Pass-through of Increased Renewable Generation to the Price of Electricity in Wholesale Markets*

Matt Butner†
University of Colorado Boulder, Economics

January 17, 2018

Abstract

Renewable generation has become a significant portion of the American electrical grid as its associated costs have declined, the technological efficiency has improved, and public policies have supported investment and production. The private cost savings associated with this increase renewable generation can be quite large, and the incidence can have important implications for investment incentives. In this paper, I use rich micro-data on generator strategies in the wholesale electricity market of the US Midcontinent Independent System Operator, from 2014 to 2016, to quantify the expected price reduction due to increased renewable generation. Comparing this expected price change to the market price, I find the expected price reduction is not fully passed-through to the market price. Further, I show this incomplete pass-through of the expected price reduction is driven by the incentive of diverse asset owners to curtail their thermal generation during periods of increased renewable generation.

JEL classification codes: L13, Q42, D44

* Draft is preliminary. Part of this work utilized the Summit supercomputer. Summit is supported by the National Science Foundation (awards ACI-1532235 and ACI-1532236), the University of Colorado Boulder, and Colorado State University. The version has benefited from comments by Jon Hughes, Dan Kaffine, participants at the Front Range Energy Camp, University of Colorado Environmental and Resource Economics Workshop, and the Heartland Environmental and Resource Economics Workshop at Illinois.

†256 UCB, Boulder, Colorado, 80309; matt.butner@gmail.com

1 Introduction

From 2008 to 2016 more than 50% of new electricity generation capacity within the U.S. has been from investments in wind and solar. At the same time, there has been a precipitous decline in the number of coal powered electricity generating units (EIA, 2017). While the environmental benefits of this market transition have been given significant attention, the private benefits associated with reduced operating costs can be just as large, if not larger (Fowlie, Callaway, and McCormick, 2017). This is because renewable generation does not require fuel to generate electricity, whereas steam and combustion generators do. The extent to which this reduced operating cost lowers the market price for electricity, or increases profit for the producers, has implications for investment incentives, public policy, and market design. To address this issue, I evaluate the effect of short run increases in wind generation on the price of electricity in a large wholesale electricity market in the Midwest United States from 2014-2016. Exploiting hourly data on ex-ante supply curves for generating units, I consider how the market price changes compared to what would be predicted by a simple equilibrium framework.

In wholesale electricity markets where demand is highly inelastic in the short run, emission costs can be perfectly passed-through to the market price (Fabra and Reguant, 2014). In the context of increased renewable generation, there are a few circumstances that might influence this result. For one, producers that do not own renewable resources do not save on reduced operating costs during periods of increased renewable generation. When the cost shock does not happen to all producers uniformly, the reduction in price will not be the same as the reduction in cost (Sweeny and Muehlegger, 2017). Further, the electricity market is comprised of horizontally integrated firms owning multiple generating units. In the context of increased renewable generation, this imperfection in competition can perfectly offset the price reduction from increased renewable generation (Acemoglu, Kakhbod, and Ozdaglar, 2017). For these reasons, it is important to empirically evaluate how increased renewable generation is passed-through to the market price of electricity.

Many papers have evaluated the integration of renewable generation in electricity markets, uncovering a "merit order effect" where low cost generation displaces high cost generation and lowers the market price. These papers either consider a simulation model (Sensfuß, Ragwitz, and Genoese 2008), or use time series techniques (Woo et al. 2016; Cludius et al. 2014). The results are location specific, often determined by the local fuel mix and fuel prices, and are not trivial in magnitude. For example, Woo et al. (2016) find that a one Gigawatt hour 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 lowers total market revenue by millions of dollars per day. While the estimates provided in these papers are informative, there is no context for what we would expect the price change to be.

My contribution to this literature is three-fold. First, I use detailed data on unit specific supply curves and economic theory to construct an estimate of the "merit order effect" for every market definition and every hour. This estimate shows significant heterogeneity in when, where, and how renewable generation is expected to impact the market price. With this method I can calculate a hypothetical estimate of the merit-order-effect for locations and times when there is in fact no wind generation. Second, using these estimates, I uncover the pass-through rate of increased renewable generation by comparing the expected merit-order-effect with the realized market price. This pass-through rate is determined by firm specific strategies, how the market is structured, and the market conditions at the time of increased renewable generation. My third contribution is exploring the role of firm specific strategies in response to increased renewable generation, and how this impacts the market price.

The methods I use in this paper most closely resemble the analysis of Fabra and Reguant (2014), however they are tied to a rich literature that uses micro-data on wholesale electricity markets.[1] When exploring firm behavior I rely on the empirical supply function equilibrium framework formed by (Hortacsu and Puller, 2008). While my testable predictions come from structure placed

[1]The foundation for the analysis is built off of work by Wolak (2001), and has since been applied in a number of international context including Spain (Fabra and Reguant, 2014; Reguant, 2014), Canada (Wolak, 2015), New Zealand (McRae and Wolak, 2009), and India (Ryan, 2017) with examples in the United States including Texas (Hortacsu and Puller, 2008; Puller, 2007), California (Borenstein, Bushnell, and Wolak, 2002), and MISO most recently (Mercadal, 2015).

on the market such as Bushnell, Mansur, and Saravia (2008), I do not estimate a full structural model or simulate a counterfactual although it is possible given assumptions on operating costs.

Across multiple specifications, I find the pass-through of the expected price decline is less than one, suggesting that producers of electricity that own renewable resources are able to capture about half of the cost savings as an increase in profits. I evaluate the extent to which this incomplete pass-through is determined by transmission congestion, strategic curtailment of thermal generators, and forecasting error. The most noticeable case is the curtailment of thermal generating units by the owners of diverse assets consistent with the theory presented by Acemoglu, Kakhbod, and Ozdaglar (2017). Comparing the quantity offered at any given price on windy days to the quantity offered on non-windy days, I show large and diverse market participants are withholding quantity to keep the market price high. This emphasizes the importance of understanding market power in wholesale electricity markets, and has implications for how we think about the merit order as wind generation might not always be displacing the high cost units.

In this paper I first consider the equilibrium impact of an increase in renewable generation as a function of observable market characteristics and make testable predictions in section 2. From there, I provide information on MISO and data in section 3. In section 4 I present the main empirical results including summary statistics of my constructed merit-order-effect compared to a conventional estimate, the estimates from the pass-through equation, and a number of robustness checks. Section 5 occupies itself with the firm level incentives to curtail the quantity offered in response to wind. After deriving the theory, I show supportive evidence empirically. I conclude in Section 7.

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 investors, or municipality owned utilities operating under cost of service regulation to ensure reliability. Since the

1980s, this structure has undergone transformations in pursuit of deregulation and the incorporation of markets through state-specific policies forcing divestment of assets or the incorporation of retail competition, and national policies increasing access to the grid by would-be competitors.[2] The main argument for the change to the regulatory environment was to increase production and cost efficiency using markets, as shown after the fact by Fabrizio, Rose, and Wolfram (2007); Davis and Wolfram (2012); Cicala (2014, 2017). As a result, a significant portion of electricity in the US is now dispatched through an Independent System Operator or a Regional Transmission Operator that manages competitive wholesale electricity markets. This market structure for electricity is similar in a number of developed countries.

Although the details vary between market operators, most markets include a hourly forward and spot wholesale market that clears all electricity that is not sanctioned by bilateral physical contracts.[3] Demand for electricity is determined by Load Serving Entities, predominately utilities, that charge customers a rate for electricity in the retail market.[4] 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 at time t in market m as $D_{mt}(p) = d_{mt}(p) + \varepsilon_{mt}$ where $d_{mt}(p)$ is the deterministic component of demand as a function of price that can be forecasted and ε_{mt} is a random variable representing fluctuations in the quantity demanded. I model ε_{mt} 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 hydro-powered based resources. Each traditional 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 of the form

[2] See Borenstein and Bushnell (2015) for a good summary of policy changes since the 1980s. State policies vary. Federal Energy Regulatory Commission (FERC) worked to create competitive wholesale electricity markets by promulgating FERC orders 888 and 889 in 1996. These outlined the definition of an impartial Independent System Operator allowing for access to the transmission grid. FERC order 2000, promulgated in 1999, encouraged the formation of Regional Transmission Organizations to serve as planning bodies over a larger geographic area. PURPA of 1978 and other executive orders have had implications as well.

[3] For example of market differences, ERCOT has an 'energy-only' market, while a number of other markets have separate markets for capacity and ancillary services.

[4] This rate is typically a time-invariant rate or increasing block pricing. Interestingly, while renewable generation decreases the wholesale electricity price, it is associated with an increase in the retail price.

$s_{kmt}(p)$.[5] This offer curve represents the quantity the market participant o is willing to produce from unit k in market m at time t for price p. As a simplification, I consider the market participant's aggregate supply sans wind generation as $S_{omt}(p) = \sum_{k \in K_o} s_{kmt}(p)$. When the market clearing price is $\hat{p}$, the market participant will produce $S_{omt}(\hat{p})$ with costs $C_{omt}(S_{omt}(\hat{p}))$.

Wind at time t is modeled by a market specific aggregate quantity, W_{mt} that is decomposed in to a deterministic forecasteable quantity, w_{mt}, and a random variable, ω_{mt}, such that $W_{mt} = w_{mt} + \omega_{mt}$. Similar to ε_{mt}, ω_{mt} is an $i.i.d.$ random variable with expectation equal to zero.[6] The proportion of market level wind that is owned by market participant o is denoted by $\theta_{om} \in [0,1]$, with $\sum_o \theta_{om} = 1$. This implies the amount of wind generated by market participant o in market m is $\theta_{om}W_{mt}$. As a simplification, this modeling assumption states that the electricity generated by wind for any market participant is directly proportional to their wind generation capacity. In this model I assume that wind generation always clears in equilibrium. This is motivated by the low variable cost. 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 curtailment rates of less that 1%.

Moving forward, I will suppress time and market subscripts for notational ease. The market operator takes the supply offers as given, forms expectations with respect to the demand and wind shocks, ε and ω, 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:

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

Implicitly differentiating the market clearing condition with respect to total wind generation, W,

[5] I define traditional units as alternating current based generators powered by thermal or hydro.

[6] It is possible that wind shocks are correlated across markets, or overtime. This doesn't play a major role in the analysis that follows.

gives the equilibrium effect of increased renewable generation on wholesale market price.[7]

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

This is the rate at which an increase in renewable generation impacts the equilibrium price, what I am calling the pass-through of increased renewable generation.

This is related to, but different from, the conventional pass-through rate of a cost shock or tax. To see how they are related, consider the specific case of perfect competition. In the context of taxes, the impact of a per-unit tax on the equilibrium outcome can be characterized by $d(p) = S(p-t)$, where S denotes market supply. Implicitly differentiating this with respect to t uncovers the well-known pass-through formula $\rho_C \equiv \frac{dp}{dt} = \frac{-S'}{d'-S'} = \frac{1}{1+\frac{\varepsilon_D}{\varepsilon_S}}$. In the context of Equation 2, perfect competition limits the firm's ability to change their supply curve in response to wind, implying $\sum \partial S_o(p)/\partial W = 0$, and $\frac{dp}{dW} = \frac{1}{d'-S'}$. This shows in the case of perfect competition that $\frac{dp}{dW} = -\frac{1}{S'}\rho_C$, where the inverse of the supply's slope acts as a correction term.[8]

Given the imperfectly competitive conditions in wholesale electricity markets, I allow the producers of traditional electricity sources to modify their offer curves in response to increased renewable generation in Equation 2. This is shown by the inclusion of $\partial S_o(p)/\partial W$ in the numerator. The sign of this term suggests the extent to which increased renewable generation has a pro- or anti- competitive effect on firm's behavior. If the term is positive the market participant offers more generation quantity to the market at any given price when there is more 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.[9] Conversely, when the term is negative, the supplier is offering less quantity to the market at any given price. This anti-competitive outcome would be an attempt by the firm to drive up the price, and offset the lower

[7] I implicitly assume that the quantity demanded does not depend on the quantity of wind generated, that is $\partial D(p)/\partial W = 0$

[8] The connection between increased cost and "exogenous quantity competition" under a number of asymmetric imperfectly competitive models is explore in detail by Weyl and Fabinger (2013).

[9] 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.

prices associated with increased renewable generation.

In section 5, I place structure on the competitive conduct of the firm to derive a prediction in regards to the sign of $\partial S_o(p)/\partial W$. Then, using the detailed data on wholesale market operations, I empirically test to see if and when this term is non-zero. For now, I will remain agnostic on the sign of $\partial S_o(p)/\partial W$, and simply assume that it is zero.[10] I make one more simplifying assumption, demand is inelastic in the short run such that $d'(p) = 0$. I am comfortable making this assumption given I observe an extremely steep hourly demand curve within the data. If the assumption on demand is violated, this prediction is an upper bound on the expected price decline. These two assumptions provide my main testable prediction regarding the change in equilibrium price from an increase in wind generation

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

for a marginal increase in wind generation. Implying the total effect on price is

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

The intuition of Equation 4 is shown in Figure 1. Increasing wind generation shifts the supply curve to the right. When the supply curve of the other generating units does not change, and demand is price unresponsive, the change in the market price is determined by the marginal unit that wind generation is displacing. The value of this marginal unit is characterized by $\frac{1}{\sum S_o'(p)}$. The merit-order-effect literature's main goal is to quantify this term, $\frac{1}{\sum S_o'(p)}$. Often a sample average estimate is obtained using time-series techniques. In contrast, I exploit the detailed data to form a market-hour specific estimate of Equation 4 using observed values of $\frac{1}{\sum S_o'(p)}$ and W.

I compare my estimate of Equation 4 to the realized market price across market hours. Provided my assumptions regarding firm conduct and demand are correct, my prior is that there should be a one to one relationship between the expected price change and the observed price

[10] Ito and Reguant (2016) present information suggesting this term is zero.

difference. In a sense, the proportion of the expected price change realized in the market price can be thought of as the pass-through of the expected price decline. In a more grounded sense, the assumption on inelastic demand suggests the tax pass-through rate is 1, $\rho_C = 1$, such that $dp = \rho_C \left(-\frac{1}{\sum S_o'(p)}\right) dW = \left(-\frac{1}{\sum S_o'(p)}\right) dW$. The extent to which $dp \neq \left(-\frac{1}{\sum S_o'(p)}\right) dW$ suggests the value of $\rho_C \neq 1$. This could be because of (1) elastic demand, (2) imperfect competition, or (3) asymmetry in the experience of wind shocks. In what follows, I define the estimated pass through rate ρ in the equation $dp = \rho \left(-\frac{1}{\sum S_o'(p)}\right) dW$ and I explore these explanations for why $\rho \neq 1$.

3 The Midcontinent Independent System Operator and Data

3.1 MISO

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.[11] The operator serves as a non-profit organization managing transmission and dispatch of electricity generating units within its foot print 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 within the United States with a total of 180 gigawatts of generation capacity, and conducts market operations in three different regions from North Dakota to Michigan to Louisiana as shown in Figure 2.[12]

Figure 3 breaks down the capacity of different types of units by MISO region, showing that over a quarter of the installed capacity in the Northern Region comes from wind turbines. This translates into wind providing 60% of all electricity in the Northern Region during periods of low demand. Figure 4 shows the location and size of all generating units within MISO by fuel type. It is evident there are a substantial number of wind turbines in Iowa and Minnesota. This portion of

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

[12] To give context to the units. 1 gigawatt is 1,000 megawatts. A electricity generator operating at 1 megawatt for one hour produces 1 mega-watt hour. This is approximately the amount of electricity consumed by an average household in a month. The amount of Megawatt hours produced by a typical electricity plant is summarized in Table 2.

the country, extending down into Texas's pan-handle, is the largest concentration of wind turbines in the United States. There are many steam powered coal plants in the Central Region, while the Southern Region consists mainly of combustion and combined cycle natural gas plants.

Most states other than Michigan and Illinois 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. The price these utilities pay for electricity is covered under cost of service regulation. Notwithstanding, the vertically integrated utilities may sell electricity in excess of the load commitment in the wholesale market. In addition, a good proportion of the electricity generators within MISO are merchant electricity providers (also called Independent Power Producers). For these reasons, market power is still a concern in MISO's wholesale electricity market and is evaluated by and Independent Market Monitor annually. The market monitor looks at market outcomes, as well as firm behavior, to identify if there is any economic withholding or if any firm is pivotal. Overall, the reports conclude that the market is competitive based on their criteria.

MISO operates a number of markets in combination with planning and oversight to achieve its goals in distribution and reliability. These 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.[13] These markets capture almost all electricity generation and transmission activities within MISO's footprint that are not part of bilateral contracts.[14]

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.[15] The day ahead market serves as a forward market, with all bids

[13] Other important components of MISO include revenue sufficiency guarantee charges to those that are causing ramping and the related make-whole payments.

[14] 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.

[15] These parameters include cost estimates, the minimum and maximum they can produce in economic and emergency

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 while market participants may submit virtual demand bids. MISO also allows for virtual bids as a financial tool for arbitrage (Parsons et al., 2015; Mercadal, 2015). 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 negative quantity.

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.[16] 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. Figure 5 shows the significant variance of the LMP across nodes within MISO during a sample hour.

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 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

scenarios, as well as if the unit must run.

[16] 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.

greatly reduced the number of manual curtailments.[17] 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.

Figure 6 shows the portfolio of electricity generating capacity by unit type for all market participants within MISO. There are a number of very large market participants, which own a diverse portfolio of assets including wind turbines. The large market participants that own a decent amount of wind based resources are exclusively within MISO's Northern Region. Figure 6 also shows that there are substantial independent power producers within the wholesale market, often owning wind turbines.

3.2 Data

MISO publishes data regarding their market operations on their website as Market Reports. The primary data I use are the daily day ahead and real time generation offers by generation units from January of 2014 to December of 2016.[18] These data provide, for every hour, a time consistent unit and owner identification number, up to ten price-quantity pairs outlining the offer curve of the generating unit, a subset of other information regarding the bid summarized in Table 1, the type of generating unit (steam, combustion, wind turbine, wind, etc.), and the ex-post quantity generated and price received at five minute intervals. I take the hourly mean price and consider this to be the price the generating unit receives that particular hour. The other data I use from MISO include hourly demand bids, wind forecasts, wind generation, hourly fuel mix, market settlements, and binding constraints.

For every hour, I take the ten price-quantity pairs provided by each generating unit and construct a unit specific supply curve. This is defined over a set of discrete prices from a lower bound

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

[18] 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.

to a upper bound, e.g. from -10 dollars to 100 dollars at an interval of 10 cents. The bid submission indicates if the quantity offered is a piece-wise linear or step function of price. I use this information to interpolate the prices between the provided price-quantity pairs. When appropriate, I extrapolate the quantity offered using the maximum and minimum quantity offered. Figure 7 shows a sample of ten offer curves from a single steam generating unit during a sample month.

I aggregate all of the generating unit supply curves within a market definition to obtain a market supply curve. For now I use the MISO geographic regions as my market definition, but explore alternative market definitions in robustness checks below.[19] This market supply curve is not everywhere continuously differentiable in price since some of the unit level supply curves are step functions. To overcome this, I construct a monotone cubic spline using Hyman filtering (Hyman, 1983). I repeat this process with the demand bids. Figure 8 shows the aggregate supply curve in combination with the aggregate demand curve for a sample market hour.

I define the market equilibrium where the constructed supply curve is equal to the constructed demand curve. 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. I also recover the slope of the residual demand curve given the relevance it has towards the ability of a firm to mark up price over cost.[20] Table 3 summarizes the equilibrium price and the slopes. All of these values are the sign that theory would predict. The equilibrium price is lower than the Locational Marginal Price in Table 2 because this price does not include congestion or transmission losses.

Additional data I use in some specifications include daily weather data from National Oceanic and Atmospheric Administration, economic indicators from the U.S. Federal Reserve, and spot prices for fuel from the Energy Information Agency. Since I use month of year fixed effects in my preferred specification, only weather is important. For a subset of the plants, I correlate their prices with EIA data to uncover plant specific characteristics including fuel type and location from EIA-860. Although I do not observe forward contracts or costs, they can be uncovered by methods employed by Mercadal (2015) and Ryan (2017) respectively.

[19]This is because I can only be confident of a generating unit's region, and nothing else in regards to their location.
[20]See Reiss and Wolak (2007) for details

4 Main results

Here I present the expected change in the market price presented in Equation 4, recovered from the market supply curves. First, I compare these values to a conventional estimate of the merit-order-effect using the MISO data. Next, I consider how well this expected price change passes-through to the market price. Last, I check the robustness of these results.

4.1 The Merit Order Effect

In the spirit of the conventional merit-order-effect, I consider the following equation to estimate the reduced form price effect of increased renewable generation:

$$LMP_{it} = \beta_1 WindMwh_{mt} + \beta_2 (ClearedMwh)_{mt} + \lambda_{mhy} + \varepsilon_{it} \tag{5}$$

where LMP_{it} is the locational marginal price for generating unit i at time t, $WindMwh_{mt}$ is the total megawatt-hours of wind generation cleared in market m at time t. Identification of β_1 comes from the inclusion of total market demand, $(ClearedMWH)_{mt}$, and month by hour by year fixed effects, λ_{mhy}. The inclusion of total demand controls for simultaneity concerns typical in price/quantity regression because demand is price inelastic. Month by hour by year fixed effects control for trending variables that might be correlated with wind generation and electricity prices. As an example, this compares the unit specific price during windy instances of 4pm in September of 2014 to the less windy instances of 4pm in September of 2014. The month-year component controls for macro trends in fuel prices. Since wind generation is determined by the weather patterns, the remaining variation is as good as random.

Table 4 shows the results from estimating Equation 5 in the full sample, across hours of the day and in different regions. I observe a one Gigawatt-hour (Gwh) increase in wind generation is associated with a decline in price of 1.27 \$/Mwh on average. For context, the same increase in wind has been associated with a 3.18% price decline in Spain (Böckers, Giessing, and Rösch, 2013), 0.8 to 2.3 €/Mwh price decline in Germany (Cludius et al., 2014), 1.5 to 11.4 \$/Mwh price decline in California (Woo et al., 2016), and 3.9 to 15.2$/Mwh price decline in Texas (Woo et al., 2011). In MISO, this effect is larger in the Northern region and during peak hours of the day. Note that I observe no effect of wind on price in the Southern, because there is no wind generation there.

As an alternative to these regression based estimates, I leverage detailed data on the market structure to form an estimate of the theoretical merit-order-effect for every market hour by calculating an expression for Equation 3. I calculate this inverse of the supply slope for all market hours from January of 2014 to December of 2016 for each regional market within MISO. This expected price represents the value of the marginal unit that wind generation would be displacing. Table 4 shows summary statistics of this measure in the full sample, across hours of the day and between regions. The value can be interpreted as the change in market price ($/Mwh) for a one Gwh increase in the amount of wind generation. As a validity check, this derived change in price is the same order of magnitude and sign as the estimated change in price.

Although comparable, these two estimates are conceptually different. The measure from Equation 5 is the average observed effect of wind on price, $\frac{\partial E(P|W)}{\partial W}$ where $E(\cdot)$ is the expectation operator, estimated from observed price and wind generation data. Embedded in this estimate are the market conditions during periods of wind generation. In contrast, the expression calculated from Equation 3 is the theoretical price change if there were a unit increase in wind generation, $\frac{\partial P}{\partial W}$, with the average $E\left(\frac{dP}{dW}\right)$. This is what the price change would be if the market is working how it is modeled in section 2. While the average expected price change estimated empirically is larger than the theoretical price change on average, there are a number of market hours with a theoretical price change that is relatively large. Further, I expect $\frac{\partial E(P|W)}{\partial W} \neq E\left(\frac{dP}{dW}\right)$ when $\frac{dP}{dW}$ is correlated with W.

4.2 Pass-through of increased renewable generation

The information in Table 4 allows me to compare the impact of wind on the price of electricity, on average, using two different methods. One of these methods is empirically based, while the other is based off of economic theory and the market structure. With the detailed resolution of the

MISO data, I directly compare these two. I do this by first calculating the total expected effect of increased renewable generation outlined in Equation 4, $dp = -\frac{1}{\sum S_o'(p)} dW$, summarized in Table 5. Then, I consider the extent to which this expected total effect on price is passed on to the realized market price by estimating the coefficients in the following equation:

$$LMP_{it} = \rho \left[\frac{dp}{dW}(W)\right]_{mt} + \beta(ClearedMwh)_{mt} + \lambda_{mhy} + \eta_i + \varepsilon_{it} \tag{6}$$

Like Equation 5, I control for the total amount of Mwhs demanded within a particular market hour as well as the month-hour-year average price. The locational marginal price (LMP) is specific to the generating unit, and the expected price change is calculated at the market level. It might be a concern that certain generating units play a particular role in the market, associated with receiving a LMP that is not random. I control for unit specific unobservables with generating unit-level fixed effects η_i. As a result, my identification strategy involves comparing the market price during periods of high and low expected price changes within a particular month-hour-year, and how this compares to the average price received by the generating unit overall.

If the assumptions that provided Equation 4 are correct, that demand is inelastic, markets clear, and there is no strategic curtailment, I expect the coefficient ρ to be close to one. In this case, the expected market wide savings associated with increased renewable generation would be perfectly passed through the price received by the firm. Table 6 presents the estimated coefficients from Equation 6. In all specifications I can reject the null hypothesis that $\rho = 1$. These results suggest that only 28 to 36% of the expected price reduction is observed in the market price.

There is a downside to having generating unit specific prices and market level expected price changes. When the unit of observation for the dependent variable is smaller than the unit of observation of the independent variable, the standard errors are expected to have a downward bias (Moulton, 1986). A downward bias on the standard errors increases the type 1 error of a hypothesis test on the parameter estimates. To address this, I first note that the number of unit level observations within a particular market-hour is relatively small (less than fifty) and that the within market-hour variation in price is small relative to the overall variation in price. These suggest the bias is not so severe. In addition, I aggregate the unit-level prices to a market average and re-estimate Equation 6 with similar results presented in Table 7. The results do not change. I re-estimate Equation 6 across hours an load deciles in Table 8 and Table 9 respectively. This shows the theoretical price changes passes through to the market price the most during mid-night and mid-day hours. There is no discernable pattern in the pass-through rate over load deciles.

4.3 Robustness

This result, that the expected price change is not fully passed on to the market price, can be driven by a number of different factors. I show this result is robust to the market definition, the local approximation, congestion and capacity constraints within the market, firm dynamics, forecasting error, or strategic curtailment. Figure 9 summarizes this section by plotting how the point estimate of interest changes when addressing each of these issues. The specifics of all estimates are explained below.

4.3.1 Firm dynamics

A characteristic of electricity generation to take into account is the inflexibility of thermal generators to adjust the quantity they are producing. This is commonly referred to as the 'ramping problem' and can have an impact on economic outcomes (Cullen and Reynolds, 2017). If the thermal units are setting the market price, and they can not ramp down to accommodate an increase in renewable generation, we would expect the expected price change to not be realized in the market price. If we don't control for this determinant of price, and it is correlated with increased renewable generation, we are biasing the coefficient on expected price change. I address this by controlling for the proportion of total electricity generation that is identified as a 'must-run' megawatt for every market hour. Table 10 shows controlling for this does not influence the point estimates significantly.

4.3.2 Congestion and Capacity Constraints

A notable characteristic of the wholesale electricity market is the fixed capacity of the transmission network. When the electricity generated from wind turbines can not reach consumers of electricity, the market isn't clearing completely. In this situation, the market price would not decrease as much as it would if the wind generation cleared perfectly. It is possible the limited ability of the transmission infrastructure to incorporate renewable generation is driving the result of incomplete pass-through of expected price reduction. In another sense, we can think of transmission capacity constraints as an omitted variable problem. If capacity constraints are correlated with increased renewable generation and a higher market price, we expect the coefficient on expected price change to be biased downwards.

MISO reports statistics for transmission constraints at the hourly level including the number of binding constraints within the system as a whole and the shadow price of relieving each constraint individually. To address the problem of capacity constraints I re-estimate Equation 6 on a subsample of that data when there is less than 1 capacity constraint in the whole system during that hour on average. In addition, I look at the full sample controlling for the number of capacity constraints during that hour. The results in Table 11 shows a moderate increase in the pass-through rate once I control for the number of binding constraints. The subsample of market hours with less than one binding constraint on average, estimated in Table 12, does not show an increase in the pass-through rate.

4.3.3 Forecasting error

Next, MISO provides day ahead forecast of the quantity of electricity generated from wind based resources. An incorrect forecast can increase the market price and is correlated with increased renewable generation. For every hour I have a market wide estimate of the quantity of wind generated as well as the day ahead forecast for that hour. I find the difference between the forecasted wind generation and the actual wind generation and call this the forecasting error. I control for this in Equation 6 and find it does not influence the point estimates, as shown in Table 13.

4.3.4 Local Approximation

The comparative static derived in Equation 4 is valid for a small increases in the amount of wind generation. This is because the slope of the supply function represents the change in cost to serve for marginal generating units. When the amount of wind generation is larger, the expected price change would have an upward or downward bias depending on if the supply curve is locally convex or concave, respectively. To address this issue I re-estimate Equation 6 on a subsample of hours when the amount of wind is small, less that 1 Gwh. Table 14 shows for this subsample the pass-through rate is now negative. That is, when we would expect to observe a decline, we see price increase, when the amount of wind in the market is less than 1 Gwh.

It is possible to address this in a more sophisticated manner. Since I observe the overall supply slope I can make a direct comment on the convexity of the supply curve. Further, I can use the supply curve to calculate the slope of a secant line instead of a tangent line. While feasible, they are not practical at this time.

4.3.5 Market Definition

Lastly, when I calculate the estimated price change, I use the slope of the market supply curve. This market supply curve is the sum of all generating unit supply curves within the market definition. When the market is ill defined, the market supply curve will have too many or too few generating units. If I incorporate too many generating units in the market, this will flatten the supply curve, giving a downward bias of the expected price change. Conversely, incorporating too few generating units will steepen the market supply curve, giving a upward bias to the expected price change.

The competitive market for electricity operations is difficult to define, as electricity becomes homogeneous once it is on the transmission grid. Above I use regional, geographic, markets in my analysis.[21] I do this because of data limitations, I only observe demand at the regional level. This isn't a bad approximation to the actual market, as the market clearing price within MISO is determined within zones, and there are a few (less than five) zones within one region.

[21] The North, Center, and Southern MISO regions shown in Figure 2.

An alternative to the geographic market definition is to define markets based on price clusters (Mercadal, 2015). The intuition is that generating units that compete with one another will have similar prices ex-post. It then makes sense to define markets such that generating units with similar prices belong to the same market. Because the market definition might be dependent on the time of day or time of year, I create market clusters for every month-year-hour (e.g. January 2016 at 2pm) independently.

To create the market clusters, I calculate the dissimilarity between all generating units in a matrix for every month-year-hour. The dissimilarity measure between two generating units is the euclidean distance between their price vectors for that particular month-year-hour. With this dissimilarity measure the generating units are agglomerated into clusters, and the clusters are agglomerated into each other if their dissimilarity measure is below a threshold. This creates a dendogram of price clusters with which I can define an arbitrary number of markets.

From hierarchical clustering I define either 4, 8, or 12 markets for every month-year-hour. It is straight forward to create a market supply curve as the sum of the supply curves of the generating units within a specific market cluster. Because demand is unobserved within these clusters I must make assumptions to find the equilibrium. I use two approaches, one evaluates the market supply at the average ex-post market price, the other finds where the market supply is equal to the ex-post quantity. I find either approach arrives to a similar answer and use the ex-post quantity to define the equilibrium below.

Table 15 re-estimates the preferred specification of Equation 6 with different market definitions: four, eight, and twelve markets. The estimated pass-through rate is negative for all market definitions, similar to the estimation results that only look at small increases in the amount of wind generation. This suggest this alternative market definition is not effective in capturing the effect of increased renewable generation on the market price. We observe the price increases when we would expect it to decline, on average. In particular, since the estimates are not close to one, this suggests the incomplete pass-through result is not based off of market definition alone.

5 Strategic curtailment by large and diverse firms

Because firms are allowed a degree of market power within wholesale electricity markets, incomplete pass-through could be driven by strategic curtailment of thermal generators owned by market participants with diverse assets (Acemoglu, Kakhbod, and Ozdaglar, 2017). The incentive to curtail thermal generators is driven by the fact that wind based generation assets are more than likely to clear in the merit order (low marginal cost), and an owner of diverse assets gets additional revenue off this unit when curtailing their traditional unit in a uniform price auction. This increased incentive to curtail is shown graphically in Figure 10. When there is increased renewable generation, an independent electricity generator with market power compares the profit under a higher price and lower quantity to that of a lower price and a higher quantity. This trade-off is the same regardless of how much wind is generated in the market. When the same electricity generator owns wind based assets, they will receive additional revenue from the higher market price for the quantity of wind that they generate. If they own more wind assets, the revenue received will increase, and so does their incentives to curtail their other assets.

To determine the role of firm's strategies, it is necessary to place structure on the incentives of the firm. In the appendix I use the supply function equilibrium framework outlined by Hortacsu and Puller (2008) to derive the market participant's best response function. Using the notation provided in section 2, the optimal strategy of market participant o with wind assets can be characterized by

$$\left[p - C_o'(S_o(p))\right] = \left[S_o(p) + \theta_o W\right] \frac{-1}{RD)_o'(p)} \tag{7}$$

where $RD_o'(p) = d'(p) - \sum_{j \neq o} S_j'(p)$ is the slope of the residual demand curve for owner o. This is a sort of inverse elasticity pricing rule. Implicitly differentiating this with respect to renewable generation, W, with the assumption of constant marginal cost, provides $\frac{dS_o(p)}{dW} = -\theta_o$. As modeled, this suggests the owners of non-wind based resources have an incentive to curtail their generation offer by exactly the proportion of the total wind capacity that they own. The result is that wind generation owned by large and diverse firms doesn't displace high cost generation units, but instead displaces assets owned by the same firm. This shuffling of their generation portfolio allows the firm to capture the surplus created by the lower operating cost. This is qualitatively similar derived under Cournot competition in quantity described by Acemoglu, Kakhbod, and Ozdaglar (2017).

In aggregate this strategic curtailment implies increased renewable generation will have the following impact on the market price

$$\frac{dp}{dW} = -\left(1 - \sum_{o \in V} \theta_o\right) \frac{1}{\sum_o S_o'(p)} \tag{8}$$

where V is the set of market participants that own both wind and non-wind based assets. In sample, I observe values of $(1 - \sum_{o \in V} \theta_o)$ ranging from 0 to 0.8 with a mean of 0.6. This is consistent with the estimated pass-through rate found in section 4 that ranges between 0.2 to 0.4. I go further and calculate the modified expected change in price for every market hour according to Equation 8. Unsurprisingly, this is an attenuated measure of Equation 3. Re-estimating Equation 6 with this modified value of $\frac{dp}{dw}$ provides estimates of ρ that are closer to one in the preferred specification, as shown in Table 16.

Because I observe the firms' strategies for every market hour, I directly test for evidence of strategic curtailment. I aggregate the supply curves of the generating units owned by each market participant to create an owner specific supply curve. This supply curve is outlined by a set of price quantity pairs (p_{otb}, q_{otb}) for owner o at time t. I interpolate and extrapolate between and beyond the price quantity pairs so the support of this owner specific supply curve is consistent across market participants.[22] I then estimate the following equation for the set of market participants that own wind and traditional assets

$$q_{otb} = \sum_b \alpha_b \mathbb{1}\left(p_{otb} = P_b\right) + \beta WindMwh_{ot} + \lambda_{mhy} + \eta_o + \varepsilon_{otb} \tag{9}$$

The set of α_b outline the average ex-ante quantity offered for all market participants. The fixed

[22]This specification uses prices from zero to eighty at intervals of 5 dollars

effects, similar to Equation 6 above, allow for a owner specific and month-year-hour intercept.[23] The coefficient of interest in Equation 9 is β, which shows the average change in the offer curve of diverse firms when they produce an additional Mwh of wind based generation. If $\beta < 0$, the market participants are curtailing their generation offer in response to increased wind generation on average. A value of $\beta = -1$ would be consistent with $\frac{dS_o(p)}{dW} = -\theta_o$ derived above. A value of $\beta = 0$ signals the market participant does not change their strategy. Table 17 shows the estimates of Equation 9. Once I look at only within year-month-hour variation, we observe approximately 20% of wind generation observed by these diverse firms is replacing curtailed generation on average.[24]

Given a market participant has flexibility in submitting a function as their strategy, it might not be that they curtail uniformly over all the prices. This might be important if the average curtailment is unevenly spread across prices, perhaps happening during more frequent price realizations. To address this I estimate a curtailment coefficient for each price bin, of the form

$$q_{otb} = \sum_b \mathbb{1}\left(p_{otb} = P_b\right)\left(\alpha_b + \beta_b WindMwh_{\{o,k\}t}\right) + \lambda_{mhy} + \eta_o + \varepsilon_{otb} \tag{10}$$

I do this for the subsample of firms that own both wind and traditional assets in response to their own wind. As a counter-factual, I re-estimate this equation for the subset of firms that own no wind assets, and consider their response to the total amount of wind generation. The coefficients along the price bins are presented in Figure 11

Overall I see the response of diverse firms to their own wind is different from the response of non-diverse firms to market level wind. In particular, the diverse firms curtail when the price is low and when the price is high. Curtailment for low prices would represent the effort of a market participant to prevent the price from dropping substantially. Conversely, the market participant would curtail at high prices knowing the supply curve is steep. When supply is steep, a Mwh curtailed can have a substantial impact on price.

[23] The results do not change if I allow for the the coefficient α_b to depend on the firm or month-year-hour or both.

[24] In actuality, the amount of curtailment varies significantly across market participants with some curtailing the offer completely and other not curtailing at all. I refrain from identifying which firms are curtailing for privacy and legal reasons.

6 Conclusion

I investigate the effect of increased renewable generation on price of wholesale electricity market in the context of what economic theory predicts. I do this by constructing an expected price reduction associated with renewable generation based on the ex-ante supply function and simple equilibrium theory. I show the expected price change is not fully realized in the market price. After exploring a number of possible explanations, I show evidence that this is in part driven by strategic curtailment of thermal generating units.

References

Acemoglu, Daron, Ali Kakhbod, and Asuman Ozdaglar. 2017. "Competition in Electricity Markets with Renewable Energy Sources." *The Energy Journal* 38 (KAPSARC Special Issue).

Böckers, Veit, Leonie Giessing, and Jürgen Rösch. 2013. *The green game changer: An empirical assessment of the effects of wind and solar power on the merit order*. 104. DICE Discussion Paper.

Borenstein, Severin and James Bushnell. 2015. "The US electricity industry after 20 years of restructuring." *Annu. Rev. Econ.* 7 (1):437–463.

Borenstein, Severin, James B Bushnell, and Frank A Wolak. 2002. "Measuring market inefficiencies in California's restructured wholesale electricity market." *The American Economic Review* 92 (5):1376–1405.

Bushnell, James B, Erin T Mansur, and Celeste Saravia. 2008. "Vertical arrangements, market structure, and competition: An analysis of restructured US electricity markets." *The American Economic Review* 98 (1):237–266.

Ciarreta, Aitor, Maria Paz Espinosa, and Cristina Pizarro-Irizar. 2017. "Has renewable energy induced competitive behavior in the Spanish electricity market?" *Energy Policy* 104:171–182.

Cicala, Steve. 2014. "When does regulation distort costs? lessons from fuel procurement in us electricity generation." *The American Economic Review* 105 (1):411–444.

———. 2017. "Imperfect Markets versus Imperfect Regulation in US Electricity Generation." Tech. rep., National Bureau of Economic Research.

Cludius, Johanna, Hauke Hermann, Felix Chr Matthes, and Verena Graichen. 2014. "The merit order effect of wind and photovoltaic electricity generation in Germany 2008–2016: Estimation and distributional implications." *Energy Economics* 44:302–313.

Cullen, Joseph A and Stanley S Reynolds. 2017. "Market Dynamics and Investment in the Electricity Sector." .

Davis, Lucas W and Catherine Wolfram. 2012. "Deregulation, consolidation, and efficiency: Evidence from US nuclear power." *American Economic Journal: Applied Economics* 4 (4):194–225.

EIA. 2017. “U.S. electric generating capacity increase in 2016 was largest net change since 2011.” Tech. rep., Energy Information Agency.

Fabra, Natalia and Mar Reguant. 2014. “Pass-through of emissions costs in electricity markets.” *The American Economic Review* 104 (9):2872–2899.

Fabrizio, Kira R, Nancy L Rose, and Catherine D Wolfram. 2007. “Do markets reduce costs? Assessing the impact of regulatory restructuring on US electric generation efficiency.” *The American Economic Review* 97 (4):1250–1277.

Fowlie, Meredith, Duncan Callaway, and Gavin McCormick. 2017. “Location, Location, Location: The Variable Value of Renewable Energy and Demand-side Efficiency Resources.” *Journal of the Association of Environmental and Resource Economists* Forthcoming.

Hortacsu, Ali and Steven L Puller. 2008. “Understanding strategic bidding in multi-unit auctions: a case study of the Texas electricity spot market.” *The RAND Journal of Economics* 39 (1):86–114.

Hyman, James M. 1983. “Accurate monotonicity preserving cubic interpolation.” *SIAM Journal on Scientific and Statistical Computing* 4 (4):645–654.

Ito, Koichiro and Mar Reguant. 2016. “Sequential markets, market power and arbitrage.” *American Economic Review* forthcoming.

McRae, Shaun D and Frank A Wolak. 2009. “How do firms exercise unilateral market power? Evidence from a bid-based wholesale electricity market.” .

Mercadal, Ignacia. 2015. “Dynamic competition and arbitrage in electricity markets: The role of financial players.” *Job Market Paper, Chicago* .

Moulton, Brent R. 1986. “Random group effects and the precision of regression estimates.” *Journal of econometrics* 32 (3):385–397.

Parsons, John E, Cathleen Colbert, Jeremy Larrieu, Taylor Martin, and Erin Mastrangelo. 2015. “Financial arbitrage and efficient dispatch in wholesale electricity markets.” .

Puller, Steven L. 2007. “Pricing and firm conduct in California’s deregulated electricity market.” *The Review of Economics and Statistics* 89 (1):75–87.

Reguant, Mar. 2014. “Complementary bidding mechanisms and startup costs in electricity markets.” *The Review of Economic Studies* 81 (4):1708–1742.

Reiss, Peter C and Frank A Wolak. 2007. “Structural econometric modeling: Rationales and examples from industrial organization.” *Handbook of econometrics* 6:4277–4415.

Ryan, Nicholas. 2017. “The competitive effects of transmission infrastructure in the Indian electricity market.” *NBER Working Paper 23106* .

Sensfuß, Frank, Mario Ragwitz, and Massimo Genoese. 2008. “The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany.” *Energy policy* 36 (8):3086–3094.

Sweeny, Richard and Erich Muehlegger. 2017. “Competition and Pass-through of Input Cost Shocks: Evidence from the U.S. Fracking Boom.” *Working paper* .

Weyl, E Glen and Michal Fabinger. 2013. “Pass-through as an economic tool: Principles of incidence under imperfect competition.” *Journal of Political Economy* 121 (3):528–583.

Wolak, Frank A. 2001. “Identification and estimation of cost functions using observed bid data:

an application to electricity markets." *Working paper, NBER* .

———. 2015. "Measuring the competitiveness benefits of a transmission investment policy: The case of the Alberta electricity market." *Energy Policy* 85:426–444.

Woo, Chi-Keung, I Horowitz, J Moore, and A Pacheco. 2011. "The impact of wind generation on the electricity spot-market price level and variance: The Texas experience." *Energy Policy* 39 (7):3939–3944.

Woo, CK, J Moore, B Schneiderman, T Ho, A Olson, L Alagappan, K Chawla, N Toyama, and Jay Zarnikau. 2016. "Merit-order effects of renewable energy and price divergence in California's day-ahead and real-time electricity markets." *Energy Policy* 92:299–312.

Appendix A: Figures and Tables

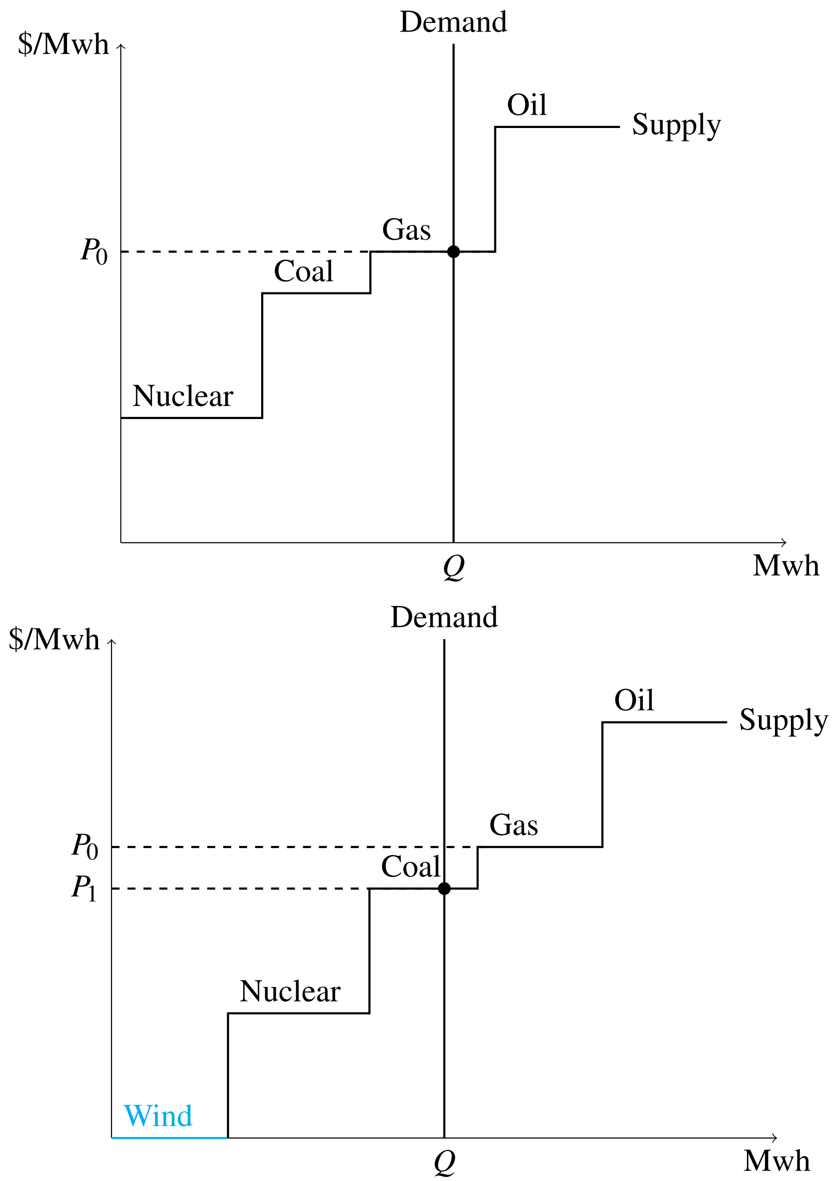


Figure 1: Wind generation shifts the supply curve to the left, decreasing the price from P_0 to P_1

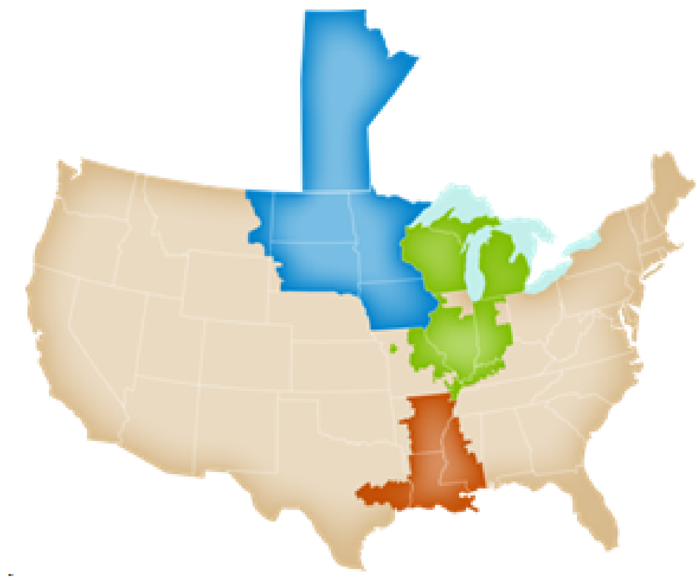


Figure 2: MISO Reliability Footprint split into three exclusive regions. The blue area extending into Canada is the Northern region. The green area containing Wisconsin, Michigan, and Illinois is the central area. The remaining area is the Southern Region.

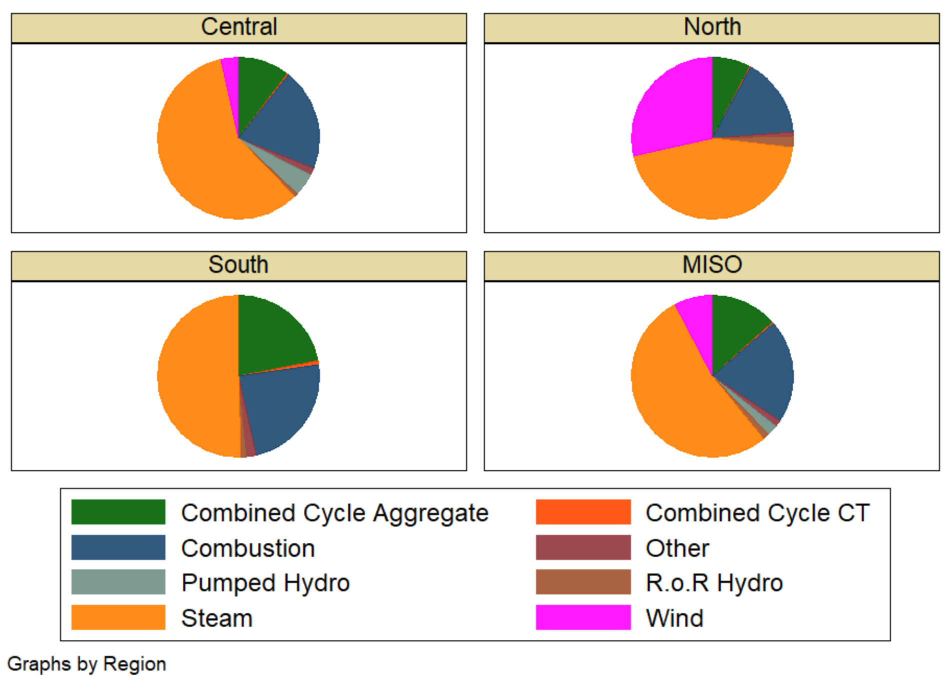


Figure 3: Fuel Mix within MISO and by region.

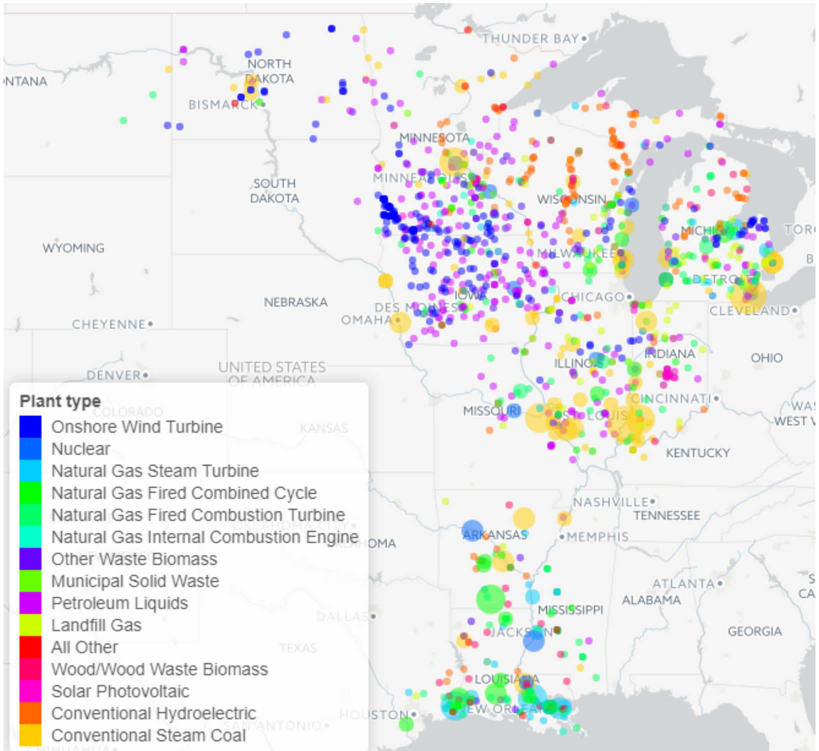


Figure 4: Author's map of electricity generating plans within MISO from EIA form 860, 2014.

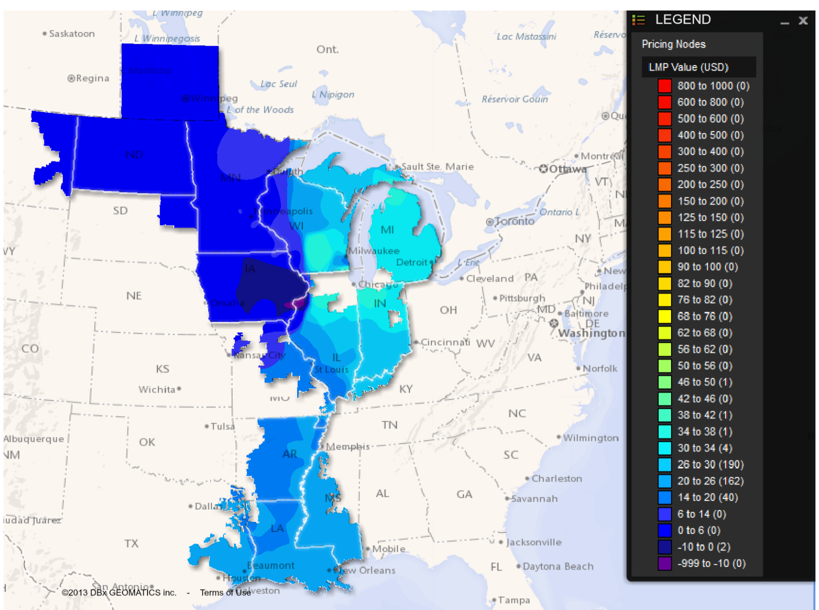
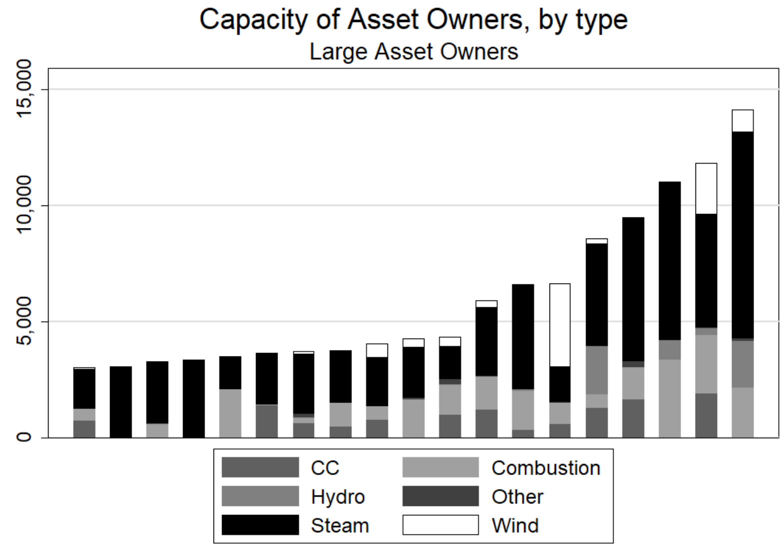
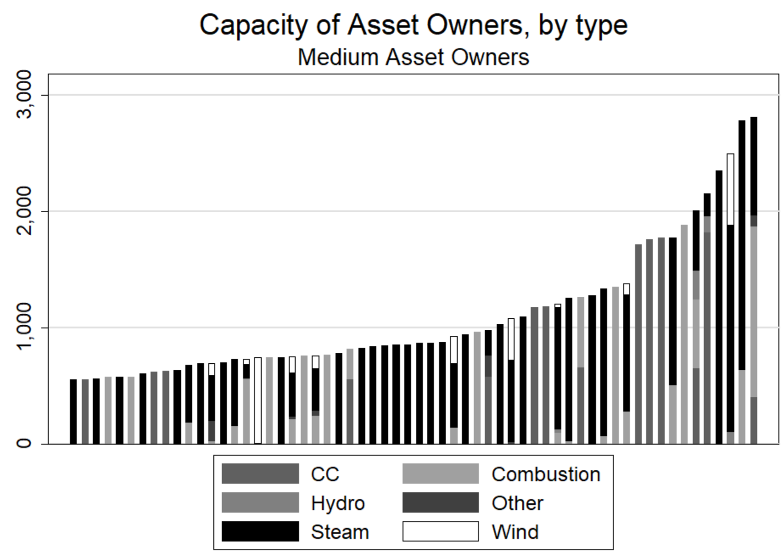


Figure 5: Map of MISO showing the variance in the nodal, locational marginal price (LMP). www.misoenergy.org accessed 4/13/2017.





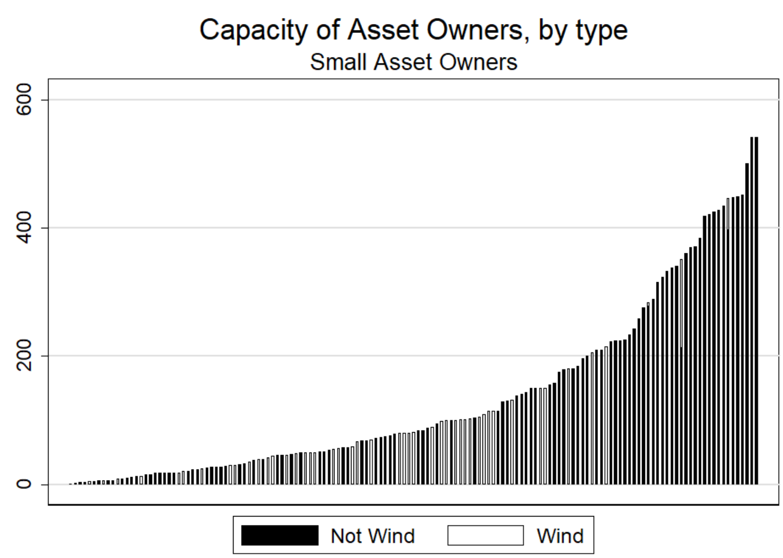


Figure 6: Generation assets by Owner. Vertical axis is Megawatts.

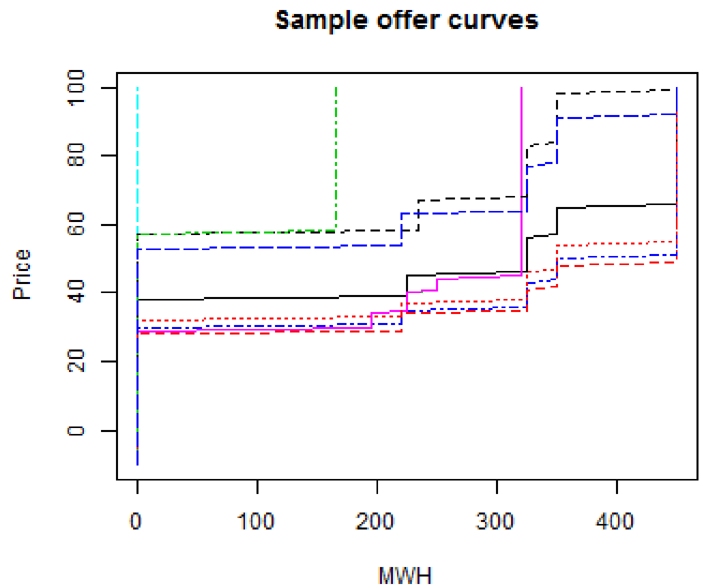


Figure 7: Sample subset of 10 offer curves from a steam unit during February 2014.

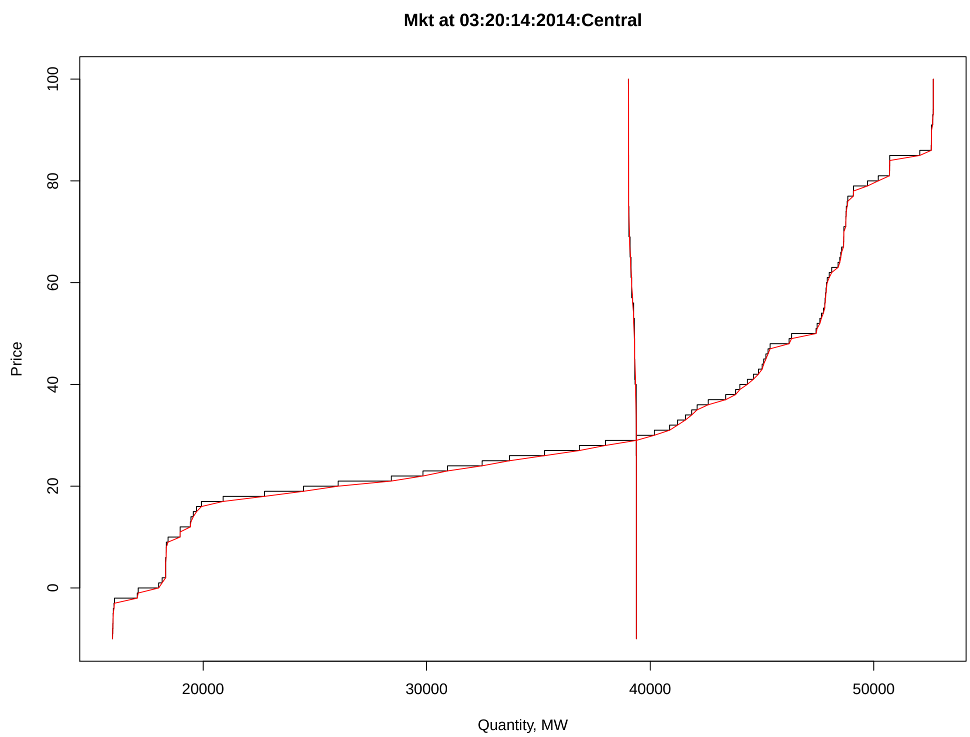


Figure 8: Reconstructed aggregate market supply and demand for a given hour within the central geographic market of MISO. The red line is a monotonic spline of best fit.

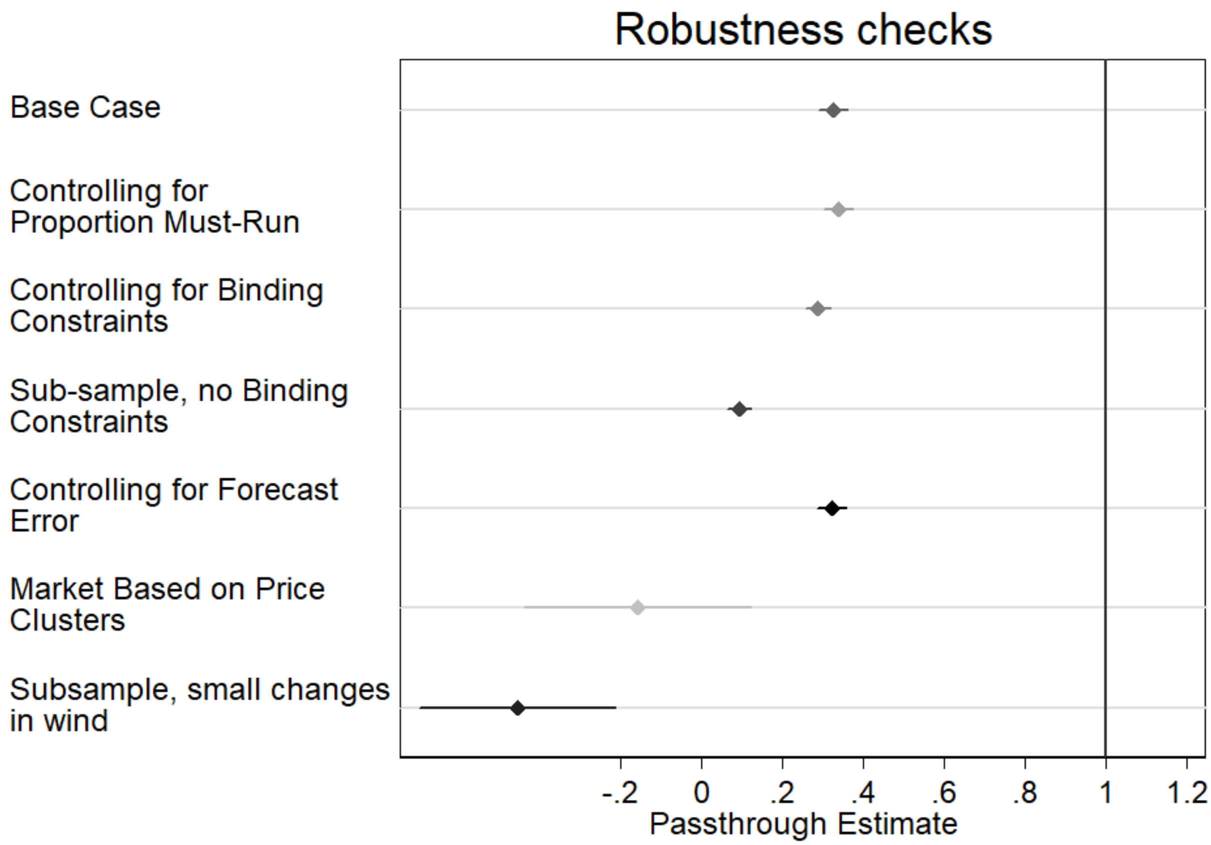


Figure 9: Point estimate and 95% confidence interval for ρ in Equation 6 including different controls and for different subsamples. The confidence interval is constructed with standard errors clustered at the owner level.

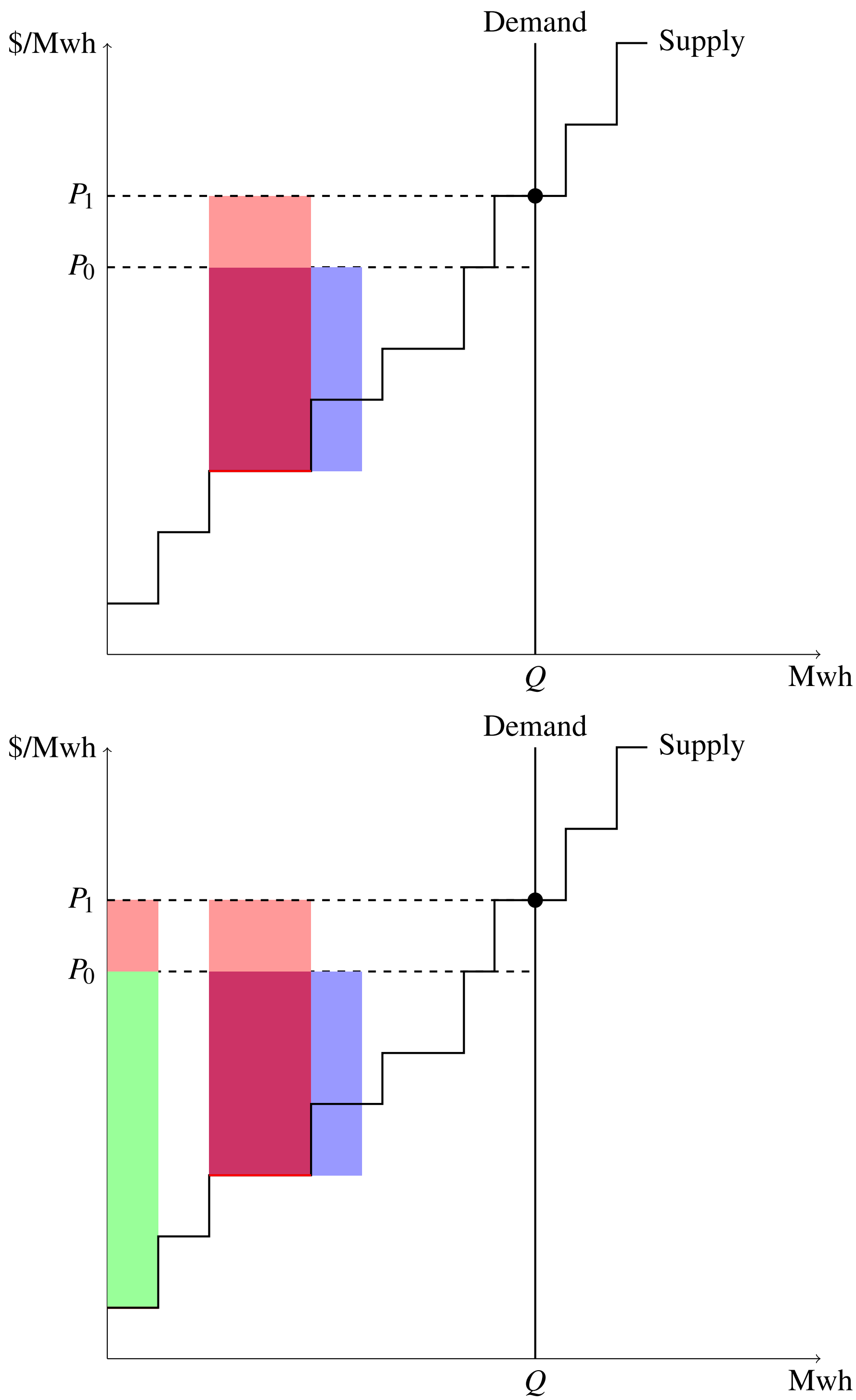


Figure 10: Difference in the incentives to curtail for an independent generator, versus a generator that owns wind assets. Generally, when a firm with market power considers the incentives to curtail the trade off a lower price with a larger quantity with a higher price and a smaller quantity. When they also own wind based assets, they receive an additional benefit of increasing the price as revenue off of the wind based asset.

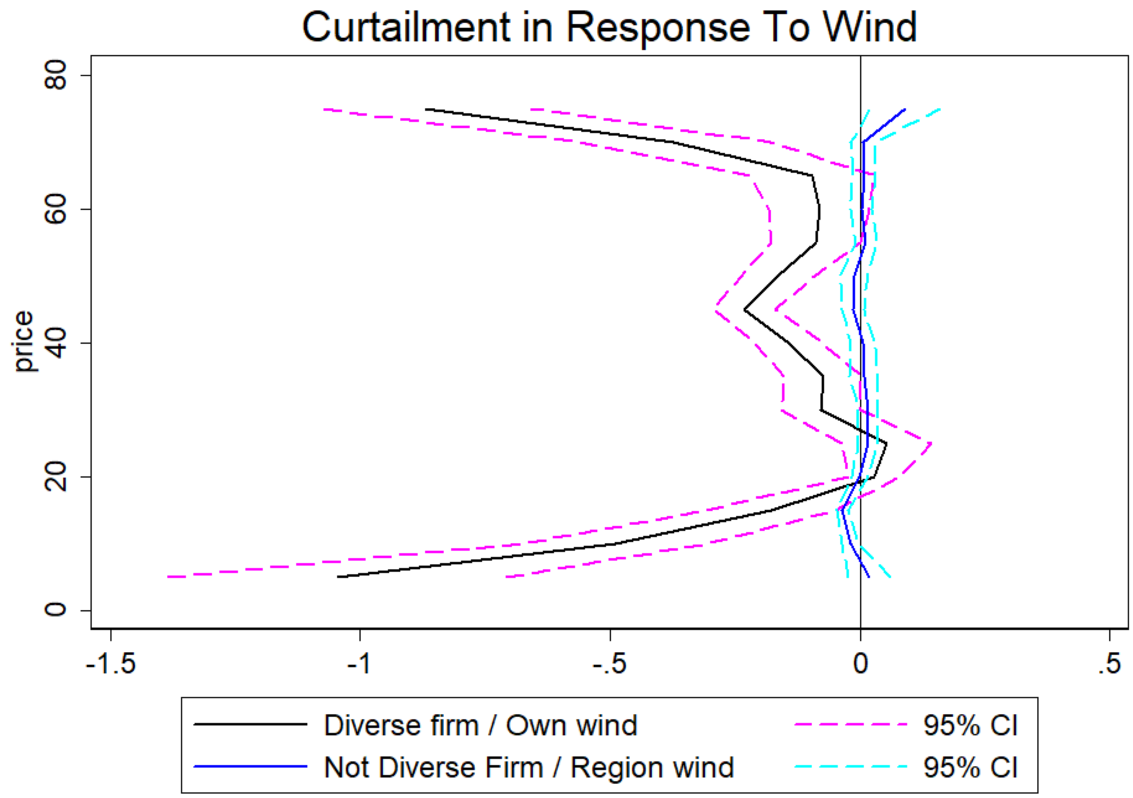


Figure 11: The set of β_b from Equation 10 for diverse firms in response to their own wind generation and for the non-diverse firms in response to total market wind. 95% confidence interval shown with robust standard errors clustered at the owner-by-month-year level.

Table 1: Summary Statistics Real Time Offer Bid Information

	Mean	Std. Dev.	Min	Max
Economic max Mw	145.40	202.31	-1.2	3710.0
Economic min Mw	84.46	153.44	-250.0	1773.0
Emergency max Mw	150.81	209.50	-1.2	7521.0
Emergency min Mw	73.15	136.06	-250.0	1773.0
Target Mw reduction	24.13	36.28	0.0	195.0
Curtailment price	845.80	282.58	0.0	1000.0
Must run flag	0.54	0.50	0.0	1.0
Unit available flag	0.94	0.24	0.0	1.0
Self schedule Mw	24.54	112.78	-10.0	1306.0
Observations	16337370			

Data come from MISO market reports from January of 2014 to December of 2016. Full sample.

Table 2: Summary Statistics of Real Time Market Outcomes

	Mean	Std. Dev.	25 p-tile	75p-tile	Obs.
Mwh Generated, unit-hour	114.21	186.66	3.51	142.80	16337370
Steam Turbine	220.28	235.80	47.92	331.00	6180633
Combined Cycle ST	140.39	66.80	86.81	191.44	468
Combustion Turbine	55.49	120.51	0.00	50.00	2604246
Diesel Unit	0.25	1.49	0.00	0.00	235724
Run of River	17.18	30.63	4.30	17.45	1299560
Pumped Storage	-19.96	199.20	-167.46	104.53	107101
Combined Cycle CT	62.62	75.50	-0.75	168.37	2486
Combined Cycle Aggregate	277.61	161.38	170.00	433.42	723668
Wind Unit	27.61	39.06	2.74	37.11	4692787
Oth. Fossil	28.92	65.31	1.95	17.00	274368
Oth. Diesel	74.72	74.21	4.00	158.00	17685
Demand Response1	1.35	6.46	0.00	0.00	167496
Demand Response2	-14.60	30.88	-53.00	7.00	31148
USD/Mwh, unit-hour	27.38	29.82	19.20	30.37	16337370
Steam Turbine	28.54	28.98	20.12	30.80	6180633
Combined Cycle ST	31.04	9.82	26.35	32.96	468
Combustion Turbine	30.13	33.69	20.70	32.26	2604246
Diesel Unit	28.65	34.07	18.94	31.46	235724
Run of River	29.57	32.64	20.26	31.93	1299560
Pumped Storage	30.69	31.47	21.44	31.35	107101
Combined Cycle CT	32.58	17.75	26.30	36.05	2486
Combined Cycle Aggregate	29.58	28.94	21.07	31.50	723668
Wind Unit	23.11	27.11	15.80	27.90	4692787
Oth. Fossil	29.09	32.49	20.01	31.50	274368
Oth. Diesel	43.56	57.34	24.22	41.16	17685
Demand Response1	26.32	19.18	20.18	28.52	167496
Demand Response2	29.07	23.44	21.50	30.10	31148
Total Mwh, market-hour	23800.39	10432.75	15918.13	31112.61	78399
Central	36563.07	7451.74	31078.53	41289.66	26133
North	15650.75	2368.73	13948.34	17242.37	26133
South	19187.34	3847.50	16493.07	21337.19	26133
Wind Mwh, market-hour	1652.43	2222.48	0.00	2261.31	78399
Central	998.41	681.70	427.67	1462.76	26133
North	3958.89	2423.96	1886.49	5870.55	26133
South	0.00	0.00	0.00	0.00	26133
USD/Mwh, market-hour	27.66	24.18	19.73	30.46	78399
Central	29.90	22.36	21.75	31.87	26133
North	23.09	21.78	15.89	27.04	26133
South	29.99	27.34	21.23	31.98	26133

Data come from MISO market reports from January of 2014 to December of 2016. Full sample.

Table 3: Summary statistics for recovered supply and demand curves

	Mean	Std. Dev.	25 p-tile	75p-tile
Equilbrium Price	20.51	6.74	16.00	24.00
Demand Slope at Equilbrium	-1.26	7.01	0.00	0.00
Supply Slope at Equilbrium	1447.26	903.38	752.24	1971.46
Owner Residual Demand Slope at Equilbrium	-1332.17	893.99	-1864.44	-640.71

Data come from MISO market reports from January of 2014 to December of 2016. Slopes represent the change in quantity (Mwh) for a one unit change in price (USD). Full sample of 78399 observations.

Table 4: Estimates for the Merit Order Effect

	Estimated eq. 5		Derived $\frac{dp}{dw}$				
	$\hat{\beta}_1$	$\hat{\beta}_2$	Mean	Std. Dev.	10th-tile	90th-tile	N
Full Sample	-1.257***	0.170***	-1.10	1.82	-1.94	-0.34	11671292
	(0.00416)	(0.00100)					
Hour 0 - Hour 3	-1.153***	0.167***	-1.09	1.36	-2.04	-0.33	1864391
	(0.00436)	(0.00198)					
Hour 4 - Hour 7	-1.215***	0.312***	-1.09	1.58	-1.99	-0.33	1897179
	(0.0160)	(0.00522)					
Hour 8 - Hour 11	-1.161***	0.205***	-1.09	1.55	-1.91	-0.34	1961603
	(0.0101)	(0.00208)					
Hour 12 - Hour 15	-1.460***	0.156***	-1.10	1.96	-1.88	-0.35	2004773
	(0.00868)	(0.00170)					
Hour 16 - Hour 19	-1.287***	0.130***	-1.14	2.11	-1.93	-0.36	2012462
	(0.0120)	(0.00217)					
Hour 20 - Hour 23	-1.197***	0.0984***	-1.08	2.17	-1.90	-0.34	1930884
	(0.00746)	(0.00162)					
Region, North	-3.574***	3.598***	-1.46	1.42	-2.37	-0.69	3469361
	(0.0127)	(0.0160)					
Region, Central	-1.614***	1.447***	-0.71	1.54	-1.06	-0.30	5902852
	(0.0143)	(0.00359)					
Region, South	0	2.576***	-1.55	2.64	-2.54	-0.63	2299079
	(.)	(0.0227)					

Data come from MISO market reports from January of 2014 to December of 2016. For the estimated coefficients from Equation 5, standard errors are in parenthesis and *** denotes the p-vale is less that 0.01. The derived $\frac{dp}{dw}$ comes from Equation 3.

Table 5: Estimates for the Total Effect on Price

	Mean	Std. Dev.	10 p-tile	90 p-tile	Obs.
Full Sample	-2.28	6.06	-6.87	0.00	78388
Hour 0 - Hour 3	-2.83	7.57	-8.26	0.00	13065
Hour 4 - Hour 7	-2.63	8.44	-7.49	0.00	13068
Hour 8 - Hour 11	-1.90	3.98	-5.99	0.00	13068
Hour 12 - Hour 15	-1.99	4.36	-6.16	0.00	13062
Hour 16- Hour 19	-2.04	5.06	-6.06	0.00	13060
Hour 20 - Hour 23	-2.32	5.51	-6.95	0.00	13065
Central	-0.71	1.81	-1.25	-0.10	26133
North	-6.15	9.17	-12.35	-0.98	26133
South	0.00	0.00	0.00	0.00	26122

Outline in Equation 4, $dp = -\frac{1}{\sum S_o'(p)} dW$. Unit of observation is a market hour.

Table 6: Pass-through of Increased Renewable Generation

	Market Price			
$\frac{dp}{dW}W$, \$	0.137***	0.255***	0.248***	0.326***
	(0.0769)	(0.0359)	(0.0595)	(0.0178)
Total Gwh, market-hour	0.443***	0.246***	1.245***	0.959***
	(0.0413)	(0.0349)	(0.0419)	(0.0772)
Year-Month-Hour Fixed Effects	no	yes	no	yes
Unit Fixed Effects	no	no	yes	yes
Observations	11671292	11671292	11671289	11671289
R-squared	0.0312	0.159	0.0851	0.183

Notes: Data comes from MISO's daily market reports from 2014 to 2016, full sample excluding wind turbines. *** denote p-vale < 0.01 for the hypothesis test $H_0 : \rho = 1$ against $H_1 : \rho \neq 1$ in row one and $H_0 : \beta = 0$ against $H_1 : \beta \neq 0$ for row two. Standard errors, clustered at the owner level, are in parenthesis.

Table 7: Pass-through of increased Renewable Generation, Market Level

	Market Price			
$\frac{dp}{dW}W$, \$	0.268 ***	0.301 ***	0.300 ***	0.312**
	(0.171)	(0.0836)	(0.122)	(0.0181)
Total Gwh, market-hour	0.404**	0.225*	1.328*	0.942
	(0.0201)	(0.0254)	(0.213)	(0.235)
Year-Month-Hour Fixed Effects	no	yes	no	yes
Unit Fixed Effects	no	no	yes	yes
Num. of Obs.	78396	78396	78396	78396
R-squared	0.0403	0.235	0.0921	0.250

Notes: Data comes from MISO's daily market reports from 2014 to 2016, sample aggregated to the market-hour of sample level. *** denote p-vale $<$ 0.01 for the hypothesis test $H_0 : \rho = 1$ against $H_1 : \rho \neq 1$ in row one and the standard hypothesis otherwise. Standard errors, clustered at the market level, are in parenthesis.

Table 10: Controlling for firm dynamics

	Market Price			
$\frac{dp}{dW}W$	0.0238 ***	0.180***	0.268***	0.339***
	(0.101)	(0.0405)	(0.0573)	(0.0187)
Total Gwh, market-hour	1.431***	0.859***	1.965***	1.430***
	(0.170)	(0.126)	(0.0324)	(0.127)
Proportion Gwh Must Run	-0.00552***	-0.00334***	-0.00446***	-0.00274***
	(0.000711)	(0.000535)	(0.000263)	(0.000349)
Year-Month-Hour Fixed Effects	no	yes	no	yes
Unit Fixed Effects	no	no	yes	yes
Observations	11672198	11672198	11672195	11672195
R-squared	0.0427	0.162	0.0887	0.184

Notes: Data comes from MISO's daily market reports from 2014 to 2016. *** denote p-vale $<$ 0.01 for the hypothesis test $H_0 : \rho = 1$ against $H_1 : \rho \neq 1$. Standard errors, clustered at the owner level, are in parenthesis.

Table 8: Pass-through of Increased Renewable Generation, by hour set

	Market Price			
Hour 0 - Hour 3 $\times \frac{dp}{dW}W$	0.507***	0.268***	0.517***	0.411***
	(0.0339)	(0.0277)	(0.0206)	(0.0360)
Hour 4 - Hour 7 $\times \frac{dp}{dW}W$	0.169***	0.216***	0.198***	0.291***
	(0.0534)	(0.0208)	(0.0464)	(0.0151)
Hour 8 - Hour 11 $\times \frac{dp}{dW}W$	-0.395***	0.296***	-0.138 ***	0.328***
	(0.152)	(0.104)	(0.140)	(0.0926)
Hour 12 - Hour 15 $\times \frac{dp}{dW}W$	0.104 ***	0.519***	0.375***	0.520***
	(0.0823)	(0.0655)	(0.0488)	(0.0381)
Hour 16- Hour 19 $\times \frac{dp}{dW}W$	-0.451***	0.144*	-0.216*	0.133**
	(0.131)	(0.0620)	(0.108)	(0.0490)
Hour 20 - Hour 23 $\times \frac{dp}{dW}W$	0.191***	0.232***	0.342***	0.304***
	(0.0816)	(0.0462)	(0.0665)	(0.0261)
Total Gwh, market-hour	0.441***	0.244***	1.228***	0.964***
	(0.0400)	(0.0358)	(0.0417)	(0.0786)
Year-Month-Hour Fixed Effects	no	yes	no	yes
Unit Fixed Effects	no	no	yes	yes
Observations	11671292	11671292	11671289	11671289
R-squared	0.0349	0.159	0.0873	0.183

Notes: Data comes from MISO's daily market reports from 2014 to 2016, full sample excluding wind turbines. *** denote p-vale < 0.01 for the hypothesis test $H_0 : \rho = 1$ against $H_1 : \rho \neq 1$ in all rows but the first one.. The first row has the standard hypothesis test. Standard errors, clustered at the owner level, are in parenthesis.

Table 9: Pass-through of Increased Renewable Generation, by load decile

	Market Price			
Total Gwh, market-hour	0.372***	0.223***	1.184***	0.940***
	(0.0315)	(0.0311)	(0.0397)	(0.0730)
Load Decile=0 × $\frac{dp}{dW}W$	0.426***	0.300***	0.431***	0.368***
	(0.0294)	(0.0243)	(0.0165)	(0.0325)
Load Decile=1 × $\frac{dp}{dW}W$	0.347***	0.322***	0.425***	0.386***
	(0.0326)	(0.0326)	(0.0221)	(0.0325)
Load Decile=2 × $\frac{dp}{dW}W$	0.414***	0.648***	0.739***	0.771***
	(0.0786)	(0.0763)	(0.0478)	(0.0597)
Load Decile=3 × $\frac{dp}{dW}W$	-0.269***	0.308***	0.157*	0.402***
	(0.0863)	(0.0819)	(0.0637)	(0.0636)
Load Decile=4 × $\frac{dp}{dW}W$	-0.991***	-0.156***	-0.647***	-0.118 ***
	(0.136)	(0.110)	(0.1000)	(0.0921)
Load Decile=5 × $\frac{dp}{dW}W$	8.840***	3.554***	-2.510***	-2.012***
	(0.574)	(0.298)	(0.374)	(0.308)
Load Decile=6 × $\frac{dp}{dW}W$	2.048***	2.082***	-1.266***	0.289***
	(0.226)	(0.130)	(0.0900)	(0.0676)
Load Decile=7 × $\frac{dp}{dW}W$	-0.163***	0.531***	-0.790***	0.207***
	(0.0724)	(0.0516)	(0.0492)	(0.0393)
Load Decile=8 × $\frac{dp}{dW}W$	-1.319***	0.710***	-1.363***	0.699***
	(0.214)	(0.150)	(0.193)	(0.144)
Load Decile=9 × $\frac{dp}{dW}W$	-2.812***	-1.683***	-2.172***	-1.304***
	(0.0759)	(0.0636)	(0.0814)	(0.0626)
Year-Month-Hour Fixed Effects	no	yes	no	yes
Unit Fixed Effects	no	no	yes	yes
Num. of Obs.	11671292	11671292	11671289	11671289
R-squared	0.0485	0.164	0.0949	0.186

Notes: Data comes from MISO's daily market reports from 2014 to 2016, full sample excluding wind turbines. *** denote p-vale < 0.01 for the hypothesis test $H_0 : \rho = 1$ against $H_1 : \rho \neq 1$ in all rows but the first one. The first row has the standard hypothesis test. Standard errors, clustered at the owner level, are in parenthesis.

Table 11: Controlling for Transmission Capacity Constraints

	Market Price			
$\frac{dp}{dW}W$	0.291***	0.305***	0.348***	0.356***
	(0.0590)	(0.0338)	(0.0465)	(0.0177)
Total Gwh, market-hour	0.349***	0.225***	1.038***	0.888***
	(0.0363)	(0.0335)	(0.0323)	(0.0703)
Average number of constraints, hour	2.121***	0.930***	1.617***	0.676***
	(0.103)	(0.110)	(0.107)	(0.0913)
Year-Month-Hour Fixed Effects	no	yes	no	yes
Unit Fixed Effects	no	no	yes	yes
Observations	11672198	11672198	11672198	11672195
R-squared	0.0640	0.163	0.103	0.185

Notes: Data comes from MISO's daily market reports from 2014 to 2016. *** denote p-vale < 0.01 for the hypothesis test $H_0 : \rho = 1$ against $H_1 : \rho \neq 1$. Standard errors, clustered at the owner level, are in parenthesis.

Table 12: Passthrough rate, subsample few capacity constraints

	Market Price			
$\frac{dp}{dW}W$	0.0128 ***	0.0677***	0.127***	0.0942***
	(0.0391)	(0.0182)	(0.0350)	(0.0149)
Total Gwh, market-hour	0.208***	0.0649***	0.923***	0.521***
	(0.0207)	(0.0113)	(0.0265)	(0.0390)
Year-Month-Hour Fixed Effects	no	yes	no	yes
Unit Fixed Effects	no	no	yes	yes
Observations	417732	417732	417732	417679
R-squared	0.0772	0.643	0.344	0.696

Notes: Data comes from MISO's daily market reports from 2014 to 2016. *** denote p-vale < 0.01 for the hypothesis test $H_0 : \rho = 1$ against $H_1 : \rho \neq 1$. Standard errors, clustered at the owner level, are in parenthesis. This subsample is for market participants during hours with less than one binding constraint on average.

Table 13: Controlling for forecasting error

	Market Price			
$\frac{dp}{dW}W$	0.130***	0.253***	0.243***	0.323***
	(0.0758)	(0.0357)	(0.0577)	(0.0175)
Total Gwh, market-hour	0.443***	0.247***	1.244***	0.960***
	(0.0410)	(0.0348)	(0.0418)	(0.0767)
Forecasting Error, Gwh	-0.556	0.133	0.120	-0.0270
	(0.289)	(0.228)	(0.344)	(0.240)
Forecasting Error, squared Gwh	-0.191***	-0.294***	-0.354***	-0.251***
	(0.0545)	(0.0482)	(0.0614)	(0.0436)
Year-Month-Hour Fixed Effects	no	yes	no	yes
Unit Fixed Effects	no	no	yes	yes
Observations	11655036	11655036	11655036	11655033
R-squared	0.0316	0.159	0.0853	0.183

Notes: Data comes from MISO's daily market reports from 2014 to 2016. *** denote p-vale < 0.01 for the hypothesis test $H_0 : \rho = 1$ against $H_1 : \rho \neq 1$. Standard errors, clustered at the owner level, are in parenthesis. Subsample is for market hours with less than 1 Gwh of wind generation.

Table 14: Pass-through rate, only local approximation

	Market Price			
$\frac{dp}{dW}W$	-2.683***	-0.840***	-2.356***	-0.302***
	(0.153)	(0.0954)	(0.196)	(0.152)
Total Gwh, market-hour	0.339***	0.145***	1.168***	1.143***
	(0.0435)	(0.0386)	(0.0330)	(0.0394)
Year-Month-Hour Fixed Effects	no	yes	no	yes
Unit Fixed Effects	no	no	yes	yes
Observations	7066973	7066973	7066973	7066967
R-squared	0.0224	0.167	0.0826	0.197

Notes: Data comes from MISO's daily market reports from 2014 to 2016. *** denote p-vale < 0.01. Subsample is for market hours with less than 1 Gwh of wind generation.

Table 15: Pass-through rate for different market definitions

	Market Price		
$\frac{dp}{dW}W$, 4 markets	-0.243***		
	(0.0286)		
Total Gwh, 4 Markets	0.0174**		
	(0.00604)		
$\frac{dp}{dW}W$, 8 markets		-0.129***	
		(0.0196)	
Total Gwh, 8 Markets		0.00561	
		(0.00562)	
$\frac{dp}{dW}W$, 12 markets			-0.133***
			(0.0186)
Total Gwh, 12 Markets			0.0000639
			(0.00552)
Year-Month-Hour Fixed Effects	yes	yes	yes
Unit Fixed Effects	yes	yes	yes
Observations	5412694	5355710	5304598
R-squared	0.151	0.152	0.157

Notes: Data comes from MISO's daily market reports from 2014 to 2016. *** denote p-vale < 0.01. Standard errors, clustered at the owner level, are in parenthesis.

Table 16: Incorporating Strategic Curtailment

	Market Price			
$\frac{dp}{dW}W$, with Strategic Curtailment	0.107	0.677***	0.346	0.802***
	(0.333)	(0.144)	(0.326)	(0.0979)
Total Gwh, market-hour	0.456***	0.260***	1.244***	0.938***
	(0.0395)	(0.0350)	(0.0428)	(0.0788)
Year-Month-Hour Fixed Effects	no	yes	no	yes
Unit Fixed Effects	no	no	yes	yes
Observations	11672198	11672198	11672198	11672195
R-squared	0.0306	0.158	0.0837	0.181

Notes: Data comes from MISO's daily market reports from 2014 to 2016. Standard errors, clustered at the owner level, are in parenthesis.

Table 17: Own wind impact on owner level ex-ante bid

	Quantity offered by owner at given price			
Own wind generated, Mwh	0.704	0.746	-0.276**	-0.216**
	(0.815)	(0.835)	(0.0898)	(0.0749)
Flexible Price Bins	yes	yes	yes	yes
Year-Month-Hour Fixed Effects	no	no	yes	yes
Owner Fixed Effects	no	yes	no	yes
Observations	2895602	2895602	2895602	2895602
R-squared	0.152	0.164	0.775	0.787

Notes: Data comes from MISO's daily market reports from 2014 to 2016. Realtime bids from owners that own wind turbines and other assets. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors, clustered at the owner level, are in parenthesis.

Appendix B: Firm's incentives

Here I derive the firm's best response in the spirit of Mercadal (2015); Puller (2007), and derive a comparative static with regards to increased renewable generation.

Given the notation presented in the Background, section 2, I can characterize market participant o's profits in market m at time t as

$$\Pi_o(S_o(p)) = p[S_o(p) + \theta_o W] - C_o(S_o(p)) \tag{11}$$

with the assumption of no interaction between markets or time periods.

The optimal strategy employed by the owners of electricity generation assets depends on the uncertainty with respect to the market clearing price. As modeled there are two different forms of uncertainty (1) the quantity demanded, ε, and (2) the quantity of wind being produced ω. The first form of uncertainty, in conjunction with uncertainty over private forward contracts, has been considered by Hortacsu and Puller (2008); Mercadal (2015). The uncertainty in regards to wind is novel.

I define a probability measure over the realizations of price for a given strategy for a particular market as follows:

$$\begin{aligned} H(p;S_o(p)) &= Pr(\hat{p} \leq p|S_o) \\ &= Pr(\sum_{j\neq o} S_j(p) + S_o(p) + w + \omega \geq d(p) + \varepsilon|S_o) \end{aligned} \tag{12}$$

Where the second inequality comes from the market clearing condition and the fact that a lower price is associated with an excess of supply. Using the profit definition with the probability measure, the market participant wants to maximize their expected profit:

$$\max_{S_o(p)} \int_{\underline{p}}^{\bar{p}} U\left[\Pi_o(S_o(p))\right] dH(p;S_o(p)) \tag{13}$$

We can rewrite $dH(p)$ as $H_p + H_S S'$ where the subscript denotes a partial derivative, and define $J \equiv U(\Pi)[H_p + H_S S']$. The first order condition for the Euler Lagrange solution is

$$J_S = \frac{\partial}{\partial p} J_{S'}$$

Where subscripts denote partial derivatives. The left hand side can be expressed as

$$\begin{aligned} J_S =& U'(\Pi)\frac{\partial \Pi}{\partial S}\left[H_p + H_S S'\right] + U(\Pi)\left[H_{Sp} + H_{SS}S'\right] \\ =& U'(\Pi)\left[p - C'\right]\left[H_p + H_S S'\right] + U(\Pi)\left[H_{Sp} + H_{SS}S'\right] \end{aligned}$$

Then noting that, $J_{S'} = U(\Pi)H_S$, we can express the right hand side as

$$\begin{aligned}\frac{\partial}{\partial p}J_{S'} =& U'(\Pi)\frac{\partial \Pi}{\partial p}H_S + U(\Pi)\left[H_{Sp} + H_{SS}S'\right] \\ =& U'(\Pi)\left[S'p + S + \theta W - C'S'\right]H_S + U(\Pi)\left[H_{Sp} + H_{SS}S'\right]\end{aligned}$$

As a result, the Euler-Lagrange condition implies

$$\left[p - C'\right]\left[H_p + H_S S'\right] = \left[S'p + S + \theta W - C'S'\right]H_S$$

which can be simplified to

$$\left[p - C'\right]H_p = \left[S(p) + \theta W\right]H_S$$

where H_p and H_{S_o} denote the partial derivatives of the probability measure with respect to the subscript. Contextually, H_p is the density of prices in the spot market and H_{S_o} is the change in the price distribution when participant o increases it's supply offer.

We can isolate all the random terms as follows:

$$\begin{aligned}H(p;S_o(p)) &= Pr(\hat{p} \leq p|S_o) \\ &= Pr(\sum_{j\neq o} S_j(p) + S_o + w + \omega \geq d(p) + \varepsilon|S_o) \\ &= Pr(\omega - \varepsilon \geq d(p) - \sum_{j\neq o} S_j(p) - S_o - w|S_o) \\ &= 1 - \Gamma\left[d(p) - \sum_{j\neq o} S_j(p) - S_o - w\right]\end{aligned} \tag{14}$$

Where $\Gamma()$ is the cumulative density function for the random variable $\eta = \omega - \varepsilon$.

From this expression of the probability measure, we can derive

$$
\begin{aligned}
H_S =& \Gamma' \left[d(p) - \sum_{j \neq o} S_j(p) - S_o - w \right] \\
H_p =& -\Gamma' \left[d(p) - \sum_{j \neq o} S_j(p) - S_o - w \right] \left(d'(p) - \sum_{j \neq o} S'_j(p) \right)
\end{aligned}
$$

We can observe that the residual demand for any market participant is $RD(p) = d(p) + \varepsilon - \sum_{j \neq o} S_j(p) - w - \omega$ making $\frac{H_S}{H_p}$ an expression for the reciprocal of the slope of the residual demand. This provides an optimality condition that is related to the inverse elasticity pricing rule:

$$
\left[p - C'_o(S_o(p)) \right] = \left[S_o(p) + \theta_o W \right] \frac{-1}{RD'(p)} \tag{15}
$$