causing ramping and the related make-whole payments.

Both the day ahead and real time wholesale markets serve as multi-unit uniform price auctions. Each generation unit submits the amount they are willing to generate at a given price and a number of bid parameters for every hour.[44] The day ahead market serves as a forward market, with all bids submitted by 11 am the day before market operations. The quantities are cleared and the dispatch order is determined by 3 pm the day before market operations. The real time market serves as a spot market for last minute adjustments, with all bids submitted at least 30 minutes before the market hour. All quantities in the forward market are cleared again in the real time market unless modified.

Concurrently to the submission of generation offers, municipalities and other load serving entities may submit physical demand bids in the day ahead and real time market while financial market participants may submit virtual demand bids in the day ahead market only. A few of the physical bids are price sensitive, however they are predominately price invariant representing inelastic demand for electricity in the short-run. Within MISO there are market participants offering demand response, however they bid into the supply side of the market with a curtailment price and target MW reduction.

A computer program uses the generation offers, demand bids, and constraint parameters to solve for the dispatch generation quantity for each unit and the market price they receive.[45] MISO's equilibrium concept is a set of locational marginal prices (LMP) at different geographic pricing nodes. The price at each node represents the market clearing price for that location as well as the marginal congestion cost and the cost of loss from transporting electricity over a significant distance. If there are no transmission constraints or transmission losses, the LMP will be the same at every location within that market.

Intermittent, or variable generation, can be a problem for the operators of transmission networks such as MISO, as unexpected deviations from the forecasted generation can impact the

[44]These parameters include cost estimates, the minimum and maximum they can produce in economic and emergency scenarios, as well as if the unit must run.

[45]The current computer programs used to determine dispatch include Security-Constrained Unit Commitment (SCUC) and Security-Constrained Economic Dispatch (SCED). SCED is used in real time. This was changed in late 2014 to compensate quickly ramping technologies.

ability to meet security commitments. MISO addressed this in 2011 by integrating wind generating units as Dispatchable Intermittent Resources that can bid into the wholesale market. This has greatly reduced the number of manual curtailments.[46] Relatedly, the day ahead forecasts that helps determine the wind based generation offers have greatly increased in accuracy in recent years. A survey of the generation offers submitted by wind turbines show they are invariably inelastic, showing a fixed quantity, however their ex-post generation quantity does differ from their ex-ante supply offer.

B.2 Utility Structure and Turbine Finance

Most states in MISO other than Michigan and Illinois never passed laws to de-regulate their electricity market. The implication is that a number of the electricity generating units are part of a vertically integrated utility, buying the electricity they are selling within MISO's wholesale market. This can mitigate the incentives to increase the wholesale price (Bushnell, Mansur, and Saravia, 2008). I use data from the U.S. Energy Information Agency to better characterize the operations of utilities. Table 8 shows details on the total capacity and wind capacity for the ten utilities in MISO with the largest installed wind capacity in MISO according to EIA-860 form. I use EIA-861 form to show the total Tera-watt hours (TWh) of electricity they provide during the year 2016, as well as the percent of the total TWh that is sourced from wholesale markets and the percent that is deposited as sale for resale. The sale for resale percentage is the amount of electricity that is not sold to retail customers, and is instead sold to a third party like the wholesale market. We can see that for a number of large utilities, the quantity that is purchased from the wholesale market is less than the quantity that is sold into the wholesale market, on average in a year. This implies that these market participants would benefit from increasing the wholesale price within MISO.

[46] Wind turbines can curtail the amount of electricity they generate by changing the angle of their blades.

Table 8: Operations of Utilities with Large Wind Capacity in MISO, 2016

Utility	Capacity	Wind Capacity	TWh	% Wholesale Purchase	% Sale for Resale
MidAmerican Energy Co	9504	4083	33.2	0.12	0.26
Northern States Power Co - MN	9563	852	48.6	0.27	0.26
ALLETE, Inc.	2098	520	14.7	0.33	0.41
DTE Electric Company	11955	449	47.3	0.21	0.05
Wisconsin Electric Power Co	7397	339	36.8	0.29	0.26
Basin Electric Power Coop	5176	287	29.6	0.37	0.94
Wisconsin Power & Light Co	4173	269	14.8	0.39	0.24
Consumers Energy Co	7639	212	38.6	0.58	0.08
Interstate Power and Light Co	3217	200	17.1	0.53	0.12
Montana-Dakota Utilities Co	547	157	3.5	0.25	0.01

Notes: Capacity is total installed, operating, capacity in megawatts. Wind capacity is the capacity of all wind turbines. All data comes from EIA-860 and EIA-861 for the year 2016. TWh stands for terawatt-hour, and represents the thousand of gigawatt-hours sourced and dispositioned that year. Of the total amount sources, the % Wholesale Purchase represents the amount of electricity they purchased from the wholesale market, the remaining percent (from 100) is the share they generated. The % Sale for Resale is the percentage of total disposition that was sold to a third party (e.g. the wholesale market) the remaining share was sold to retail customers.

The predominate way to finance renewable energy electricity generation projects is through long term purchasing power agreements. Here the owner of the electricity generating resource signs a contract with an offtaker, who agrees to purchase a set amount of electricity at a fixed price.[47] The electricity generators that sign this contract still sell in the wholesale market, in which case the off-taker pays the difference between the preset rate and the market rate. When the wholesale price is higher than the preset rate, the off-taker receives the revenue in excess of the preset rate. Projects financed in this way have no incentive to increase the market price. Ideally I would be able to identify these projects in the MISO data, however it is impossible given how the owner information is coded. Instead I present data from the American Wind Energy Association WindIQ database on all wind turbine projects on-line within MISO's footprint.

Figure 11 shows the total capacity in megawatts of all wind projects in MISO and the purchase type that finances them. Of the projects that are financed by only one purchase type, the most common purchase type is direct use by the utility that owns the wind project. To the extent to which the utility is selling the electricity in the wholesale market, these projects benefit from a higher wholesale market price. There are a number projects that are financed through merchant

[47] This differs from a hedge contract in that it is a purely financial arrangement.

purchase type and purchase power agreements. Merchant projects, but not the power purchasing agreement projects, also benefit from a higher wholesale electricity price. With the data provided it is impossible to determine which percentage of the project is financed by a purchasing power agreement of through merchant sales.

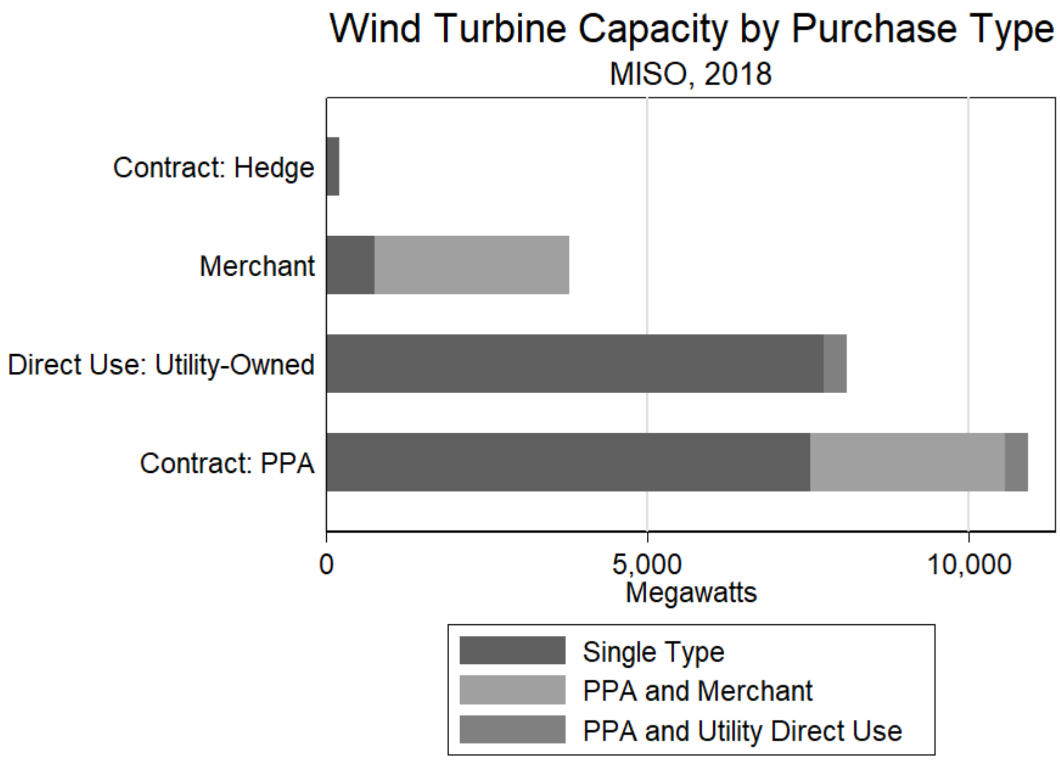


Figure 11: Notes: The sum of total project capacity by generation purchase type, for purchase for all wind turbine projects online in MISO as of June 2018. Contract: Hedge is a physical contract for differences. Merchant projects sell electricity to the wholesale market. Direct Use: Utility-Owned is direct use of the wind turbine by the utility that owns the project. Contract: PPA is a purchasing power agreement that is a virtual contract for differences. There are a number of projects that have multiple purchase types listed.

B.3 Market Monitoring and Mitigation

To address concerns of uncompetitive conduct in the wholesale electricity market, independent system operators will contract with an independent market monitor. These monitors continuously monitor the market for uncompetitive conduct and release semi-annual reports detailing the overall competitiveness of the market. MISO's independent market monitor is Potomac Economics. As of 2016, the assessment from Potomac is that MISO's markets are competitive except for local areas that experience chronic transmission constraints (Potomac Economics, June 2017). This is based off characterizations of the market structure and direct evaluation of market conduct.

The market structure is characterized by a Herfindahl-Hirschman Index (HHI) and the number of hours when at least one firm's output is necessary to meet total demand. In MISO, the HHI varies from 600 (not concentrated) to over 3750 (very concentrated) depending on the region. While the number of pivotal firm's is informative, a firm can still influence the price and not be pivotal.

Taking a more micro approach, Potomac directly looks the conduct of market participant by evaluating their price-cost markup, and looking for instances of economic and physical withholding. The price-cost markup is found by comparing a simulated market price under two different scenarios, for all hours. One with the market participants actual bids, another using a "reference level" based on the suppliers start-up cost, no-load cost, and incremental energy cost. These two simulated market prices are averaged over a year, with the difference of the two averages being the price-cost markup. Overall MISO finds these mark ups to be small, almost zero (Potomac Economics, June 2017). This could be the case because only the averages are being compared.

A generation offer is considered to be an instance of economic or physical withholding if it fails a conduct threshold test. Potomac has different conduct thresholds depending on if a electricity generation facility is in chronically constrained area, call a Narrowly Constrained Area (NCA), or in an area that is temporarily constrained with a limited number of firms, called a Broad Constrained Area (BCA). For example, in a BCA, a plant fails the economic withholding conduct threshold if there is a binding transmission constraint and the energy offer is more than the minimum of the reference level generation price plus $100/MWh or the the reference level generation price times four. A market participant in a BCA fails the physical withholding conduct test if a plant is taking an unapproved deration or outage, there is a binding transmission constraint, and they are withholding the minimum of 5% of their portfolio or 200 MW (MISO, 2018). Overall, in 2016, Potomac identifies 5 to 10% of the total capacity in MISO was a derating or outage.

For Potomac to mitigate a generation offer, it must fail a conduct test for physical or economic withholding and it must fail an impact test. An impact test evaluates if the generation offer, instead of the reference level default bid, increases the market price beyond an acceptable level. For a Broad Constrained Area, the impact threshold is the minimum of 3 times the reference Energy LMP or the reference LMP plus $100/MWh. It's likely that the type of anti-competitive behavior I model in this paper would not fail an impact test. This is because the incentive is to allow the wind generation to replace the market participant's more expensive generation plants. This behavior would not create a significant increase in the market price, but instead prevent it from decreasing by the amount of the merit order effect. Table 3 suggest this value, on average is $3.73/MWh.