# Gone with the Wind: Consumer Surplus from Renewable Generation*

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**Abstract**

I use a supply function equilibrium framework to show how increased renewable generation can increase electricity generators' incentive to withhold capacity. As a result, strategic behavior from conventional generators attenuates the impact of low marginal cost generation on the market price. Taking advantage of detailed data on the largest wholesale electricity market in the United States, I provide direct evidence that horizontally integrated firms that own wind turbines and conventional generation will withhold their conventional generation when their own wind turbines are generating electricity. As a result, over 30% of wind generation is replacing withheld units suggesting a decrease in potential consumer surplus of 3.3 billion US Dollars from 2014 to 2016.

JEL classification codes: L13, Q42, D44

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# 1 Introduction

Since 2008, over half of new electricity generation capacity in the US has been in the form of renewable energy (EIA, 2017). As a result, wholesale electricity markets have been inundated with a large quantity of electricity generated at a low marginal cost. This lower operating cost has created immense value and has the potential to have a large impact on the price of electricity.[1] However, the extent to which the lower operating cost impacts the price of electricity depends on the conduct of the firms in the market. This is especially true in wholesale electricity markets, where inelastic demand and capacity constraints allows market participants some degree of market power.

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 a simple 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. 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.[2] This physical withholding attenuates the consumer benefit associated with renewable generation, and showcases how firms can exert market to internalize the benefits of a low cost technology.[3]

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 quantity offered by a mar-

[1] Callaway, Fowlie, and McCormick (2018) show the value of renewable generation associated with avoided operating cost can be just as large, if not larger, than the public benefit of avoided emission externalities.

[2] Throughout, I use the term *diverse* to define market participants that own wind turbines and conventional electricity generators.

[3] 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.

ket 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 exports. 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.

Overall 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, estimated parameters of firm level withholding suggest only $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 the importance of understanding the incentives of the firm. 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.[4] The results are location specific, often determined by the fuel mix and fuel prices, and are large.[5] Overwhelmingly, these

[4] 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).

[5] 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 24,000 MWh in a hour, for twenty-four hours, revenue declines by 5.6 million USD

empirical papers do not consider how the increased 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; Acemoglu, Kakhbod, and Ozdaglar, 2017).

[Figure 1]

This understanding of how a firm might change their strategy in response to a new technology extends its importance to policy design. A number of states with in the U.S. support renewable generation for the benefit it provides to consumers, not necessarily because it reduces emissions from electricity generation. Not taking into account how existing electricity generators might internalize the benefits for renewable generation will cause these policies to under-deliver. Overall I show the cumulative strategic response by all electricity generators is large enough to decrease the realized consumer benefit by more than 30%.

My second contribution it to provide direct evidence strategic bidding in multi-unit auctions. 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 electricity generators 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 (Hortacsu 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

that day.

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 is an update on the status of competition in wholesale electricity markets. Ever since the California electricity crisis in 2000 and 2001, 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 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. 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.[6] 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 regarding the MISO including an introduction to the data. Section 4 focuses on estimating and calculating the how wind generation should impact the price of electricity. Section 5 turns to micro-data on firm strategies, showing evidence of physical withholding during windy hours. Section 6 summarizes the implications of withholding for consumer surplus, section 7 concludes.

[6]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 MISO, as well as characterize the market in terms of forward contracts and vertical commitments.

# 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 the potential for increased efficiency (for example Joskow, Schmalensee et al. (1988)).[7] 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 market cover 60% of generation capacity within the US and they are effective in reducing production cost by reallocating output (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. Demand for electricity is determined by Load Serving Entities, predominately utilities, that charge customers a rate for electricity in the retail market.[8] 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 $\varepsilon_t$ is a random variable representing fluctuations in the quantity demanded. I model $\varepsilon_t$ 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

[7]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.

[8]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.

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 time $t$ for price $p$. As a simplification, 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 $\hat{p}S_{ot}(\hat{p})$.

The quantity of electricity generated by wind turbines at time $t$ is modeled by an aggregate quantity, $W_t$. Because weather conditions are imperfectly forecast-able, it is most realistic to decompose wind generation into a deterministic forecast-able quantity and a random variable representing the forecast error. Here I abstract from the random component, as it does not contribute to any of the comparative statics in this section.[9] The aggregate quantity, $W_t$, is common knowledge to all market participants and perfectly forecast-able. 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. [10]

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 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

[9] Acemoglu, Kakhbod, and Ozdaglar (2017) shows the incentives to withhold output remain when wind generation is a random value, and with private information.

[10] 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%.

the same at every location within the market while the losses and congestion components vary by node.[11] Analytically, I consider the price $p$ to represent the MEC of the LMP.[12] 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 for notational ease. The market operator takes the supply offers as given, observes the realized demand shock, $\varepsilon$, to solve for the dispatch quantity for each firm and the price received in accordance with a security constrained dispatch algorithm. 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.[13]

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

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,

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

[12] 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.

[13] I assume that the quantity demanded does not depend on the quantity of wind generated, that is $\frac{\partial D(p)}{\partial W} = 0$.

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 $\varepsilon_D$ and $\varepsilon_S$ denote the own-price and market supply elasticities respectively. The denominators of Equation 2 and the conventional pass-through equation are identical, representing a marginal deviation from the market equilibrium. This value will increase, decreasing the pass-through, when supply or demand is more inelastic. 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.[14]

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 anti- 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.[15] The implications is that renewable generation would decrease the price by more than the change in cost. Conversely, when the term is negative, the supplier is offering less quantity to the market at any given price. This anti-competitive outcome could be an attempt by the firm to keep the price high, offsetting the lower price associated with increased renewable generation.

[14] 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.

[15] 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.

## 2.2 Market Participants' Strategy and Testable Predictions

To understand how a firm might change their strategy in response to increased renewable generation, I consider two models of the market participants' behavior. One model assumes that market participants choose their strategies as if they are in a perfectly competitive wholesale electricity market, the other uses a supply function equilibrium framework. These will provide two different predictions for $\frac{\partial S_o(p)}{\partial W}$, implying different values for the analytical merit order effect, $\frac{dp}{dW}$. For each prediction, I use the detailed data I have on market hourly supply and demand to explicitly calculate the analytical merit order effect. I then test which one is better realized in the observed market price.

In a perfectly competitive market, firms are price takers and submit a supply function that outlines the inverse of their marginal cost of production. This would be independent of $W$ implying that $\frac{\partial S_o(p)}{\partial W} = 0$. Substituting this into Equation 2 we have that

$$\frac{dp_{comp}}{dW} = -\frac{1}{\sum S_o'(p) - d'(p)} \tag{3}$$

and for an observed quantity of wind based generation in an hour, the total price effect would be

$$dp_{comp} = -\frac{1}{\sum S_o'(p) - d'(p)} dW \tag{4}$$

From an incidence perspective, this represents the upper bound of the price reduction associated with increased renewable generation and can be used to calculate to the potential consumer surplus available.

Conversely a firm with market power might 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 additional revenue from the infra-marginal wind turbine but do not incur any cost.

[Figure 2]

I use the supply function equilibrium framework (SFE) outlined by Klemperer and Meyer (1989) to derive the market participant's best response function. Market participants choose the $S_o(p)$ that maximizes their expected profit, with the expectation taken over the uncertainty in price due to demand shocks. Appendix A proves the optimal strategy of market participant $o$ with conventional assets and wind turbines can be characterized by

$$p - C_o'(S_o(p)) = -\frac{S_o(p) + \theta_o W}{d'(p) - \sum_{j \neq o} S_j'(p)} \tag{5}$$

It is clear that an increase in the amount of electricity produced by wind, $W$, will be associated with a reduction in the supply curve offered to the market. For simplicity I assume that the marginal cost is constant near the equilibrium price, $C_o''(S(p)) = 0$, and that market participants do not change the slope of their offer curve in response to increased renewable generation, $\partial S_i'(p)/\partial W = 0, \forall i$, near the equilibrium price.[16] This provides $\frac{\partial S_o(p)}{\partial W} = -\theta_o$, a market participant will reduce their generation offer in response to a unit increase in renewable generation by the proportion of total wind generation they are producing.

More broadly, this comparative static suggests that a market participant will withhold their conventional generation by the quantity of wind generated, one for one.[17] Overall they are generating the same quantity of electricity, however they are replacing their conventional generation with wind generation. From this we can get a number of testable predictions for how firm's will respond to increased wind generation under a supply function equilibrium model:

[16] This assumption greatly simplifies the analysis. In the context of forward markets, an "additive separability" assumption with similar implications is common Hortacsu and Puller (2008); Mercadal (2015). In application, I find some market participants do change the supply slope, in-line with the theoretical prediction on bid shading. I consider it to be a second order effect, and the assumption plays no direct role in any of my results.

[17] In particular we are talking about physical withholding, where the quantity offered is reduced. This is in comparison to economic withholding, in which market participants are submitting their offer curves above the marginal cost of production.

**Testable Predictions**

*(A)* *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.*

*(B)* *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. This follows from* $\frac{\partial^2 S_o(p)}{\partial W \partial \theta_o} = -1 < 0$

*(C)* *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 5. Their optimal strategy does not depend on* $\sum_{j \neq o} \theta_j W$*.*

Substituting the values of $\frac{\partial S_o(p)}{\partial W}$ into Equation 2, we have that the analytical merit order effect is

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

where $V$ is the set of market participants that own both wind turbines and conventional assets. In aggregate this strategic withholding implies increased renewable generation will have the following impact on the market price

$$dp_{SFE} = -\left(1 - \sum_{o \in V} \theta_o\right) \frac{1}{\sum S_o'(p) - d'(p)} dW \tag{7}$$

This shows the impact on the price paid by consumers in wholesale electricity markets depends on the ownership of the wind turbines. If all wind turbines are owned by market participants that also own conventional assets, then $\sum_{o \in V} \theta_o = 1$ and there would be no effect on price. Conversely, if wind turbines were owned exclusively by independent producers that own only wind turbines, then $\sum_{o \in V} \theta_o = 0$ and the expected price change would be identical to Equation 4.

# 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.[18] 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 on reliability, efficiency, and the development of electricity resources. Since the incorporation of the Southern Region in 2013, MISO has become the 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 the Texan panhandle.

[Figure 3] [Figure 4]

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.[19] Supplemental information on MISO, its markets, regulated utility operations, wind turbine ownership, and market monitoring are provided in the Appendix B.

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 generation units from January of 2014 to December of 2016.[20] I focus on the real time market because there are no purely financial players

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

[19] A market report from 2011-2012 suggests 20 to 30% of electricity generated in a year is through bilateral contracts. These bilateral contracts include agreements with groups outside of MISO as well as grandfathered contracts within MISO.

[20] 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.

in the real time market, increasing the benefits from withholding output. These data provide, for every hour, 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. 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.

[Table 1]

As show by Equation 7, 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 measure 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 to calculate the portfolio of assets for every owner code. 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.

[Figure 5]

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 exports. 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. The first panel 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 with MISO, and wind can meet up to 20% of load during periods of low demand.

[Table 2]

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, $p_{ikt}$ $q_{ikt}$, $i = 1 \dots N$, 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 $\Phi$ is the standard normal cumulative distribution function and $h$ is smoothing parameter.[21] I aggregate these unit level supply functions by market participant. Figure 6 shows all offer curves of two sample market participants for one hour of the day in a month.

[21] I use a bandwidth of three dollars, as does Kim (2017). Changing the bandwidth does not alter the results presented below.

[Figure 6]

To find the slopes at equilibrium, I aggregate all of the generating unit supply curves within MISO to obtain a market supply curve.[22] I go through an identical process of interpolating and aggregating using the demand bids by the Load Serving Entities. To find the market equilibrium, I find the price where supply is equal to demand as shown in Figure 7.[23] 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 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.

[Figure 7]

# 4 Empirical Impact on Price

I use the slope of supply and demand, summarized in Panel B of Table 2 to calculate an exact expression of Equation 3 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. 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

[22] 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). Because the Marginal Energy Component is the same for all units in MISO, and I am interested in how wind impacts the Marginal Energy Component, any other market definition is inappropriate.

[23] 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 demand, as this is a measure of demand net of imports. I consider alternative equilibriums, including wind and ignoring exports, and the results presented below do not change.

(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).[24]

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 $dp_{SFE}$ from Equation 4 and Equation 7. 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.

[Table 3]

As a validity check, I also estimate the empirical merit order effect for MISO. I consider the following equation to estimate the reduced form price effect of increased renewable generation:

$$\begin{aligned} Price_t = &\beta_1 WindGWh_t + \beta_2 ClearedGWh_t + \beta_3 NetExports_t + \beta_4 WindForcastError_t + \\ &\beta_5 GasPrice_d + \beta_6 Temperature_d + \lambda_{ymh} + \varepsilon_t \end{aligned} \tag{8}$$

where $Price_t$ is the hourly, market wide, price measured as the Marginal Energy Component (MEC) or the mean Locational Marginal Price (LMP). $\beta_1$, the coefficient on the quantity of wind energy generated for hour $t$, is the parameter of interest. $ClearedGWh_t$ in combination with $NetExports_t$ control for demand within the market and addresses any simultaneity issues. The remaining variables, hourly wind forecast error, daily gas price, and daily temperature are important determinants of the price of electricity. Month of sample by hour fixed effects control for omitted trending variables that might be correlated with wind generation and electricity prices. As an example, these fixed effects compare the market price during windy instances of 4pm in September of 2014 to the less windy instances of 4pm in September of 2014. Since wind generation is determined by the weather patterns, the remaining variation is as good as random.

[24] 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.

[Table 4]

Table 4 shows the results from estimating Equation 8 on the full sample. I observe a one GWh increase in wind generation is associated with a decline in price of 1.35 $/MWh on average if considering the LMP, and 0.77 $/MWh if looking at the MEC. The difference in these values is the average effect that wind generation has on the congestion and transmissions losses component of the LMP. This estimated change in price is the same order of magnitude and sign as the analytical merit order effect in Equation 2. Although comparable, the estimates of the merit order effect presented in Table 3 and Table 4 are conceptually different. The measure from Equation 8 is the average effect of wind on price conditional on other factors that are observed in the data. In contrast, the expression calculated from Equation 3 and Equation 6 is the theoretical price change if there were a unit increase in wind generation based only on the slope of supply and demand.

## 4.1 Pass-through of Analytical Merit Order Effect

To test which assumption on conduct, price taking competition or the supply function equilibrium with withholding, better characterizes the change in price from increased renewable generation, I estimate the following equation

$$\begin{aligned} Price_t = &\rho_1 \left[dp_{(comp,SFE)}\right]_t + \rho_2 ClearedGWh_t + \rho_3 NetExports_t + \rho_4 WindForcastError_t + \\ &\rho_5 GasPrice_d + \rho_6 Temperature_d + \rho_7 ShadowPriceofConstraints_t + \lambda_{mhy} + \varepsilon_t \end{aligned} \tag{9}$$

with identification, notation, and covariates similar to Equation 8. Here I include the analytical total price effect $dp$ calculated from equations Equation 4 and Equation 7 instead of the quantity of wind generation. The shadow price of constraints is included as a control to account for how wind impacts congestion and dispatch that is out of merit order. I am interested in the coefficient $\rho_1$ and how close it is to one. If the analytical price change is perfectly represented in the market price, $\rho_1$ is equal to one exactly. Comparing the value of $\rho_1$ between assumptions on conduct informs which assumption on firm conduct best represents the market.

Table 5 presents the results from estimating Equation 9 on the full sample using the MEC as the price measure. Because there are a number very large negative values for the analytical merit order effect, columns 2, 3, 5, and 6, show the estimates from a 1% left tail winsorized sample. This effectively replaces any values of $dp$ less than the first percentile with the first percentile.[25] Overall the estimate of $\rho_1$ is closer to one for $dp_{SFE}$ than $dp_{comp}$. Consider the hypothesis test $H_o : \rho_1 = 1$ versus $H_a : \rho_1 \neq 1$. For the winsorized sample can reject the null hypothesis at the 0.01 significance level under the assumption of perfect competition, but fail to reject the null hypothesis at the 0.1 under the assumption of strategic withholding in a supply function equilibrium framework.

[Table 5]

Overall, the estimates imply 45 to 54 % of the expected price change under perfect competition is realized in the market price, while over 100 % of the expected price change is observed under the assumption of strategic withholding. This suggests that the true price effect is somewhere between the perfectly competitive price change and the supply function equilibrium price change. Columns (3) and (6) of each table shows how the estimate of $\rho_1$ changes during peak and off peak hours.[26] It is clear that the analytical merit order effect is realized in the market price more so during the off-peak hours when it more difficult to exert market power. However, the point estimate for the supply function equilibrium model during on peak hours is equal to one suggesting that the price effect of renewable generation with strategic withholding is fully realized when market participants benefit the most from strategic withholding.

# 5 Evidence of Strategic Withholding

While the merit order effects presented in Table 3 are informative, they rely on modeling assumptions. Here, I instead use detailed data on the strategies of all market participants for all hours to

[25]The first percentiles are the $-30.10$ and $-8.08$ for the competitive and supply function equilibrium analytical merit order effects respectively. The large negative values are a result of $dp$ being a local approximation to the price change and the supply curve being convex.

[26]I define peak hours as 3pm to 8pm inclusive.

directly test for physical withholding. I begin by aggregating the conventional unit supply curves, described in section 3, by owner codes for every hour. This gives me a hourly supply curve of the conventional assets for every market participant on a common support, every \$3 interval between 0 and 60 dollars. These curves are defined by a set of $b = 1 \dots 21$ 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.

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

$$q_{otb} = \gamma_0 ClearedGWh_t + \gamma_1 NetExports_t + \delta WindGWh_t + X\beta + \eta_{op_bymh} + \varepsilon_{otb} \tag{10}$$

where $q_{otb}$ is the quantity offered, in MWh, by market participant $o$ at time $t$ and price bin $p_b$. $X$ represents other determinants of a market participant's strategy including daily temperature measures, daily natural gas prices, the hourly number of binding constraints in MISO, and the hourly shadow price of all constraints. Identification comes from owner specific, month-of-sample by hour, fixed effects for every price bin, $\eta_{op_bymh}$. 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 $\delta$ is identified off the deviation from the market participants month-of-sample hour average supply curve. Because these data represent the ex-ante strategy of a 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 $\delta$ should be (A) negative only for diverse market participants that own both wind turbines and conventional assets, (B) increasing in the share of total wind owned by the diverse market participant, and (C) negative only in response to a market participants own wind generation.

[Table 6]

Table 6 shows the estimate of the $\delta$ in Equation 10 is negative. Overall, a 1 GWh increase in wind generation in an hour is associated with a 2.8 MWh reduction it the quantity offered at a given price on average across all market participants. In column (2), I interact $WindGWh_t$ with a 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 MWh on average, while the independent market participants only reduce the quantity offered by 1.2 MWh. 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.

The estimates presented in Table 6 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.[27] I interact $WindGWh_t$ in Equation 10 with the owner code of every market participant to get a unit specific estimate of $\delta_o$. In particular, I estimate the parameters in the following equation

$$q_{otb} = \gamma_0 ClearedGWh_t + \gamma_1 NetExports_t + \delta_o WindGWh_t \cdot OwnerCode_o + X\beta + \eta_{op_bymh} + \varepsilon_{otb} \tag{11}$$

and plot the density of the coefficients in Figure 8 by if the market participant is diverse.[28] 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, $p_b + 3$.[29] This shows the coefficients for the market participants that do not own wind generation are near zero, where as the density for diverse market participants has an obvious left skew and is centered below zero.

[Figure 8]

[27] Hortacsu and Puller (2008) show evidence of imperfect bidding behavior by market participants in Texas's ERCOT market.

[28] Both densities use a Epanechnikov kernel with a bandwidth of 2 MWh.

[29] I add three to the price bin because the price bins are at three dollar intervals.

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.

[ Figure 9]

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

$$
\begin{aligned}
q_{otb} =& \gamma_{0o} ClearedGWh_t + \gamma_{1o} NetExports_t + \delta_{op_b} OwnWindGWh_t \cdot p_b + \\
& \chi_{op_b} OtherWindGWh_t \cdot p_b + X\boldsymbol{\beta_o} + \eta_{p_b ymh} + \varepsilon_{tb}
\end{aligned}
\tag{12}
$$

where $\delta_{op_b}$ represents how owner $o$ changes the quantity offered at price $p_b$ in response to electricity generated from their own wind turbines, and $\chi_{op_b}$ 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 two 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 then the electricity generated form other wind turbines.

[Figure 10]

These results are robust to concerns regarding transmission congestion. Ideally, I would be able to spatially differentiate the electricity generators and see how their behavior depends on transmission congestion near their pricing node. Unfortunately, my data is not that granular in the cross section. In all the specifications I control the system wide number of binding constraints, and the total shadow price of the binding constraints, which captures some of the variation of interest. Re-estimating all of the equations above for the subsample of hours for which there are zero binding constraints, or a low shadow price, does not change the estimates significantly. Regardless if a market participant expects their own wind turbines to contribute to congestion and wish to produce less as a result, they should not submit a different ex-ante offer curve, representing their cost, to the market operator.

# 6 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. 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

$$\Delta CS = -\sum_t D_t(p)\frac{dp}{dW}_t dW_t. \tag{13}$$

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 considered a supply function equilibrium framework with $\frac{dp_{sfe}}{dW}_t = -\left[1-\sum_{o\in V}\theta_o\right]\frac{1}{\sum_o S_o'(p)-d'(p)}$

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 11 as an estimate of $\frac{\partial S_o}{\partial W}$. Table 7 shows the estimates of $\delta_o$ for all diverse market participants. The sum of these estimates, presented in the bottom of Table 7, suggests that over 30% of wind generation is replacing withheld offers by diverse market participants.

[Table 7]

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

$$\Delta CS_{comp} = \sum_t D_t(p) \frac{1}{\sum_o S'_{ot}(p) - d'_t(p)} dW_t \tag{14}$$

$$\Delta CS_{SFE} = \sum_t D_t(p) \frac{1 - \sum_{o \in V} \theta_{ot}}{\sum_o S'_{ot}(p) - d'_t(p)} dW_t \tag{15}$$

$$\Delta CS_{obs} = \sum_t D_t(p) \frac{1 - \sum_{o \in V} \hat{\delta}_o}{\sum_o S'_{ot}(p) - d'_t(p)} dW_t \tag{16}$$

I calculate the value of Equation 14, Equation 15, and Equation 16 using all hours between January 1st 2014 and December 24th 2016.[30] I do this in two ways to account for import and exports of electricity within MISO. One uses net generation within MISO as a proxy for demand net of imports. This is making claims on all electricity generated within MISO. The other considers total demand within MISO.

Table 8 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.[31] The potential consumer surplus from increased renewable generation, according to Equation 14, is huge, 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

[30] I consider alternative $\Delta CS_{obs}$ that weights the withholding estimate by the owner specific wind generation, but the results do not change.

[31] 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.

participants withhold perfectly, as calculate by Equation 15. 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 16, the surplus per person per year is 34 to 47 USD, suggesting that observed withholding by diverse market participants reduces consumer surplus by 16 to 22 USD per person per year.

[Table 8 ]

# 7 Conclusion

The increase in renewable generation capacity within the United States has created immense value by providing low marginal cost electricity. 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-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 16 to 22 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 anti-competitive behavior.

There are several of 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. Moving forward, it is important to quantify how renewable generation impacts producer surplus in these wholesale electricity markets. Producers can benefit from increased renewable generation because it reduces their fuel cost, or can be harmed if it decreases the price they receive. With accurate information on the cost of production, it would be straight forward to calculate producer surplus and compare them to my estimates of consumer surplus. Finally, this paper shows that wind generation might not be replacing the most inefficient generation 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.

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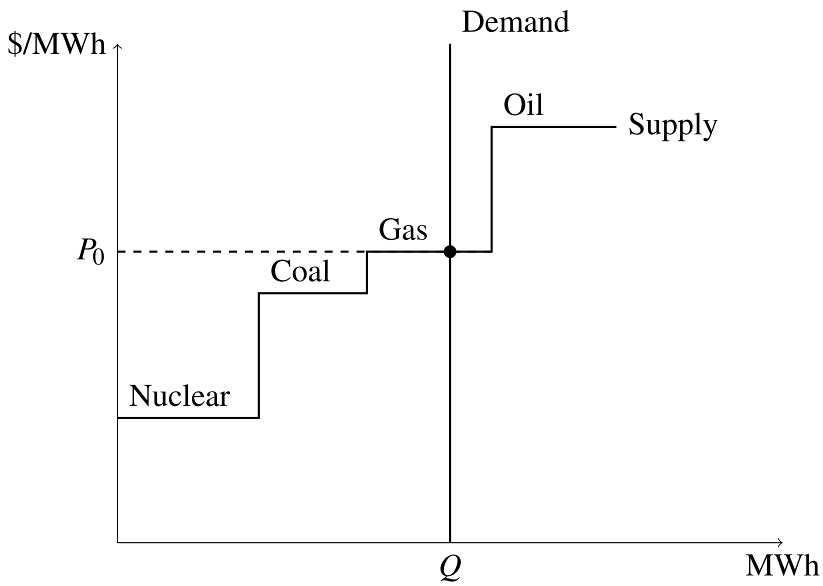
# Tables and Figures



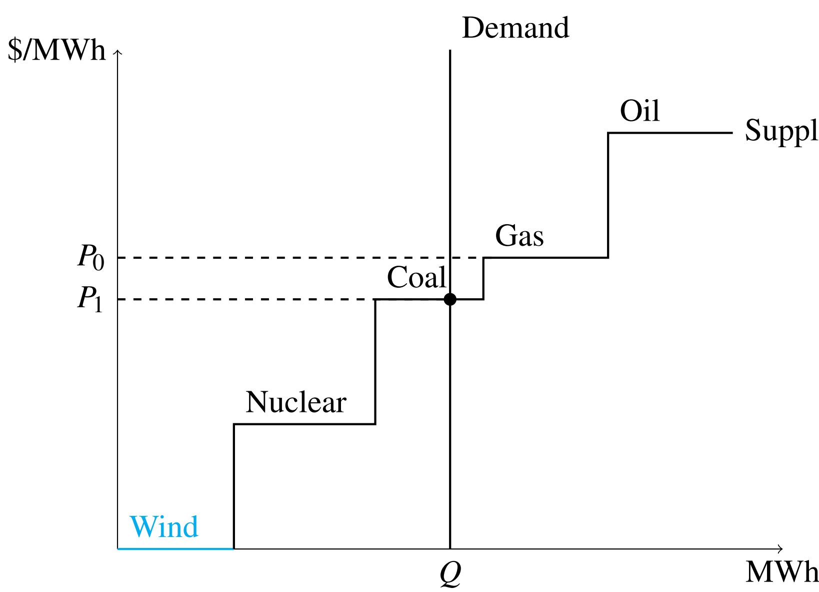




Figure 1: The Merit Order Effect of Increased Renewable Generation. Electricity markets are conceived as a Merit Order, where the lowest cost resources have merit and are dispatched first. When wind turbines generate electricity, it is believed they displace higher cost units as wind generation shift 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 does not consider how increased wind generation might impact the incentive to withhold capacity.

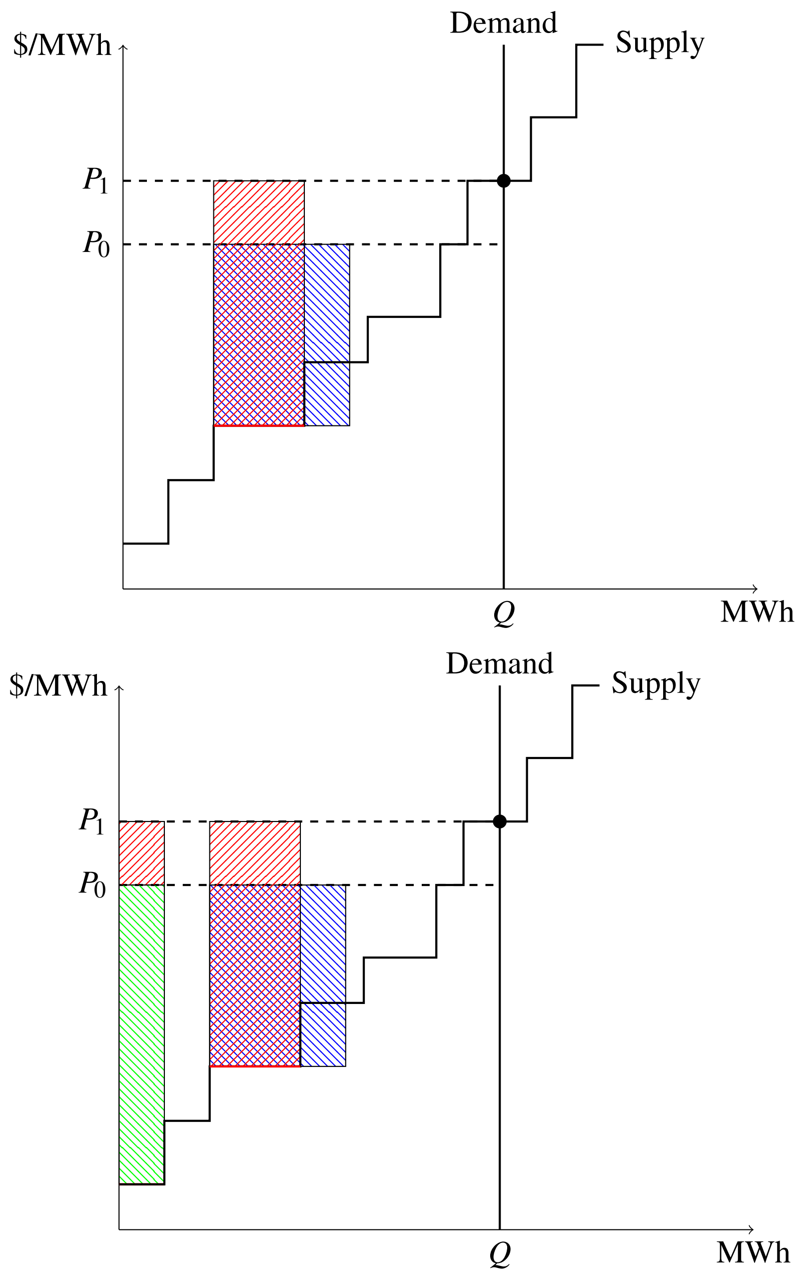



Figure 2: Incentive for diverse market participants to withhold output. When a firm with market power considers the incentives to withhold their output they trade off a lower price with a larger quantity with a higher price and a smaller quantity. This trade off is represented in the top figure, for 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 high 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.

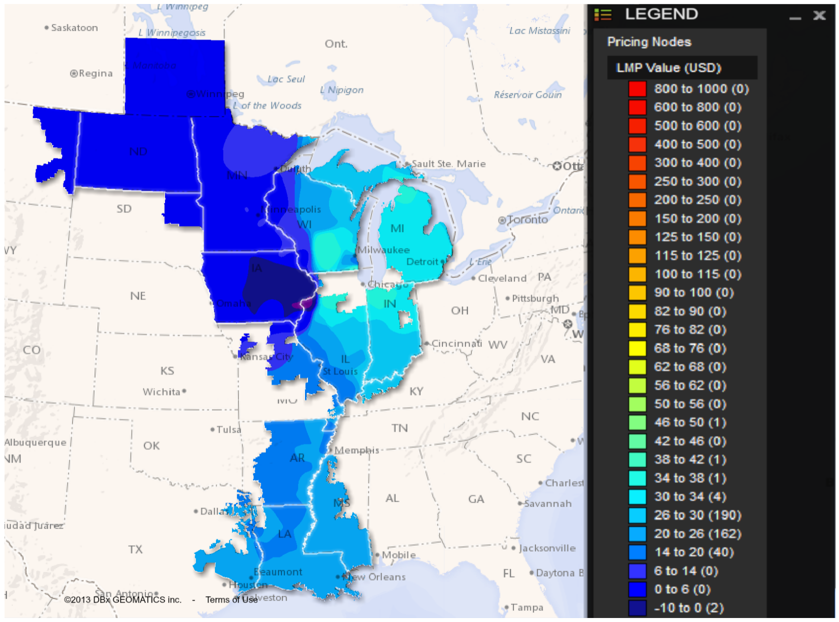



Figure 3: MISO's foot print and nodal prices in MISO during one moment during the sample period. Cross sectional variance is determined by congestion and transmission losses. Lower prices are darker in color.

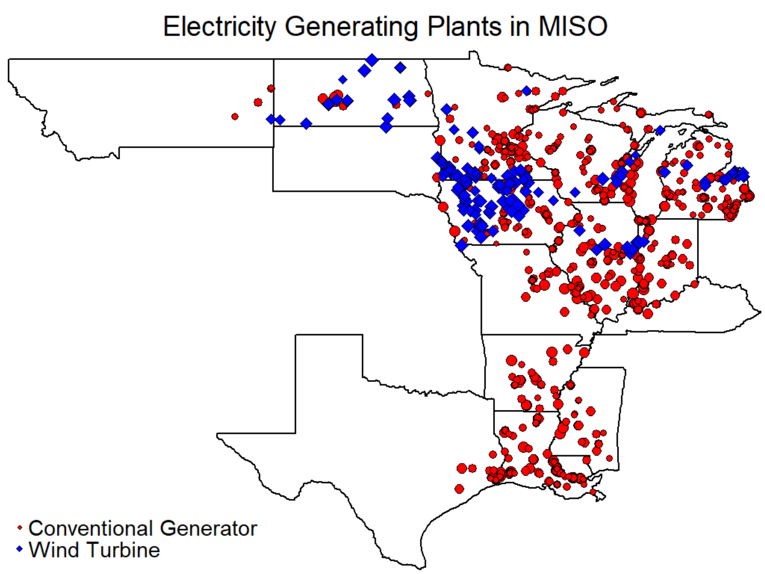



Figure 4: The locations of all electricity generating units in MISO according to the Energy Information Agency form 860 for the year 2016. Wind turbines are blue diamonds while conventional generators are red circles. The size of the point is proportional to the log of the generating unit's capacity.

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.

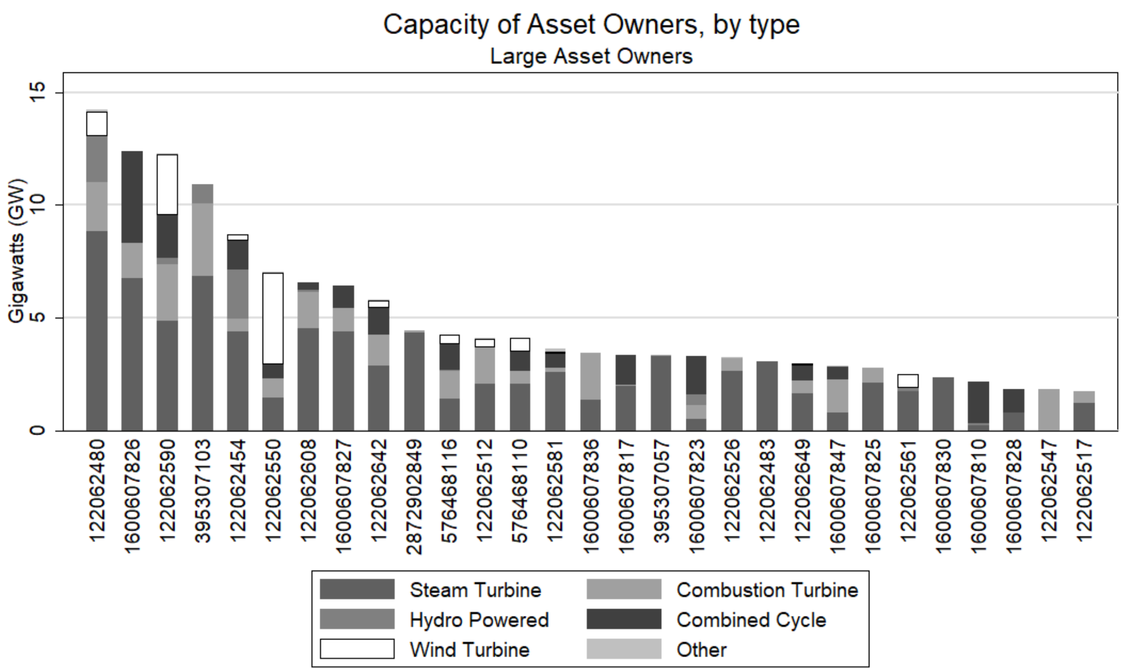



Figure 5: The capacity and portfolio of the thirty largest market participants in MISO. Capacity is measured as the maximum MWh produced by a unit during the entire sample period. The bar labels are the Market Participant's coded identification number. This shows large market participants own wind generation and conventional assets. There are approximately 220 small market participants that appear during the sample period.

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 exports.

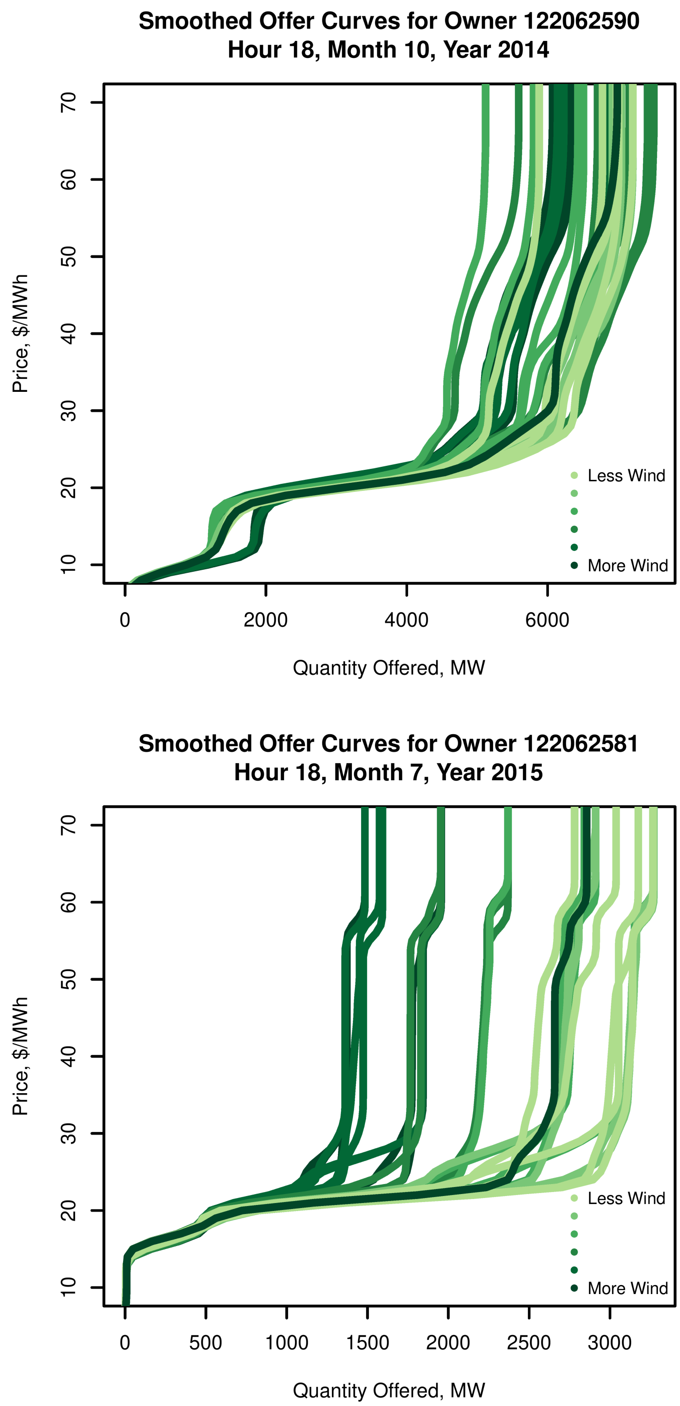



Figure 6: Set of all offer curves by two market participants in a single year-month-hour. An offer curve is the hourly supply curve offered by the market participant for a given hour, this represents the ex-ante quantity they are willing to produce across all units for a given market price. This also 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.

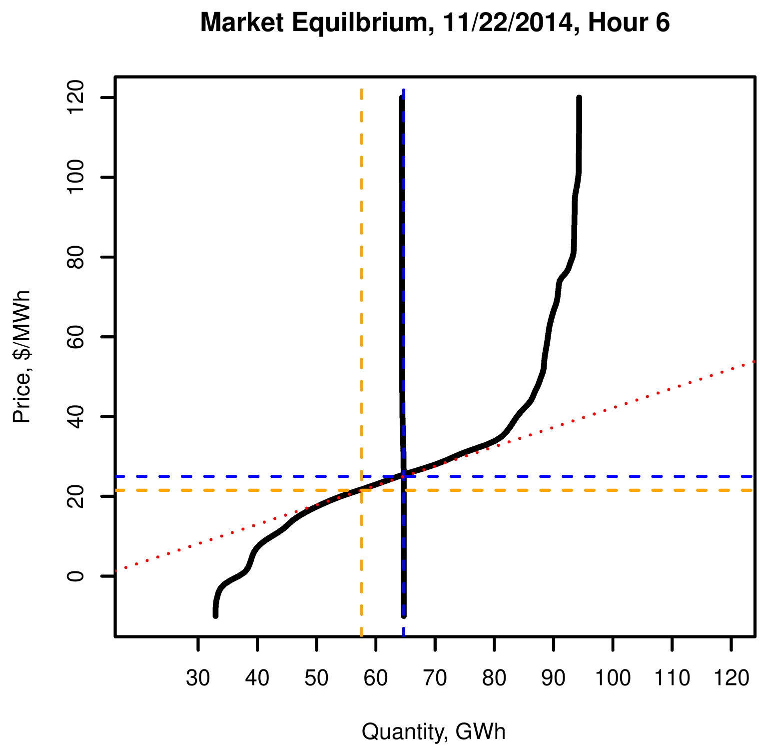



Figure 7: The reconstructed market supply and demand curves, in black, for a sample hour form the equilibrium price. The equilibrium is denoted by the dashed blue lines. The calculated merit order effect for a one unit increase is shown by the dashed red line. Walking down the merit order effect from the equilibrium shows the expected price reduction at with the yellow dashed lines.

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 3, the supply function equilibrium (sfe) corresponds to Equation 6. The values of $dp_{comp,sfe}$ come from Equation 4 and Equation 7 respectively, where the analytical merit order effect is multiplied 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 exports. 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: Estimated Merit Order Effect

| | (1) Market LMP, USD/MWh | (2) Market MEC, USD/MWh |
|---|---|---|
| Wind GWh | -1.345*** | -0.765*** |
| | (0.167) | (0.127) |
| Market GWh Generated | 0.749*** | 0.839*** |
| | (0.101) | (0.114) |
| Net Exports GWh | 0.390 | 0.329 |
| | (0.222) | (0.215) |
| Max Daily Temperature, C | -0.476* | -0.394 |
| | (0.205) | (0.215) |
| Natural Gas Price, USD/MMBtu | 3.508 | 4.136 |
| | (2.286) | (2.070) |
| Wind Forecast Error, GWh | 0.296 | 0.557* |
| | (0.175) | (0.226) |
| Year-Month-Hour Fixed Effects | Yes | Yes |
| Observations | 26,093 | 26,093 |
| R-squared | 0.36 | 0.36 |

Notes: Market-hour data comes from MISO Market Reports and NOAA, from January 1, 2014 to December, 24, 2016. Column one estimates the effect of 1 GWh of wind generation on the hourly Locational Marginal Price (LMP). Column two estimates the impact of 1 GWh wind on the Marginal Energy Component (MEC) of the LMP. Standard errors, in parenthesis, are clustered by month of sample. *, **, *** denote p-value less than 0.1, 0.05, and 0.01 respectively for hypothesis test $H_0 : \beta = 0$ vs. $H_1 : \beta \neq 0$.

Table 5: Pass-through of Calculated Merit Order Effect on Market Level Prices

| | MEC, USD/MWh | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $dp_{comp}, USD$ | 0.10*** | 0.45*** | | | | |
| | (0.04) | (0.14) | | | | |
| $dp_{sfe}, USD$ | | | | 0.31*** | 1.41 | |
| | | | | (0.15) | (0.48) | |
| Off Peak$\times$ $dp_{comp}, USD$ | | | 0.54*** | | | |
| | | | (0.17) | | | |
| On Peak$\times$ $dp_{comp}, USD$ | | | 0.32*** | | | |
| | | | (0.12) | | | |
| Off Peak$\times$ $dp_{sfe}, USD$ | | | | | | 1.70 |
| | | | | | | (0.59) |
| On Peak$\times$ $dp_{sfe}, USD$ | | | | | | 1.00 |
| | | | | | | (0.39) |
| Market GWh Generated | 0.45*** | 0.47*** | 0.47*** | 0.45*** | 0.47*** | 0.47*** |
| | (0.04) | (0.04) | (0.05) | (0.04) | (0.05) | (0.05) |
| Net Exports GWh | 0.55* | 0.51* | 0.50* | 0.55* | 0.52* | 0.52* |
| | (0.22) | (0.22) | (0.22) | (0.23) | (0.22) | (0.22) |
| Max Daily Temperature, C | -0.45* | -0.46** | -0.46** | -0.45* | -0.46** | -0.46** |
| | (0.17) | (0.17) | (0.17) | (0.17) | (0.17) | (0.17) |
| Natural Gas Price, USD/MMBtu | 2.69 | 3.14 | 3.21 | 2.68 | 3.08 | 3.15 |
| | (2.33) | (2.26) | (2.25) | (2.34) | (2.29) | (2.28) |
| Wind Forecast Error, GWh | 0.61*** | 0.52** | 0.51** | 0.62*** | 0.55** | 0.54** |
| | (0.17) | (0.15) | (0.16) | (0.17) | (0.16) | (0.16) |
| Shadow Price of Constraints | -6.80*** | -7.00*** | -7.01*** | -6.78*** | -6.93*** | -6.93*** |
| | (1.05) | (1.09) | (1.09) | (1.05) | (1.07) | (1.07) |
| Year-Month-Hour Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| $dp$ Winsorized | No | Yes | Yes | No | Yes | Yes |
| Observations | 26,093 | 26,093 | 26,093 | 26,093 | 26,093 | 26,093 |
| R-squared | 0.44 | 0.45 | 0.45 | 0.44 | 0.44 | 0.44 |

Notes: Data comes from MISO market reports, NOAA, and Yes Energy from January 1, 2014 to December 24, 2016. The sample includes all market-hour observations from January 1st 2014 to December 24th. Peak hours are between 3pm and 8pm, inclusive. Standard errors, in parenthesis, are clustered by month of sample. *, **, *** denote p-value less than 0.1, 0.05, and 0.01 respectively for each hypothesis test. The hypothesis test conducted on the coefficients of $dp_{comp,sfe}$ and its interactions is $H_0 : \rho = 1$ vs. $H_1 : \rho \neq 1$. The hypothesis test for all other coefficients is $H_0 : \beta = 0$ vs. $H_1 : \beta \neq 0$. The sample size varies because of missing wind forecast observations.

Table 6: 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 daily temperature, daily natural gas price, hourly number of binding constraints, hourly shadow price of all constraints. 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. The hypothesis test for all coefficients is $H_0 : \beta = 0$ vs. $H_1 : \beta \neq 0$.

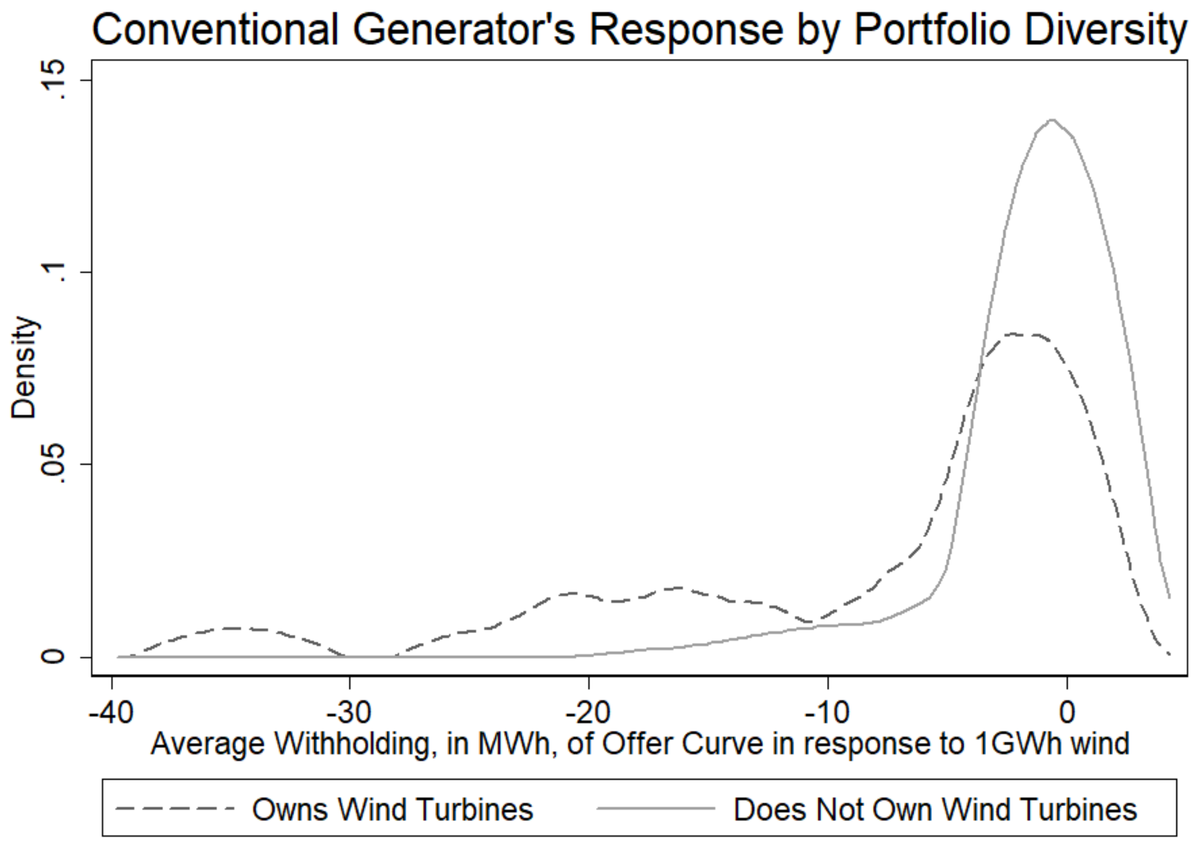



Figure 8: Kernel density of withholding coefficients for ever market participant separated by the market participant's portfolio diversity. Withholding coefficients are how the market participants offer curve changes in response to increased wind generation controlling for the month/year/hour/price/owner average quantity. Both densities use a Epanechnikov Kernal with a bandwidth of two dollars.

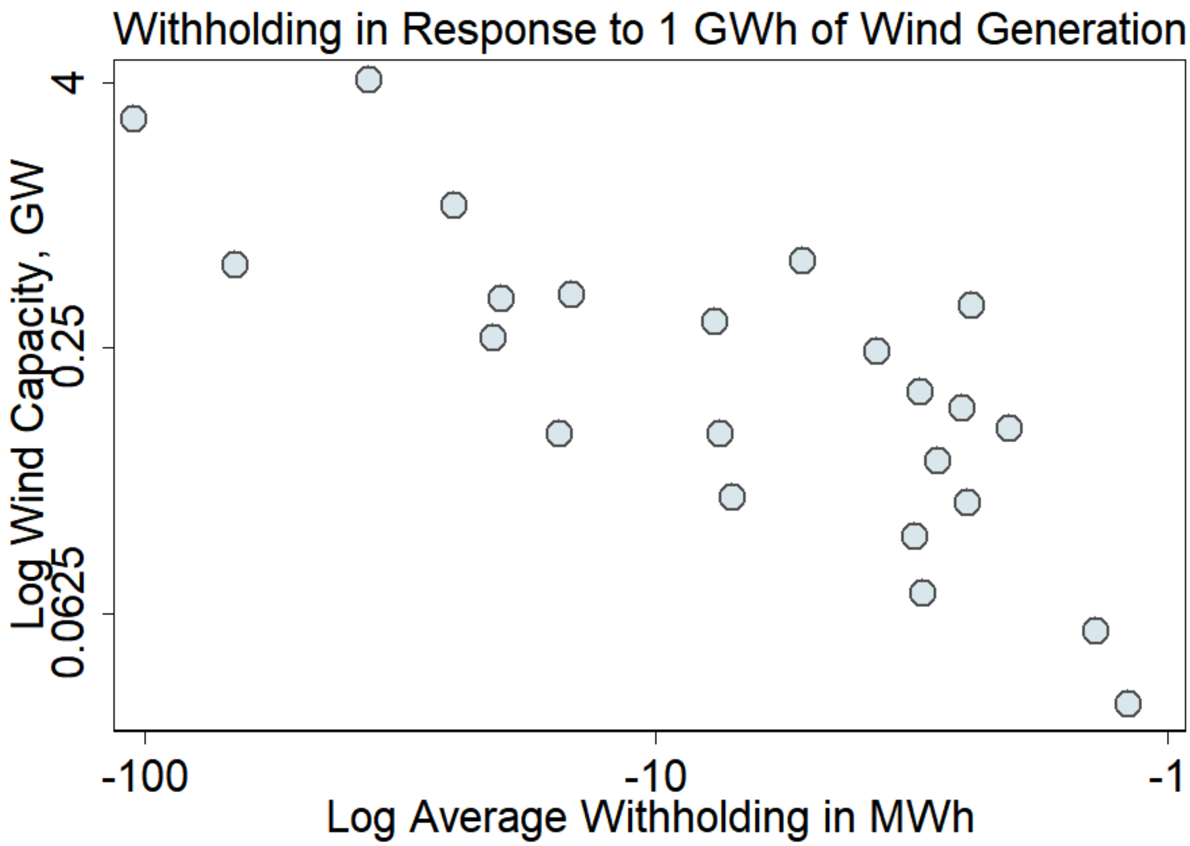



Figure 9: Owner specific withholding coefficient and owner total wind turbine capacity for diverse market participants. Withholding coefficients are estimates from Equation 11, turbine capacity is the sum of each turbine's maximum output in the sample period. Note the horizontal axis is in $\log_{10}$ and the vertical axis is $\log_2$).

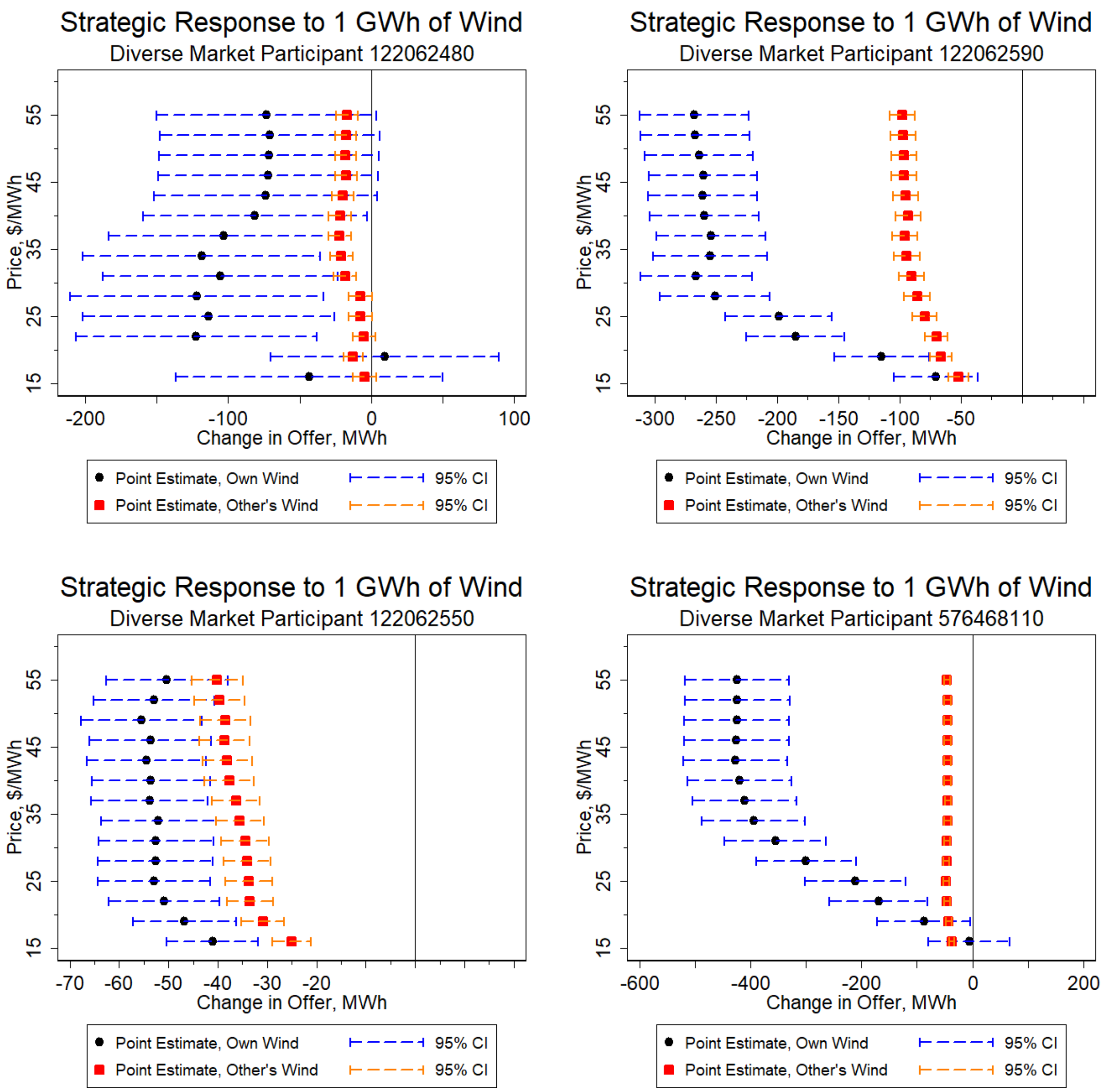



Figure 10: Withholding coefficients at every price bin for a select number of large and diverse market participants. Estimates come from estimating Equation 10 with flexible price bins interacted with WindGWh, separately for each market participant. Confidence interval uses robust standard errors.

Table 7: 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 demand. Other controls include daily temperature, daily natural gas price, hourly number of binding constraints, hourly shadow price of all constraints. 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. The hypothesis test for all coefficients is $H_0 : \beta = 0$ vs. $H_1 : \beta \neq 0$.

Table 8: Impact of Withholding on Consumer Surplus

| | Net Demand | | MISO Demand | |
|---|---|---|---|---|
| | Total, Bil.USD | Annual USD/person | Total, Bil.USD | Annual USD/person |
| Revenue | 55.33 | 371.34 | 58.70 | 393.93 |
| $\Delta CS_{comp}$, no curtail | 7.38 | 49.51 | 10.22 | 68.62 |
| $\Delta CS_{obs}$, observed | 5.01 | 33.60 | 6.94 | 46.57 |
| $\Delta CS_{sfe}$, full curtail | 2.03 | 13.61 | 2.78 | 18.66 |
| $\Delta CS_{comp} - \Delta CS_{obs}$ | 2.37 | 15.91 | 3.29 | 22.05 |
| $\Delta CS_{comp} - \Delta CS_{sfe}$ | 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 14, Equation 15, Equation 16. 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

$$\Pi_o(S_o(p)) = p[S_o(p) + \theta_o W] - C_o(S_o(p)) \tag{17}$$

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 $S_o(p)$.[32] 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 $\varepsilon$ is an $i.i.d.$ random variable with expectation equal to zero.[33] Taking the strategies of the other market participants as given, all uncertainty in the market participant's payoff is from the demand forecast error, $\varepsilon$. 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 $\varepsilon$ 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 $\varepsilon$ 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

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

[33] Demand is strictly decreasing in price.

the market participants profit function as

$$p[RD(p,\varepsilon)+\theta_o W]-C_o(RD(p,\varepsilon)) \tag{18}$$

with the first order condition with respect to price provides

$$p-C'(RD(p,\varepsilon))=-\frac{RD(p,\varepsilon)+\theta_o W}{RD_p(p,\varepsilon)} \tag{19}$$

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 $\varepsilon$, $p^*_o(\varepsilon)$, 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 $\varepsilon$ 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 19 we have

$$p-C'(S_o(p))=-\frac{S_o(p)+\theta_o W}{d'(p)-\sum_{j\neq o}S'_j(p)} \tag{20}$$

# 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.[34] 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.[35] 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

[34]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.

[35]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.[36] 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 9 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.

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

Table 9: 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.[37] 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

[37]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.

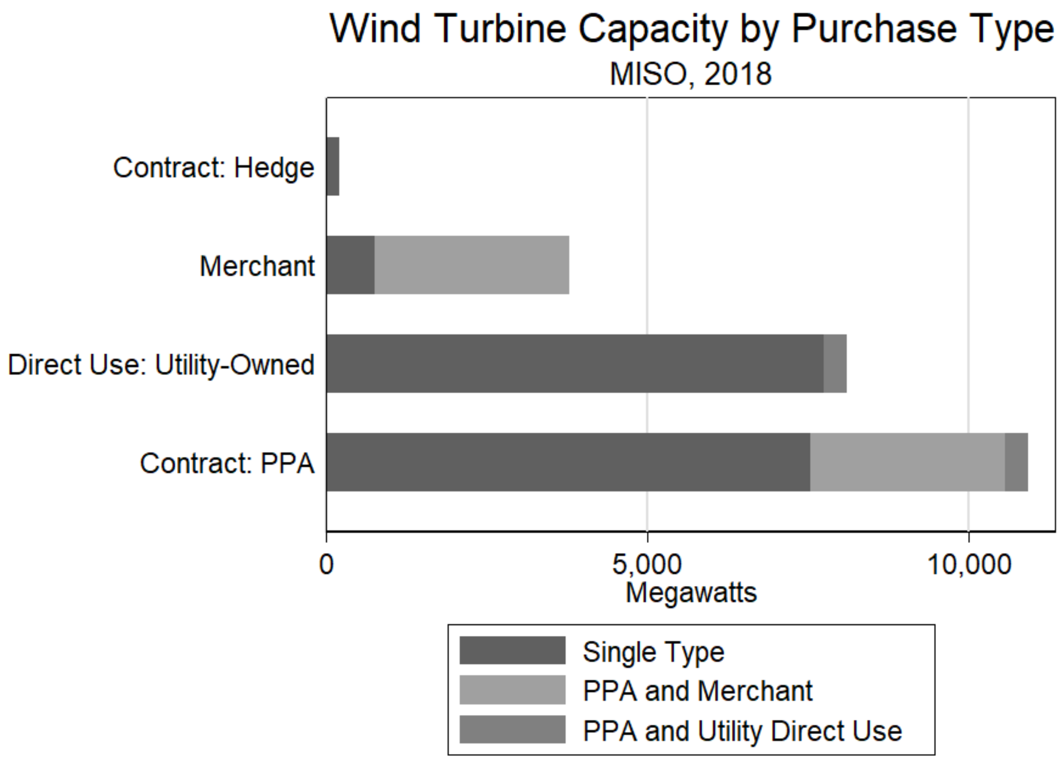



Figure 11: Notes: The sum of total project capacity by generation purchase type, for purchase for all wind turbine projects online in MISO as of June 2018. Contract: Hedge is a physical contract for differences. Merchant projects sell electricity to the wholesale market. Direct Use: Utility-Owned is 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.[38] 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.

[38]Economic withholding is when a market participant submits an offer above their marginal cost in an attempt to increase the market price. Physical withholding is when a unit that should be able to produce at the prevailing market price instead withholds some or all of its output. The model presented in this paper is most concerned with physical withholding.

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 participants 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.