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# Dynamic Competition and Arbitrage in Electricity Markets: The Role of Financial Players

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# Dynamic competition and arbitrage in electricity markets: The role of financial players

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**Abstract**

I study the role of purely financial players in electricity markets, where they trade alongside physical buyers and sellers. Using detailed individual data, I examine physical and financial firms' response to regulation that exogenously increased financial trading. I find this reduced generators' market power and increased consumer surplus. I develop a structural test of static Nash equilibrium, and reject it in favor of dynamic competition consistent with tacit collusion by a group of firms. To implement the test, I present a new method to study the competitive structure of electricity markets using machine learning tools to define markets.

## 1 Introduction

The role of financial traders in commodity markets is controversial. Although they are expected to facilitate risk sharing and increase informational efficiency, distrust of financial traders is so widespread that some politicians have proposed restrictions and bans on their activity. In this paper, I employ a unique dataset to study the role of speculators as competitors of physical producers in the Midwest

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electricity market.

Typically, it is hard to identify the effect of speculation on a commodity market because only aggregate market outcomes are observed and the physical good is not traded together with its derivatives. Electricity markets provide an excellent setting to study the effects of financial trading since all transactions involving both physical producers and financial players occur in a single market. This paper focuses specifically on the Midwest electricity market (MISO[1]), which has two additional advantages. First, a regulatory change in 2011 that exogenously attracted more financial traders, which allows me to identify the effect these traders had on the market. Second, I observe individual-level behavior and can separately analyze how buyers, producers, and financial traders reacted to the regulatory change. Exploiting these unique features, this paper shows that financial trading decreases physical producers' market power and increases consumer welfare.

In electricity markets, financial trading takes place in sequential markets where physical energy is traded. There is first a forward market that schedules production a day in advance, and then a spot market that balances demand and supply immediately before operation. In such markets, generators have incentives to engage in intertemporal price discrimination. Instead of fully scheduling their intended production in the forward market and using the spot market for unexpected shocks, producers withhold part of their generation in the forward market in order to increase the forward price (Ito and Reguant, 2016). This results in a forward premium that has been documented in several wholesale electricity markets. [2]

Because a forward premium distorts planning decisions and therefore results in inefficiencies, wholesale electricity markets have introduced financial traders to

[1]Midwest Independent System Operator until 2013, then Midcontinent ISO.

[2]Bowden et al. (2009) and Birge et al. (2018) find it in the Midwest, Saravia (2003) in New York, Jha and Wolak (2018); Borenstein et al. (2008) in California, Ito and Reguant (2016) in the Iberian market, among others.

arbitrage these price differences. These traders sell (buy) in the forward market, and their transaction is then reversed in the spot market, such that their profits are the (negative) forward premium times the quantity traded. In the Midwest electricity market the forward premium persisted despite the presence of financial traders because high transaction costs made arbitrage unprofitable (Birge et al., 2018). A regulatory change lowered these costs significantly in April 2011, after which financial trading increased and the forward premium became smaller.

I show that generators' withholding in the forward market, measured as the difference between spot and forward sales, also decreased, as would be expected when there is price discrimination and arbitrage becomes cheaper. Interestingly, generators did not only react to the regulatory change by exerting less market power in the forward market, but they did it months before it was implemented. This response is not consistent with the static Nash equilibrium that we typically assume in structural estimation of auctions, since in a static setting firms are not expected to respond to the sole threat of competition. Moreover, if firms are in a static Nash equilibrium, we would conclude that there is no effect of financial players on competition because generators' behavior is the same right before and right after the regulatory change. If firms were in a dynamic equilibrium, on the other hand, and their behavior was an anticipated response to future competition, financial traders would have an important role in reducing generators' market power.

In order to understand the generators' reaction, I use individual bid data to estimate a static model of optimal generator behavior and test the hypothesis of static Nash equilibrium. Following the approach of Wolak (2000) and Hortacsu and Puller (2008),[3] I build a static model of a generator that decides how much

[3] There are a number of papers following this approach in electricity markets. Wolak (2007) uses the optimality conditions obtained from static profit maximization to estimate firm's marginal costs. He tests the hypothesis of profit maximization and finds no evidence against it. Hortacsu and Puller (2008), on the other hand, find that while it describes big firms' behavior well, small firms are far less sophisticated. Reguant (2014) studies an auction in which firms' bids can include complementarities across production hours, which she uses to estimate startup costs. Ryan (2014) estimates marginal costs from bids in the Indian market, taking into account

to bid in the forward and spot markets. In MISO, these markets are organized as sequential auctions in which firms bid step functions specifying how much they are willing to sell or buy at each price, so I extend Hortacsu and Puller (2008)'s model of optimal bidding in the spot market to the case of a sequential market.

In my model, a firm's optimal bid depends on its contract position[4] and on the elasticity of its residual demand, *i.e.* total demand minus the quantity sold by competitors. Since future competition does not affect residual demand today, the model predicts that generators in the Midwest will only lose market power when transaction costs are reduced and financial trading increases. Consequently, the model rationalizes the observed change in behavior as a reaction to changes in current market conditions, *i.e.* residual demand or contract positions, which are not coming from increased financial trading. I test the model's optimality condition empirically and find that it does not hold, suggesting that, rather than reacting to current market conditions, generators changed their behavior in anticipation of increased competition in the future.

I consider two alternative hypotheses, *i.e.* two mechanisms that could explain why firms changed their conduct before market conditions changed. The first is a cooperative equilibrium in a repeated game, which is sustained as long as a player's benefits from continued cooperation outweigh the gains from deviating and stealing the market today. In the context of this paper, increased arbitrage in the future eliminates the benefits from future cooperation, because speculators will arbitrage away any resulting price gap. Given that the same firms interact with each other every day, and have good information about demand and each others' costs, a cooperative equilibrium is in principle possible.[5]

The second mechanism is entry deterrence. If generators expected financial, or "virtual", traders to enter the market and arbitrage the forward premium,

transmission constraints to estimate the consequences of transmission investment

[4]Wolak (2000) shows that the forward contract position affects a firm's incentives to exert market power.

[5]Evidence of tacit collusion in electricity markets has been found by Fabra and Toro (2005) in the Spanish electricity market.

they might have tried to make the market less attractive by lowering the forward premium. Entry deterrence does not seem to be sustainable in equilibrium, as there is no link between periods that could make today's competition affect the entrant's profits in the future.[6] Nonetheless, I include this mechanism for the sake of completeness, since the generators' pricing changes might have been a failed attempt to deter the entry of financial traders.

The test I use to evaluate generators' conduct is based on a simple intuition. In a repeated game cooperative equilibrium, firms do not play best response, but behave as if the market were *less* competitive than it is. Under entry deterrence, generators do not play best response either, but they act as if the market were *more* competitive than it is. Therefore, if I reject the null of static Nash and find that firms' markup is higher than what would be statically optimal, their behavior is consistent with a cooperative equilibrium. If, on the other hand, the observed markup is lower than statically optimal, their behavior is consistent with entry deterrence. Although these hypotheses do not exhaust the space of alternatives, they can be taken as examples of two different ways in which the null hypothesis of static best response can be rejected, *i.e.* behaving *more* or *less* competitively than what would be optimal under static best response.[7]

The implementation of the test of static Nash equilibrium requires to compute the residual demand faced by each firm, which in principle can be done by adding up the demand bids and subtracting the supply bids of the generator's competitors. However, this exercise is complicated by the fact that the Midwest electricity market is a nodal market, *i.e.* there may be a different clearing price

[6]Like dynamic demand, for instance, as in Goolsbee and Syverson (2008). In this context, increasing capacity as in **?** would not make a firm's threat more credible. Obtaining reputation as a fighter could justify lowering today's profits to deter future entry (Mil), but in this case the market became more competitive before entry.

[7]Puller (2007) studies the competitiveness of the electricity market in California. Using a Cournot model for the spot market, he simulates the price that would have resulted under perfect competition, Cournot-Nash, and tacit collusion, concluding that the market is well described by the static Nash equilibrium. My approach is similar but I have the advantage of observing all bids. Additionally, I am mainly interested in the effect of financial trading on competition, instead of assessing the overall competitiveness of the market.

in each location or node where electricity is traded. This price represents the marginal cost of supplying energy at that node, which varies significantly because nodes are connected by transmission lines with limited capacity. When the lines reach maximum capacity, demand cannot necessarily be satisfied by the lowest cost generator and is instead satisfied by the lowest cost feasible generator.

To deal with nodal pricing, I assume the MISO market is split into several independent markets. I define these markets empirically by using machine learning techniques that cluster nodes together based on the correlation of their prices. Unlike most applications of these clustering techniques, I build a measure of fit that allows me to choose the market definition that better fits the data. To do this, I simulate prices that would clear under each alternative market definition and compare them with those observed in the data. I find that the clusters fit the data fairly well. To the best of my knowledge, this paper is the first to use a structural model to study a nodal market, which is made possible by these market definitions.

My findings indicate that, prior to learning of the impending regulatory change, firms acted as if they were facing a less competitive market than they were, and therefore exerted more market power than would be optimal given the elasticity of the residual demand they actually faced. After learning about the future fall in transaction costs for financial traders, the market moved to a static Nash equilibrium. Moreover, I find that this effect comes mainly from firms located in the West area of the market; for generators in the rest of the market I cannot reject the null of static Nash equilibrium. This reaction is consistent with a repeated game cooperative equilibrium that unravels when future benefits from cooperation disappear.

While financial traders reduce generators' market power in the forward market, they do not eliminate their market power altogether since generators could exert more market power in the spot market once they are not able to intertemporally price discriminate. I estimate the firms' markups in the spot market and find that they remain roughly at the same level during the whole period of analysis, as opposed to what Ito and Reguant (2016) find by running a counterfactual in which they introduce financial traders into a sequential market that does not have them. There are two reasons behind the differences. First, in this paper firms move from a dynamic to a static equilibrium instead of going from price discrimination to uniform pricing in a static setting. Second, the market operator closely monitors production withholding in the spot market but not in the forward market, reducing firms' ability to exert market power in the spot market.

As firms exert less market power in the forward market and there are no big changes in the spot market, financial trading has a positive effect on welfare. Consumers are better off because they pay less for energy, saving roughly $1,800,000 per day on average; producers are worse off because they cannot price discriminate. Nonetheless, the total effect is not just a transfer from producers to consumers because production costs go down. Less underscheduling in the forward market results in better planning, which allows cheaper generating units to be scheduled and decreases production costs. Though I do not quantify it, this effect is likely to be sizable since 98 to 99 percent of production is scheduled in the forward market.

This paper makes two main methodological contributions. First, it presents a data driven method to define markets that does not require to impose a particular form of competition between firms. Further, I propose a measure of fit that allows to select the market definition that better describes the data, which is not typically possible with clustering tools from machine learning. This methodology is what makes possible to analyze a nodal market following a structural approach.

Second, this paper presents a case in which the standard assumption of static Nash equilibrium does not hold. This assumption would need to hold not only for a structural estimation to be able to identify structural parameters, but also for any analysis that compares variables of interest before and after the policy change and attributes the differences to the respective policy. Though in most markets it is not possible to obtain a dataset rich enough to implement the test of static Nash equilibrium proposed in this paper,[8] the fact that in this case firms are in a dynamic equilibrium suggests a careful consideration of how results would change under alternative equilibria is important for robust analysis.

The rest of this paper is organized as follows: The next section describes the Midwest electricity market. Section 3 then describes the market's reaction to lower transaction costs for financial traders. Section 4 presents the model, and Section 5, the data. The empirical strategy is described in Section 6, and results are presented in Section 7. Section 8 concludes.

# 2 The MISO energy market

The Midcontinent Independent System Operator (MISO) serves 42 million people in the American and Canadian Midwest, and collects US$20 billion in gross charges per year. Its energy market is organized as an auction in which participants submit bids to buy or sell energy in particular nodes or locations; MISO then clears the market at the lowest prices for each location given the capacity of the transmission network. This is known as nodal pricing and results in prices that typically vary across nodes because transmission constraints do not always allow demand to be covered by the cheapest generator.

Like many deregulated electricity markets, the MISO energy market is structured as a sequential auction. There is first a day-ahead or forward market that schedules production for the 24 hours of the next day. It takes place once a day and clears simultaneously for each hour of the next day. Then, there is a real-time or spot market, which takes place thirty minutes before operation and balances demand and supply to accommodate last minute shocks.

The forward market is purely financial in the sense that no energy is traded. Firms are paid for the quantity sold in the forward market regardless of how

[8] In structural analysis, optimality conditions are usually imposed on the data and used to obtain an estimate of primitive parameters from the model. Instead, the richness of my data allows me to compute every component of the optimality condition for the forward market.

much they actually produce, but the difference between the forward schedule and the actual production is settled at the spot price. For instance, if a generator schedules 100MWh in the forward market, but then clears 80MWh in the spot market, she receives the forward price for 100MWh but has to pay the spot price for 20MWh, as if she were buying.

The rationale behind a sequential market is that generation is cheaper when it is planned, so scheduling forecasted demand in advance decreases production costs. Generators with lower marginal costs generally have high startup costs and cannot adjust the level of production easily. On the other hand, generators that can start and vary production quickly, called peakers, often have high marginal costs. By scheduling production in the forward market, it is easier to satisfy expected demand with cheaper generators and only unanticipated shocks with peakers. Additionally, scheduling the 24 hours of the next day in the forward market increases efficiency by taking into account complementarities across hours, which come from the startup costs faced by some generating units.[9]. The existence of the forward market also allows market participants to face less risk, as price is more volatile in the real-time than in the day-ahead market.[10]

## 2.1 Price discrimination and arbitrage

In a perfectly competitive market, firms would schedule their intended generation in the forward market and sell in the spot market only when they face unexpected shocks. However, market power is a concern in electricity markets even with concentration levels that would be considered competitive in other industries(Borenstein et al., 2002; Ito and Reguant, 2016; Ryan, 2014; Fabra and Toro, 2005). When generators have market power, they have incentives to withhold sales in the forward market in order to increase the forward price, which results in a forward premium (Ito and Reguant, 2016). This forward premium

[9] See Reguant (2014) for an analysis of the welfare consequences of allowing complementarities in bids.

[10] Additionally, Allaz and Vila (1993) show that sequential markets enhance competition among firms when they compete à la Cournot.

has been observed in several deregulated wholesale electricity markets (Saravia, 2003; Ito and Reguant, 2016; Saravia, 2003; Jha and Wolak, 2018), including MISO (Bowden et al., 2009; Birge et al., 2018).[11]

Financial or virtual traders have been introduced into several wholesale electricity markets to arbitrage this forward premium. These bidders profit from the differences between the forward and the spot price. For instance, selling 1 MWh in the forward market yields profits equal to $P^{forward} - P^{spot}$ because it implicitly requires the purchase of 1MW in the spot market. In the presence of a forward premium, financial participants have incentives to sell in the forward market, neutralizing generators' underbidding and leading to price convergence.

The introduction of financial traders to wholesale electricity markets has been controversial. On the one hand, the forward premium decreased after arbitrageurs were allowed (Jha and Wolak, 2018; Saravia, 2003), leading to a reduction in production costs and emissions (Jha and Wolak, 2018). On the other hand, Birge et al. (2018) find that while arbitrage was limited by institutional constraints on financial bidding, financial bids were used to unlawfully manipulate the price of a related financial instrument used to hedge congestion in the MISO market.

In MISO, the forward premium persisted even in the presence of financial traders, because financial bids were subject to high transaction charges that made arbitrage unprofitable (Birge et al., 2018). These charges are Revenue Sufficiency Guarantee (RSG) charges, which are imposed on deviations from forward schedules that result in higher spot market demand (less available generation or more demand than scheduled). These deviations require plants to ramp up production or to start inactive plants. Because the clearing price does not cover ramping or startup costs, but only marginal cost, firms that buy in the spot market are subject to these deviation charges. The revenue collected is then distributed among participants who incurred ramping or startup costs.

[11] Generators are able to price discriminate between the forward and the spot market because demand is not responsive. Appendix B discusses potential reasons behind this, as well as demand's response to the regulatory change.

Virtual bidders do not sell any physical energy, so a virtual forward sale entails an equal spot purchase and was therefore subject to RSG charges in full. In 2010 the average forward premium was \$0.9 and RSG charges were \$1.8 per MWh on average, making arbitrage unprofitable. On April 2011, the Federal Energy Regulatory Commission (FERC) approved MISO's proposal to modify the way RSG were calculated, so that charges were significantly lowered from \$1.8 per MWh to \$0.3 per MWh on average.[12] In this paper, I use this exogenous change in virtual trading to study the effect of arbitrageurs on the competitiveness of the market.

The change in RSG charges did not come as a surprise to market participants, but instead occurred after a long debate about how to compute RSG charges and who should be subject to them. After the proposal to alter RSG charges was submitted to FERC, the market started preparing for implementation of the changes, which were expected to occur in March 2011. For instance, MISO began training sessions in January 2011, so firms affected by the change were expected to be aware of it before the proposal was approved and implemented.[13]

# 3 Reaction to the regulatory change

## 3.1 Financial players

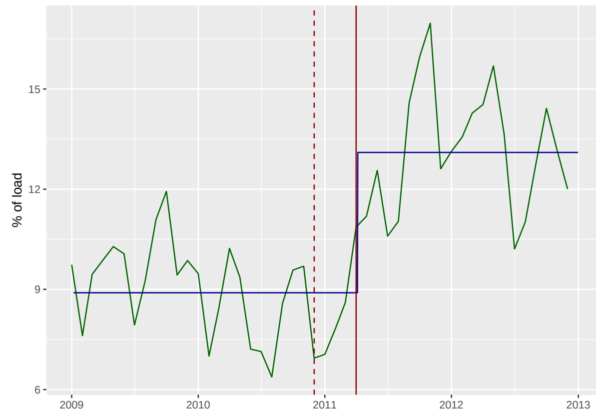
When RSG charges dropped, hedging became cheaper and profitable arbitrage opportunities appeared (Birge et al., 2018), so the volume traded by financial players increased. This can be observed in the top panel of Figure 1, which shows the monthly average of the daily volume traded by virtual bidders. The dashed red line indicates the announcement on December 1, 2010 that the proposal to redesign RSG charges had been submitted to FERC. The solid red line on April

[12] See Appendix A for computation details.

[13] In MISO, proposals to change market rules are discussed in groups of stakeholders. The change in RSG charges was reviewed by the Revenue Sufficiency Guarantee Task Force, a group specially created for this purpose. The minute from their meeting in December 2010 states that training sessions for all market participants were going to be held in January, while the minute from January 2011 states they expected the proposal to become effective in March, 2011. These are all available in the MISO website.

1, 2011 indicates the date on which the new RSG proposal was actually approved and implemented. The green line is the monthly virtual trade volume.

**Figure 1: Virtual trading over time** The green line indicates the monthly average of the daily volume traded by virtual bidders. The first dashed red line is December 1, 2010, when the proposal to redesign RSG charges was submitted to FERC. The solid red line on April 1, 2011 indicates the moment in which the RSG change was implemented.




In order to confirm that there was a change in virtual activity, I look for a structural break in the time series of daily traded virtual volume.[14] The standard test for structural break at a known date is the Chow test, which estimates the parameters before and after the break separately, and then tests for equality using an F statistic. As the date of the break is unknown in this case, I compute the F statistic for all dates in the sample. The maximum value is known as Quandt statistic (Hansen, 2001; Quandt, 1960). I use the critical values provided by Andrews (1993) and largely reject the null hypothesis of stable parameter values across the sample.

I follow Bai and Perron (1998) to find the break dates in the time series. The bottom panel of Figure 1 plots the residual sum of squares for each potential break date. The minimum is reached on April 9, 2011, with the confidence interval between April 6, 2011 and April 12, 2011 (Bai and Perron, 1998). This

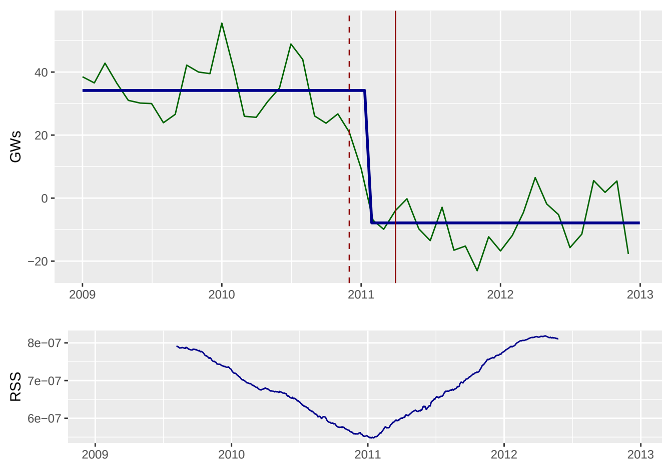
[14]These tests have been used in the applied micro literature before by Greenstone and Hanna (2014); Fabra and Toro (2003). Similar to the spirit of this paper, Fabra and Toro (2003) examine the British electricity market's response to a regulatory change and use breakpoint test to determine whether the response is anticipated, and thus consistent with collusion.

break point in the daily time series confirms that virtual bidders changed their behavior after RSG costs were reduced. The blue line in Figure 1 shows the mean traded volume before and after the breakpoint, which increased around 40 percent. This shows that the reduction in RSG charges indeed attracted more financial trading.

## 3.2 Generators

If generators price discriminate between the forward and the spot markets, their average spot sales will be positive, i.e. they will, on average, use the spot market to increase their sales. This is precisely what we observe in Figure 2, which shows in green the average daily spot sales for each month.

**Figure 2: Spot sales over time** The green line indicates the monthly average of the daily difference between the quantity cleared in the forward and spot markets. The first dashed red line is December 1, 2010, when the proposal to redesign RSG charges was submitted to FERC. The solid red line on April 1, 2011 indicates the moment in which the RSG change was actually implemented. The structural break occurred on January 10, with a confidence interval between January 5 and January 15.




Secondly, Figure 2 shows that spot sales became smaller when RSG charges were reduced. This is also in line with expectations if generators are exerting market power. Once transaction costs are lower, virtual traders will arbitrage the gap between the forward and spot prices, making underbidding by generators less attractive.

Lastly, in Figure 2 it seems that generators reacted after the announcement of the regulatory change (dashed line), but before its implementation (solid line). In fact, using the same tools described in the previous section, I find that there was a structural break on January 10, 2011, with a confidence interval between January 5 and January 15. I do not find other breaks that are robust to changing the sample periods.[15]

The generators' early reaction to the regulatory change is surprising, since future financial arbitrage did not restrict generators' market power in advance. Moreover, it implies it is not possible to identify the effect of financial players on competition without knowing what kind of game firms are playing. If firms are in a static Nash equilibrium, as we often assume in empirical work, they only respond to changes in current competitive conditions. In this case, increased financial trading would have no effect on competition since the generators' strategy change would be due to other factors that made the market more competitive. On the other hand, if firms were in a dynamic equilibrium in which they respond to future competition, financial players were effective in restricting producers' market power.

The next section presents a model of generator behavior from which I will develop an empirical test of static Nash equilibrium that will allow me to distinguish between these two interpretations. And additional advantage of using a structural test of static Nash equilibrium is that it should capture changes in competitive conditions unobserved to the econometrician as long as they alter the residual demand faced by each firm.

To the best of my knowledge, there were no important changes in the market clearing algorithm or the market structure around these dates. Wind power became subject to RSG charges in August 2010, and intermittent power sources

[15] Appendix B shows that physical buyers also changed their behavior before financial trading increased, but after generators stopped price discriminating. Figure **??** shows the evolution of the forward premium over time, though the effect is not as clear since the premium is very volatile. Figure **??** show the evolution of the forward and spot prices.

like wind became dispatchable -*i.e.* able be turned on or off by the market operator according to demand- in July 2011, but it is not clear how this could affect quantities cleared in the forward and spot market in the observed manner. Regarding the change in RSG charges itself, though it affects firms' incentives to schedule more in the forward market than what they produce, there is no reason why firms' behavior would change before the change is implemented.

# 4 Model

## 4.1 Static Model

In this section I consider the decision of a generator that sells its production in a sequential auction. I assume firms decide simultaneously how much to produce and how to split sales between the forward and spot markets.

My model modifies that of Hortacsu and Puller (2008) by introducing sequential markets instead of focusing on the spot market. Additionally, I account for the limited capacity of electrical transmission lines by assuming that both the forward and spot markets are segmented into $M$ independent markets. This is a simplifying assumption, since in practice any node can potentially affect any other at a given moment, depending on the level of congestion and the characteristics of the transmission network. I make this assumption for two reasons. First, it makes the model tractable by allowing each market to clear independently. Second, it matches the empirical strategy that I follow to deal with congestion and nodal pricing, which in turn matches the observed data fairly well (see Section 6.1).

Empirical papers on wholesale electricity markets have avoided this problem by studying markets in which congestion is adjusted for in a separate market (Ito and Reguant, 2016; Reguant, 2014), looked at hours without congestion (Hortacsu and Puller, 2008), or studied zonal markets for which congestion data are available (Ryan, 2014). Jha and Wolak (2018) study the effect of financial traders in California, where prices are nodal as well, but do not fit a structural model because CAISO does not publish bid data. To the best of my knowledge, this is the first paper in the economics literature to use a structural model to analyze a nodal market.

**Demand**

Demand for each market has the same structure in the forward and spot markets. I assume demand in each market $m$ and period $t$ is given by $D_{m,t}(p) = d_{m,t}(p) + \epsilon_{m,t}$, where $d_{m,t}(p)$ is a non-stochastic component and $\epsilon$ is a demand shock. I will omit the period subindexes $t$ because I am using a static model, and therefore all equations are the same for every period and there are no connections between periods.

For the spot market, this is a natural assumption since demand comes from households, who mostly pay a fixed rate per MWh and are thus price insensitive. In fact, there are no demand-side bids in the spot market, as enough generation is cleared to cover MISO's short-term load forecast for each hour. For the forward market, this equation is a simplification, since demand is expressed by bids and can be strategic. Appendix E shows that optimality conditions for generators do not change in a model with strategic demand.[16]

**Generators' schedules**

Generators decide how much to produce, and how to split sales between the forward and spot markets. Each generator $i$ submits a schedule $Q_i(p^F)$ to the forward market auction, and a schedule $S_i(p^S)$ to the spot market auction. These schedules specify how much a generator is willing to sell at each price. In this section, the quantity cleared in the spot market when the clearing price is $\tilde{p}^S$, $S_i(\tilde{p}^S)$, is the total quantity produced by generator $i$, *not* the difference between total production and the quantity scheduled in the forward market. Note that this is a different definition than the one used in previous sections, where I used "spot quantity" to refer to the quantity in excess of that sales in the forward market.[17]

[16]The residual demand they face will change, but not the condition for the optimality of the generator's bid.

[17]In practice, the spot market is cleared for total production, as in this section. Generators are paid the spot price only for the difference between the quantity scheduled in the forward

Each generator's strategies $Q_i(p^F, x^F)$ and $S_i(p^S, x^S)$ depend on the firm's positions $x^F$ and $x^S$ in financial contracts used to hedge risk. These contracts specify a certain quantity $x$ and a price $h$. If the market clearing price $\tilde{p}$ is greater (lower) than the contract price, the firm has to pay (is paid) $(\tilde{p} - h)x$ to (by) the buyer of the contract (Green, 1999; Wolak, 2000, 2003a). They are settled in terms of the differences between the prices because these contracts are purely financial and do not require physical delivery of energy. It is important to account for forward price hedging contracts in the analysis of generators' decisions, because a firm's financial position determines whether it has incentives to increase or decrease the forward price.[18] [19]

Each generator $i$ has a cost function $C_i(q)$, where $q$ is the quantity cleared in the spot market, *i.e.* the quantity actually produced. I assume generators know each others' cost functions. This is not a strong assumption since the same firms interact with each other over long periods, and the only information required to compute costs are the technical characteristics of the plant, which do not change over time, and fuel prices, which are easy to observe. Forward hedging positions, on the other hand, are harder to observe because they change over time for each firm, which is why I assume that the hedging positions are private information.

**Market clearing**

In the forward market, the market clearing price $\bar{p}$ in market $m$ is determined by the forward market clearing condition $\sum_{j \in m} Q_j(\bar{p}) = d_m(\bar{p}) + \epsilon_m$. Market clearing in the spot market is the same; the clearing price is determined by balancing demand and supply: $\sum S(\bar{p}^S) = d(\bar{p}^S) + \epsilon$.

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market and sold in the spot market. This is the sense in which the forward market is financial.

[18] See Wolak (2000) for the importance of contracts on incentives to exert market power.

[19] Often generators hold physical contracts in addition to financial ones. These specify a price and a quantity as well, but in this case energy is delivered to the buyer, who pays the price specified in the contract. These contracts can be treated as sunk costs because they are negotiated in advance and therefore do not affect the generator's decision about how to split sales between the forward and the spot market. Physical contracts affect costs if production costs are not linear, but even in such cases we can simply assume that $C(0)$ in the model is equal to the cost of producing the quantity specified in the physical contract. For this reason, physical contracts are not explicitly included in the model.

**Generator's uncertainty**

Each generator $i$ faces uncertainty over the clearing prices $\tilde{p}^F$ and $\tilde{p}^S$, because she does not know what clearing price will result from submitting different schedules. This uncertainty comes from two sources, which combine into uncertainty over the residual demand.[20] First, the demand function has a stochastic component that shifts its level unpredictably. Second, a generator does not know other generators' bids because she does not know their financial contract positions.

Bidder $i$'s uncertainty is represented by $F(x_{-i}, \epsilon | x_i)$, the joint distribution of other firms' contract positions and the demand shock. It is conditional on $i$'s own position because $i$'s position may contain information about others' contracts.[21]

Following Hortacsu and Puller (2008), I define a probability measure over the realizations of the forward clearing price from the perspective of firm $i$, conditional on $i$'s private information about its contract position $x_i^F$, $i$'s submission of a schedule $\hat{Q}_i(p, x_i^F)$, and her competitors playing their equilibrium strategies $\{Q_j(p, x_j^F), j \neq i\}$. $H(p, \hat{Q}_i(p); x_i^F) \equiv \Pr(\tilde{p}^F \leq p \mid x_i^F, \hat{Q}_i)$ represents the uncertainty over the forward market clearing price faced by firm $i$. It is the probability, given $i$ 's contract position, that generator $i$ will be paid a price $p$ when she sells a quantity $\hat{Q}_i(p)$ and all other generators submit the equilibrium offer functions. The event $\tilde{p}^F \leq p$ is equivalent to the event of excess supply at price $p$. Equivalently, generator $i$'s uncertainty over the clearing price in the spot market can be represented by the probability measure $G(p, \hat{S}_i(p); x_i^S) \equiv \Pr(\tilde{p}^S \leq p | x_i^S, \hat{S}_i)$.

[20] *i.e.* the market demand minus the schedules submitted by all other generators in the market.

[21] Correlation between the demand shock and the contract positions of the competitors is allowed, but note that this remains a private value setting since $i$'s profits do not depend on its competitors' contracts (Hortacsu and Puller, 2008).

**The generator's problem**

At clearing prices $\tilde{p}^F$ and $\tilde{p}^S$ in the forward and spot market, respectively, the ex-post profits for generator $i$ are given by[22]

$$\Pi_i(\tilde{Q},\tilde{S}) = \tilde{p}^F\tilde{Q} + \tilde{p}^S[S-Q] - C(\tilde{S}) - [\tilde{p}^F - h^F]x^F - [\tilde{p}^S - h^S]x^S \qquad (1)$$

where $\tilde{Q}$ is $Q(\tilde{p}^F, x^F)$ and $\tilde{S}$ is $S(\tilde{p}^S, x^S)$ (the arguments are omitted for clarity). The last two terms come from the financial position held by the generator in the forward and spot markets.

A firm chooses schedules $Q_i(p^F, x_i^F)$ for the forward market and $S_i(p^S, x_i^S)$ for the spot market so as to maximize its expected profits, where the expectation is with respect to $H$ and $G$. If bids are additively separable in price and contract positions, as in Hortacsu and Puller (2008), the optimality conditions for the generator's problem can be written as follows:[23]

$$p^F - p^S = -[Q^*(p^F) - x^F]\frac{1}{R'(p^F)} \qquad (2)$$

$$p^S - c' = -[S^*(p^S) - Q^*(p^F) - x^S]\frac{1}{R'(p^S)} \qquad (3)$$

These conditions are similar to an oligopolist's first order condition. In the forward market, the markup is with respect to the spot price instead of the marginal cost, since this is the opportunity cost of selling in the forward market. Whether the generator wants to have a positive or negative markup will depend on her hedging contract position, i.e. on whether she is a net seller or a net buyer in the forward market. This is weighted by a function of the elasticity of the residual demand faced by the firm, $R(p)$, which determines the generator's market power. This condition can be rewritten as $\frac{p^F - p^S}{p^F} = \frac{Q - x^F}{Q}\frac{1}{\eta}$, where $Q$ and $\eta$ are functions of $p^F$.

A similar trade-off is present in the spot market. The optimal markup for a

[22] Subindexes $i$ are omitted from now on unless necessary to avoid ambiguities.

[23] See Appendix C for a detailed presentation of the model and derivation of Euler-Lagrange conditions. See Appendix D for a discussion of the additive separability assumption and evidence suggesting that it holds in this particular market.

generator depends on whether she is a net seller o buyer in the spot market, which depends on both her contract position in the spot market and her forward sales. Additionally, the importance of this position is weighted by the firm's ability to affect prices with bids.

# 5 Data

Most of the empirical work in this paper is done using an hourly panel that is publicly available on MISO's website. It contains each participant's bid, as well as the corresponding cleared quantity and price for each hour between 2010 and 2011. The panel has around 100 millions observations, 20 millions from generators' bids, and 80 millions from demand and financial participants' bids.

Generators may submit price-taker or price-sensitive bids, and they also have the option of submitting an increasing piecewise linear function instead of a step function. In my sample, 70 percent of generator bids and 82 percent of the megawatts hour cleared by generators correspond to piecewise linear bids. I discretize these bids as step functions in intervals of 0.1 MWh in my analysis. Supply bids also include information about the technological restrictions of each plant, such as the minimum/maximum number of hours it needs to operate, ramping times and costs, and startup costs, but I do not observe these variables. MISO only publishes the bid, cleared price and quantity, maximum and minimum production levels under normal and emergency conditions, and the amount a generator sells as a price taker.

The data identify buyers who place bids at multiple nodes, and sellers who own multiple units, but it is not possible to know which participants are vertically integrated utilities, nor whether a generator is also using virtual bids to hedge or arbitrage. While around 90 percent of physical demand bids are cleared in the forward, only around 10 percent of virtual bids and 50 percent of physical supply bids are cleared. Summary statistics on bids are presented in appendix tables G.4, G.1 and G.2.

Additionally, MISO posts the clearing prices at each pricing node in the market, information I use to match bids, which are not reported by node, to the corresponding nodes. In my data, a node is just an identifier number and a name where one or more participants submit bids. Each node's geographical location is not disclosed.

I use data on prices and volumes of traded Intercontinental Exchange (ICE) futures for the Indiana hub during peak hours. These data are available on the EIA website. Data on oil, coal, and natural gas prices were obtained from the Federal Reserve Bank of St. Louis. They correspond to daily crude oil prices (West Texas Intermediate - Cushing, Oklahoma), the Henry Hub natural gas spot price, and coal prices in two coal regions (Illinois Basin and Powder River Basin).

# 6 Testing static Nash equilibrium

The model presented above can be used to understand the generators' change in behavior. For this, define the Best Response Deviation (BRD) as follows:

$$
\begin{aligned}
BRD &\equiv p^F - p^S - [Q(p^F) - x^F]\frac{1}{|R'(p^F)|} \\
&\equiv \frac{p^F - p^S}{p^F} - \frac{Q - x^F}{Q}\frac{1}{\eta}
\end{aligned}
$$

where the second line results from rearranging the terms. The BRD is the difference between the two sides of the optimality condition described by Equation 2, which implicitly defines the static best response function for a firm.

If the static model is a good representation of the firms' behavior, $BRD = 0$. This is the null hypothesis, under which financial traders have no effect on market competitiveness. If $BRD \neq 0$, firms are not in a static Nash equilibrium and generators' change in behavior is consistent with an anticipated response to increased financial trading in the future. I will consider two alternative hypothesis, which can be distinguished based on the sign of the $BRD$.

If $BRD > 0$, the observed markup is higher than what would be optimal if firms were in a static equilibrium, given the competitive conditions they face at the moment. This is consistent with firms playing a repeated game in which a cooperative equilibrium is sustained as long as future benefits exceed the profits from deviating. Once firms learn that the equilibrium will not be sustained in the future, when financial traders' arbitrage is cheaper, the equilibrium unravels.

If $BRD < 0$, firms are acting as if the market were less competitive than it actually is. I.e. they choose a smaller markup than what is optimal given the elasticity of the residual demand they face. This would be consistent with generators attempting to deter financial traders' entry by making the market less attractive at the time of the regulatory change.

The two alternative hypotheses have different predictions regarding the evolution of the BRD over time as well. If the market is in a static game equilibrium, the BRD should not change over time. If this is the case, the observed anticipatory reaction of the generators would have been caused by changes in the contract positions or the demand, and the firms would have been playing their static best response to the market conditions they faced at the moment.

If firms were in a cooperative equilibrium that broke with the announcement of increased competition in the future, the BRD would be initially positive, and then move toward zero after the announcement of the regulatory change. How close to zero it ends up depends on financial bidders' effectiveness in arbitraging the forward premium. The speed of the adjustment depends on the pace at which the collusive equilibrium breaks.

A tacit collusive equilibrium does not need to be an explicit agreement in which firms sit around a table and agree upon each group member's bid. The equilibrium could take the form of a simple rule of thumb for bids in the forward and spot markets. Firms do, however, have some contact, since the large ones are often MISO stakeholders. These stakeholder firms meet periodically to discuss market design and draft joint proposals for market reform. The likelihood that large firms follow similar strategies is also increased because many of these large firms hire outside firms to do their trading. Furthermore, any collusion between these large firms could have a significant impact on prices, since production is fairly concentrated, with 20 percent of firms controlling 80 percent of generation capacity.

Finally, under entry deterrence, the BRD is expected to start at zero before the announcement, become negative when the market learns about future competition, and increase towards zero when generators feel safe from the threat of entry. It is not clear when this last step would happen, as financial participants can increase their trading as soon as generators open the gap enough to make virtual trading profitable.

Following a structural strategy has the advantage of capturing changes in firm behavior that are unobserved to the econometrician. To the best of my knowledge, there were not other changes in the market around the time in which generators' underbidding went down, had there been they should be captured by changes in either firms' contract positions or the residual demand they face.

The richness of the dataset allows me to compute the BRD for each firm in each hour and market in which it is active. For this, I will use observed forward prices and quantities, and estimate spot price expectations and residual demands. The next sections describe how this is done.

## 6.1 Residual demand and its elasticity

In principle, the residual demand for each generator could be computed directly from the data by just adding up the demand bids and subtracting the supply bids. However, this is not always a close approximation in a market with nodal pricing. When transmission lines are at capacity, the set of generators and physical buyers that enter a given generator's residual demand is a subset of the MISO market. Determining that subset is therefore crucial to correct computation of the residual demand.

**Market definition**

The MISO energy market has over 2000 pricing nodes and often becomes congested (transmission lines reach capacity), so in practice there is significant price dispersion among the nodes and prices can substantially differ geographically and over time. The presence of congestion is relevant for the empirical analysis of this market because when lines are at capacity demand cannot always be served by the cheapest generator. As a consequence, congestion segments the market, creating local markets in which firms have more market power than they would otherwise. This poses a challenge for empirical analysis, because the degree of market power enjoyed by a firm depends directly on the degree of congestion and its transmission structure. I address this problem by using prices to define independent markets within the MISO market with a machine learning algorithm.

I define markets using hierarchical clustering. In general, clustering techniques group elements of a set into groups or clusters, based on a predefined notion of similarity. The number of clusters is typically determined exogenously. In hierarchical clustering, each element is initially its own cluster.[24] The first step is to merge the two most similar objects into one cluster, according to the similarity measure. In each of the following steps, the two most similar elements or clusters are joined into one cluster. There are several ways to compute the similarity between two clusters; I use the distance between the centroids of the cluster.[25]

I use the price correlation between nodes as the similarity measure for the clustering algorithm, since we would expect prices to move together if the nodes belong to the same market (Stigler and Sherwin, 1985). Although in principle it is possible that two nodes that are geographically far from each other have correlated prices, this would only happen if both the congestion and line loss components coincide. Figure G.1 in the online appendix shows a heat map of prices in MISO in two different moments. Nonadjacent areas do not seem to have the same color in the two maps, making high price correlation between geographically separate nodes unlikely.[26]

[24]This is the agglomerative algorithm. In the divisive algorithm, all elements start together in one single cluster, and each step splits the most different elements.

[25]The fit is similar or worse using alternative measures like complete or single linkage.

[26]I cannot verify that only prices from geographically adjacent areas are correlated because I do not observe the nodes' geographical location.

The main source of uncertainty in this problem are physical contracts among market participants, which do not affect market clearing prices or quantities, but do use the transmission network. Therefore, they affect flows and network congestion for a given set of observed bids. For this reason, I run the market-definition algorithm over periods in which firms' contractual obligations are likely to remain constant. I define markets separately for each month, year, and hour of the day. For instance, I take the prices for all nodes during hour 5 of September 2011 and compute the correlation matrix. I then use these correlation data to define markets for the hour between 5 a.m. and 6 a.m. of September 2011.[27]

The hierarchical clustering algorithm returns a set of potential market definitions, one for each step of the algorithm. For instance, if there are 5 nodes there are 5 potential market definitions: There could be only one market {1,2,3,4,5}, or three markets {1},{2},{3,4,5}, etc. Generally, there is no appropriate measure of fit for the clusters, and it is not clear which number of separate markets best represents the data. To remedy this uncertainty, I use bid data to test the ex-post fit of alternative market definitions. To do this, I take a market definition (e.g. 3 markets) and clear each of the market clusters by adding up the demand and supply bids submitted at the nodes belonging to each cluster. For instance, to evaluate the market definition with three clusters, I clear market 1 by crossing aggregate demand and supply bids at node 1. To clear market 3 I add up demand and supply bids from nodes 3, 4, and 5 to obtain aggregate supply and demand, and then clear the market. This process results in a simulated clearing price and quantity for each market under each market definition, which can be compared to the clearing prices and quantities observed in the data.

The difference between the observed and simulated clearing prices for each market definition is then regressed on a constant to test the null hypothesis that this difference is zero. This is done with both an OLS and a quantile regression for

[27] I also tried accounting for day of the week effects, caused by contracts to deliver electricity during weekdays, for instance. This did not improve the fit.

the median.[28] All market definitions for which the null is rejected are discarded. When there are several market definitions for one month-hour, I select the market definition that is most common for that hour across all months. The mean difference in prices is below 10 percent for all hours, and below 5 percent for the majority of them. Because the inelasticity of demand makes quantities much less variable than prices, I use only price deviations when selecting market definitions.

For some hours and months, the difference between the observed and simulated cleared prices is statistically different from zero for all market definitions. When this is the case, I exclude that hour from the sample. This happens with for at least one month in hours 1, 3, 4, 12, 16, 22, and 23.

This method to define markets is an approximation, because in reality all nodes in the MISO market can affect each other's price. The fact that the simulated clearing price is, on average, not far from the observed one indicates that the ex-post fit of these definitions is good. As long as market conditions remain constant within the month, these definitions can also be used ex-ante to represent generators' rational beliefs about the residual demand they will face.

Using the generators' physical locations to group nodes into markets may appear to be a simpler way to define markets. However, MISO does not include generators' locations in the dataset because this information is considered a matter of national security. Even if I could obtain location information, it is not possible to infer which firms compete with each other without having more information about the transmission network's capacity. As Figure G.1 shows, neighbor nodes may have very different prices and thus, belong to different markets. Finally, even if I had all of the relevant data, I would need to solve a complex optimization problem multiple times for each generator in order to estimate residual demand. This process would be computationally demanding, and most likely far from what firms actually do when they make bidding decisions.

Zheng (2016) also uses clustering tools to define markets in her estimation of

[28]If a market does not clear in the simulation, because demand's maximum willingness to pay is smaller than supply's minimum price, I assume the cleared price was 0.

an entry game between discount retailers. She splits the market into independent submarkets to lower the computational burden and make the estimation of the model possible. In my case, the richness of the electricity dataset allows me to define markets and a measure of fit that do not depend on the model of firm behavior.

**Residual demand and its elasticity**

Because of the richness of the data, market definitions are all is needed to obtain the residual demand faced by each firm. I construct the residual demand faced by each firm in each market simply by adding up demand bids and subtracting the competitors' supply bids. A residual demand is defined for each firm in each market, which is assumed to be the information that each firm uses to make decisions.[29]

Seventy-five percent of the bids and 82 percent of the megawatts cleared by generators are to piecewise linear bids, while the rest are step functions. I convert these piecewise linear bids into step functions by splitting them into 0.1 MW increments. As a consequence, residual demand is expressed in step functions with very small steps. To compute the elasticity, I fit a cubic spline to the resulting residual demand, and take the derivative. I also compute the derivative as the difference between one step and the next, divided by the size of the step.

## 6.2 Expected spot price

My model assumes that firms take the decision of how to split sales between the forward and the spot market simultaneously. In this case, the optimality condition in Equation 2 is pointwise optimal. Nonetheless, in reality the spot market takes place once the forward market has cleared. For this reason, I use an estimate of the expected spot price by each firm to compute the best response deviation. For this, I assume rational expectations: generators are forward-looking and use all available information to predict the spot price. For

[29]This assumes that decisions are taken independently by a same company in different markets. Although it seems a strong assumption, given that markets are independent there would not be any gain from making the decisions jointly.

each node, I run the following regression with data from the prior month

$$p^S = \alpha + \beta_1 f_p^S + \beta_2 f_q^S + \beta_3 p_{lag}^S + \beta_4 p_{lag}^F + \varepsilon \tag{4}$$

where $f_p^S$ is the price and $f_q^S$ the traded volume of the futures for the Indiana hub in peak hours traded in the Intercontinental Exchange (ICE). These are spot price futures traded one day before the underlying production date, so their prices are almost identical to the forward price. $p_{lag}^S$ and $p_{lag}^F$ indicate the lags of the spot and forward price, respectively. The lags used are one, two, and three days before for the same hour and the previous one, plus the price in the previous 12 hours. The same lags are used for the forward and spot prices. I estimate the coefficients of Equation 4 using data for the month preceding $t$, the day for which I want to predict the price. Then I predict the spot price for day $t$ using data on day $t-2$, as bids are submitted on day $t-1$, while markets for that day are still clearing.

Table 1 describes the difference between rational expectations and the observed spot price. Although the predictions are not unbiased, the magnitude of the bias is small. Note, also, that the estimated expected spot prices are much closer to the spot price than the forward price.[30] After having the predictions at the node level, I compute each generator's belief as the quantity-weighted mean of the forecast separately for each market in which the generator is ever active. Mean deviations from the observed spot price for the firm specific expected spot price are 8 cents in 2010 and 20 cents in 2011.

[30]Predictions can alternatively be computed by running predictive regressions for each generator, including firm-specific variables like whether the bid sets the price or the bid price is close to the clearing price. Nonetheless, this approach resulted in much worse predictions.

**Table 1: Expected spot prices**

| | 2010 | 2011 |
|---|---|---|
| $E[P^S]_{RE} - P^S$ | 0.036 | 0.163 |
| | (0.006) | (0.007) |
| $P^F - P^S$ | 1.142 | 0.500 |
| | (0.005) | (0.006) |
| Spot price | 31.101 | 30.310 |
| | (0.006) | (0.007) |
| Observations | 16,920,576 | 16,350,480 |
| $R^2$ | 0.000 | 0.000 |

## 6.3 Hedging contracts

I back out the hedging contract position held by each generator from the optimality condition in Equation 2, as in Hortacsu and Puller (2008). Recall the optimality condition is: $p^F - p^S = [Q(p^F) - x^F]\frac{1}{|R'(p^F)|}$. The optimal schedule for the forward market is such that when the forward and spot prices are the same, the total quantity offered by each generator in the forward market equals its forward contract quantity, *i.e.* $Q(p^S) = x^F$. From this equation, I obtain the contract position for each generator in each market.

The forward hedging contract position can be correctly backed out when the optimality condition holds, *i.e.* under the null hypothesis of static Nash equilibrium. As the hedging positions are correct under the null, the test is valid. Although the contract position will be biased whenever the null is rejected, the bias moves the BRD towards zero. If the BRD is positive, contract positions will be biased upwards, which in turn biases the BRD downwards. The opposite happens if the BRD is negative. For this reason, the bias is not a big concern since it goes against rejecting the null of static Nash.

### 6.4 Best response deviation (BRD)

The previous sections have shown how to compute each of the components of the BRD: the forward hedging position, the derivative of the residual demand, and the expected spot price. Each of these elements is obtained separately for each hour, market, and firm. As there are many nodes in each market, each with a potentially different clearing price, I define the market price as the quantity-weighted average. With all these elements, I can build a panel in which I observe the BRD for each generator in each hour and market in which she was active.

To analyze the evolution of the BRD over time, I define three time periods according to market events related to the change in RSG charges. These periods are the following:

**Before** : The four months prior to December 1, 2010. On that date, MISO announced that it submitted a proposal to FERC for the redesign of RSG charge and the market began to prepare for the expected implementation of the proposal. The before period therefore provides data about baseline market conditions.[31]

**Transition** : the four months between December 1, 2010 and April 1, 2011, the date on which the change was implemented. During this period, the market knew the regulatory change was likely to occur, but it had not yet been implemented.

**After** : the four months between April 1, 2011 and July 31, 2011. This period represents the first four months after the RSG charges were lowered. There were two major events in July 2011: (1) renewable plants became dispatchable, meaning they could be started and stopped by the market operator according to demand like any other plant, and (2) a large producer firm left MISO to join the PJM Interconnection, which serves a market adjacent to MISO's. The latter event changed the market structure because the firm's transmission lines were

[31] Training sessions to explain market participants how these costs were going to be computed started in January. A group of market participants was in charge of the redesign proposal. In January, they wrote they expected it to be implemented on March, 2011.

transferred to PJM as well. Additionally, the summer of 2011 was particularly hot. For these reasons, I add a dummy for July 2011 to the regressions.

I examine the evolution over time of the best response deviation running the following regression of the BRD on the time periods defined above:

$$BRD_t = \alpha_0 \text{before} + \alpha_1 \text{interim} + \alpha_2 \text{after} + \text{July 2011} + \varepsilon_t \tag{5}$$

where $BRD_t$ is the mean best response deviation for each hour and market, weighted by the size of the firm, defined as the maximum quantity sold during that month.

The main specification assumes rational expectations to compute the expected spot price, computes the elasticity using a spline, discarding observations for which the elasticity is positive. In order to avoid effects from monthly and hourly market fluctuations, I regress the BRD on month and hour dummies using data on 2010 and 2011. I then use the residual as the main dependent variable, and add the mean of the month fixed effects to get a more accurate level. I also add the number of generators in a market and the HHI (Herfindahl-Hirschman Index) as controls to understand how the BRD is affected by market structure.

My sample does not include peakers, which are fast responding generators typically used to cover last minute increases in demand. Therefore, they are very likely to produce when demand in the spot market exceeds production scheduled in the forward market. Including them in the analysis may add effects coming from technical characteristics instead of from firm behavior. Furthermore, the BRD estimation produce a few extreme values that have a disproportionate effect on the results. For this reason, I remove the top and bottom 1 percent of my observations.

As I have a different BRD for each market definition, and more than one market definition for some hours, I use the market definitions that are most prevalent for each hour. That is, I count the number of months for which each market definition is a good fit, and for each month select the one with the highest number.

### 6.5 Market power in the spot market

Although financial participants decrease generators' market power in the forward market, because they cannot intertemporally price discriminate, they do not eliminate it altogether. Rather, firms retain the ability to withhold production in the spot market in order to drive up the spot price. This is analogous to an instance where increased arbitrage forces a monopolist to stop price discriminating between two sets of consumers. Just as the monopolist's new uniform price will be higher than the original price in the low-demand market, electricity generators will use their market power to raise spot prices after arbitrage decreases the forward premium.

I examine the effect of increased arbitrage on market power looking at firms' spot-price markups. I back out the spot markup for each firm from the optimality condition in Equation 3. I assume that firms' hedging position in the spot market is 0, because firms generally hedge with respect to the forward market, since that is where they sell the bulk of their production. For expositional clarity, I rewrite Equation 3 here for the case without hedging

$$\text{markup} = p^S - c' = -[S^*(p^S) - Q^*(p^F)]\frac{1}{R'(p^S)}$$

I estimate the markup in the spot market from the right hand side of this equation. I observe the cleared quantities in the forward and spot markets, and estimate the residual demand as I do for the forward market. For consistency, I use the same market definitions as in the forward market. I then run a regression of the quantity weighted average markup for each market and hour on the same time period dummies used in the BRD analysis. The next section describes the results.

Notice that the output from this estimation is the markup with respect to the firm's opportunity, which is not necessarily equal to actual production cost. Therefore, I cannot quantify the change in production costs using this mechanism.

Nevertheless, this equation is sufficient to determine firms' market power, since the firms use marginal opportunity cost, rather than physical cost, to make their bidding decisions.

# 7 Results

## 7.1 Market definitions

Table 2 presents summary statistics from the markets defined using hierarchical clustering and selected by matching clearing prices. MISO is split into several markets, typically with one large market and many smaller ones, which explains the low mean and the high maximum number of firms and MWhs sold, as well the large number of markets. Concentration is not too low and there are even some monopolies, a much less competitive market structure than what would result from analyzing MISO as a single market. Notice that the market is never best described as a single market, since the minimum number of markets is three, which underscores the importance of defining separate markets instead of assuming a single one.

**Table 2:** Markets summary statistics

| Statistic | Mean | St. Dev. | Min | Median | Max |
|---|---|---|---|---|---|
| # markets | 31 | 13 | 3 | 35 | 49 |
| # of f traders | 9 | 9 | 0 | 7 | 57 |
| # of buyers | 5 | 17 | 0 | 0 | 105 |
| # of sellers | 7 | 17 | 1 | 2 | 111 |
| HHI sellers | 0.4 | 0.4 | 0.0 | 0.1 | 1.0 |
| MWh sold | 3,094 | 10,909 | 0 | 109 | 87,747 |

Though I do not observe the pricing nodes' location, I know to which load balancing authority (LBA) they belong. LBAs are areas that were typically served by a single utility, which was also in charge of balancing demand and supply. For this reason, they are more likely to have enough transmission to move energy within the area and therefore to belong to the same market. With my market definitions, 88% of load balancing authorities are in a single market for a given hour in a month and year. Those that are split are the larger LBAs, i.e. those that include more nodes.

## 7.2 Best response deviation (BRD)

Results from the BRD regressions are presented in Table 3 and are consistent across the three first specifications: main specification, 9 months sample, and controlling for HHI and number of producers. The BRD was positive in the initial "before" period, went down in the interim period, and stayed low after financial trading increased. This means that firms initially exerted more market power than they had in a static Nash sense, and moved closer to a behavior consistent with static Nash between the announcement and the implementation of the policy change that reduced transaction costs for financial traders. This is consistent with a tacit collusive agreement that breaks as soon as firms learn they will not be able to sustain it in the future.[32]

Table 3 also presents results from testing the hypothesis that the *interim* and *after* coefficients are the same, as well as that *before* and *after* are the same, which is equivalent to the BRD going to zero and therefore behavior being consistent with a static Nash equilibrium. My findings indicate that the full adjustment in generators' behavior took place before financial participants effectively increased their activity, which is again consistent with a tacit collusive equilibrium unraveling with the announcement of an end period.

While tacit collusion among the over 90 firms active during the sample period seems unlikely, I am able to identify a small group of firms that seem to be driving the results. Running individual regressions for each firm, I find that generators for which the BRD went down in the interim and after period have a few features in common. They are medium or large in size, and together they own 72 percent of the total capacity of the west area and 86 percent of the wind capacity. Most importantly, they are concentrated in the west area of the market. Though I

[32] Fabra and Toro (2005) find evidence of collusion in the Spanish electricity market, although they observe price wars together with periods of price stability.

**Table 3: Best response deviation analysis** Results from regressing the BRD on time period dummies using data between August 2010 and July 2011. The BRD is computed as the mean for each hour and market, weighted by the size of the firm. The top and bottom 1 percent of the sample are removed to avoid extreme values. I remove month and hour averages by defining the dependent variable as the residual from a regression of the forward premium on monthly and hourly dummies using 2 years of data, then I add the mean fitted value. Robust standard errors reported.

| | Main | 9 months | Controls | West | No west |
|---|---|---|---|---|---|
| Interim | $-0.47^{***}$ | $-0.76^{***}$ | $-0.45^{***}$ | $-0.85^{***}$ | 0.02 |
| | (0.15) | (0.15) | (0.15) | (0.16) | (0.18) |
| After | $-0.70^{***}$ | $-0.82^{***}$ | $-0.64^{***}$ | $-0.92^{***}$ | $-0.26$ |
| | (0.16) | (0.16) | (0.16) | (0.18) | (0.20) |
| HHI | | | $-1.88^{**}$ | | |
| | | | (0.89) | | |
| Market size | | | $-0.17^{***}$ | | |
| | | | (0.03) | | |
| July 2011 | $2.09^{***}$ | | $2.11^{***}$ | $2.39^{***}$ | $1.98^{***}$ |
| | (0.24) | | (0.24) | (0.26) | (0.37) |
| Market size×HHI | | | $0.293^{**}$ | | |
| | | | (0.14) | | |
| Constant | $0.64^{***}$ | $0.58^{***}$ | $1.86^{***}$ | $0.73^{***}$ | $0.21^{*}$ |
| | (0.11) | (0.10) | (0.27) | (0.12) | (0.13) |
| interim = after | Y | Y | Y | Y | Y |
| after = before | Y | N | N | Y | Y |
| Observations | 37,436 | 32,421 | 37,436 | 30,262 | 19,719 |
| $R^2$ | 0.002 | 0.001 | 0.004 | 0.004 | 0.002 |

cannot observe the location of the different pricing nodes, the names of the nodes indicate the load balancing authority (LBA) to which they belong.[33] These firms belong to LBAs in the west area of the market.

Using this information, I split the sample between the west and the rest of the sample and run the same regression as above. Results are in the last two columns of Table 3, and indicate that the changes in BRD come from firms in the west. These generators were exerting more market power than they had in a static Nash sense in the initial period, and moved to a behavior consistent with a static Nash equilibrium after the announcement of increased financial activity

[33]Using LBAs to define markets does not result in clearing prices close to the observed ones.

in the future. In contrast, firms in the rest of the market did not change their behavior during this period. When Figure 2 is plotted excluding firms in the west I also find no change in underbidding.

Even though the west is less concentrated that the rest of the market, with an average HHI of 0.1 as opposed to 0.19 in the rest of the market, most medium or large firms are in the west. In fact, when I split the market into large and small firms and plot underbidding over time as in Figure **??**, I only find a change in behavior for the large firms. These firms are more often isolated from the rest of the market because the most observed congestion pattern in MISO is west-to east- congestion.

**Table 4: Residual demand elasticity and forward contract positions** Regression of the quantity weighted residual demand elasticity and forward contract position on time period dummies between August 2010 and July 2011. The derivative of the residual demand is computed using a spline. The top and bottom 1 percent of the sample were removed to avoid extreme values. I remove month and hour averages by defining the dependent variable as the residual from a regression of the forward premium on monthly and hourly dummies using 2 years of data, then I add the mean fitted value. Robust standard errors reported.

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Residual demand elasticity | | | Contract position | | |
| | All | West | No west | All | West | No west |
| Interim | $-26.37^{***}$ | $-17.55^{***}$ | $-31.92^{***}$ | $26.82^{***}$ | $30.34^{***}$ | $-127.45^{***}$ |
| | (2.33) | (3.30) | (6.08) | (8.46) | (10.59) | (14.44) |
| After | $-33.27^{***}$ | $-27.72^{***}$ | $-34.26^{***}$ | $-60.11^{***}$ | $-11.55$ | $-190.80^{***}$ |
| | (2.52) | (3.41) | (6.42) | (9.02) | (11.09) | (16.03) |
| July 2011 | $-50.74^{***}$ | $-65.16^{***}$ | $-84.27^{***}$ | $107.37^{***}$ | $188.69^{***}$ | 24.76 |
| | (3.37) | (4.14) | (9.42) | (13.88) | (16.96) | (28.17) |
| Constant | $-80.57^{***}$ | $-111.35^{***}$ | $-210.04^{***}$ | $678.57^{***}$ | $643.39^{***}$ | $1,089.5^{***}$ |
| | (1.81) | (2.52) | (4.87) | (6.25) | (7.35) | (11.49) |
| N | 33,264 | 27,117 | 17,647 | 80,008 | 60,680 | 33,989 |
| $R^2$ | | | | 0.002 | 0.002 | 0.005 |
| *Note:* | | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | | |

Table 4 shows the evolution of the residual demand elasticities and backed-out contract positions over time. For the elasticity, I use a robust regression that weights observations with large errors less since errors are not distributed symmetrical and results are bias. Elasticity went down, though less for firms in the west than in the rest of the market. Contract positions changed differently for the two sectors in the market. In the west, firms increased their forward position in the interim period, but went back to the initial position afterwards. Firms in the rest of the market, on the other hand, lowered their forward contract positions over time.

As expected, the forward premium decreased after the announcement as well, as shown in Table 5. As for the BRD, the effect comes from firms active in the west area of the market. Though the coefficient for the *after* period is smaller than the one for the *interim* period, they are statistically the same.

**Table 5: Forward premium over time** Regression of the quantity weighted forward premium on time period dummies between August 2010 and July 2011. The top and bottom 1 percent of the sample were removed to avoid extreme values. I remove month and hour averages by defining the dependent variable as the residual from a regression of the forward premium on monthly and hourly dummies using 2 years of data, then I add the mean fitted value. A dummy for July 2011 is included. Robust standard errors reported.

| | All | West | No west |
|---|---|---|---|
| Interim | $-0.58^{***}$ | $-0.96^{***}$ | 0.23 |
| | (0.19) | (0.21) | (0.24) |
| After | $-0.37^{*}$ | $-0.64^{***}$ | 0.21 |
| | (0.20) | (0.22) | (0.25) |
| Constant | $1.35^{***}$ | $1.85^{***}$ | $0.66^{***}$ |
| | (0.14) | (0.15) | (0.17) |
| interim = after | Y | Y | Y |
| Observations | 37,578 | 30,600 | 19,930 |
| $R^2$ | 0.001 | 0.002 | 0.001 |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | | |

## 7.3 Spot market markups

Table 6 presents the results from the spot markups analysis, showing that spot markups stayed roughly at the same level during the whole sample period, since the coefficients are economically small even if they are significant. Though we would have expected markups to increase in response to increased financial trading, there are a few reasons why firms would not exert more market power. First, this is not exactly a case in which firms go from price discrimination to uniform pricing, but rather from dynamic to static competition. For this reason, firms do not necessarily have incentives to exert more market power in the spot market. Secondly, MISO carefully monitors firms' behavior in this market and can easily find out if firms are withholding since the plants' capacity is public knowledge. On the other hand, in the forward market the focus of the market operator is on avoiding situations in which there is more demand than scheduled generation, not on intertemporal price discrimination. For this reason, generators' market power is likely to be much more restricted in the spot than in the forward market.

**Table 6: Spot market markups** Regression of the markup in the spot market on time period dummies between August 2010 and July 2011. The derivative of the residual demand is computed using a spline and as the ratio of differences using two points (slope). The top and bottom 1 percent of the sample were removed to avoid extreme values. I remove month and hour averages by defining the dependent variable as the residual from a regression of the forward premium on monthly and hourly dummies using 2 years of data, then I add the mean fitted value. Robust standard errors reported.

| | Markup | | Markup over spot price | |
|---|---|---|---|---|
| | Spline | Slope | Spline | Slope |
| | (1) | (2) | (3) | (4) |
| Interim | $-0.08^{***}$ | $-0.12^{**}$ | $-0.002^{*}$ | $-0.003$ |
| | (0.03) | (0.06) | (0.001) | (0.002) |
| After | $-0.18^{***}$ | $-0.18^{***}$ | $-0.01^{***}$ | $-0.004$ |
| | (0.03) | (0.07) | (0.001) | (0.003) |
| July 2011 | $0.11^{**}$ | 0.09 | $0.003^{*}$ | 0.002 |
| | (0.05) | (0.10) | (0.002) | (0.004) |
| Constant | $0.29^{***}$ | $0.22^{***}$ | $0.01^{***}$ | $0.01^{***}$ |
| | (0.02) | (0.04) | (0.001) | (0.002) |
| Observations | 36,097 | 41,514 | 36,307 | 37,224 |
| $R^2$ | 0.001 | 0.0002 | 0.001 | 0.0001 |
| *Note:* | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | | |

## 8 Welfare analysis

Financial trading made consumers better off, since the reduction of the forward premium means that they pay less and total quantity does not change because final demand is perfectly inelastic. Producers, as a group, are worse off because they lose market power.

Additionally, costs are likely to go down because production underscheduling in the forward market lead to productive inefficiencies that then disappeared. First, because more expensive producers will be scheduled in the forward market to cover demand. Second, because some units will need to be dispatched in the spot market, and the units that can react on short notice often have higher marginal costs. Jha and Wolak (2018) compare production costs and carbon emissions before and after the introduction of financial traders into the California market, and find that both decreased. Given that 98 percent of the energy sales happen in the forward market, i.e. that most production is scheduled in advance, total costs are likely to decrease when generators cannot engage in price discrimination. A precise quantification of this effect requires cost data and is therefore left for future research.

Consumers are unambiguously better off, since they pay less for their electricity purchases. To quantify this, I look at changes in total expenditure per MWh over time. After controlling for fuel prices and the forecasted demand level, total expenditure decreased in the period between announcement and implementation of the regulatory change and stayed below the initial level after implementation, as Table 7 shows. The coefficients indicate that total expenditure was between 3 and 9 percent higher before the announcement than after implementation. Given that total demand is $1,500,000$ MWh a day on average, and the price is around \$30 per MWh, this means that consumers save at least $\$1,350,000$ per day on average. Note, however, that it is important to control for demand and fuel prices. Simply looking at changes in total expenditure, without controls, would indicate that, relative to the period after implementation, total expenditure was

10 percent lower in the "before" period, and 10 percent higher in the "interim" period.

Consumer savings come from two sources. The first is the direct effect of financial traders on generators' ability to engage in price discrimination in the forward market. The second mechanism is the change in the dynamic equilibrium. The evolution of the best response deviation over time indicates that firms' initial conduct was consistent with more market power than they had, and that after the change, increased arbitrage pushed their conduct closer to the static Nash equilibrium. This effect can be roughly quantified by multiplying the change in the BRD, which is measured in dollars, by the average daily load. Using the lowest estimate for the change in the BRD in the after period, this calculation yields an average savings of about $\$750,000$ a day($\$0.5$ times $1,500,000$ MWh). This indicates that about half of the reduction in consumer cost is attributable to firms reverting to a static Nash equilibrium.

**Table 7: Total expenditure** Total expenditure was computed as total purchases in each market, times the average clearing price at demand node. The total is the sum of the purchases in the forward and spot market. Specifications (1) and (2) includes hour and month fixed effects were used. Data is hourly. Fuel prices and their 24 and 48 hours lags are included as controls. The sample goes from August 2010 to July 2011. HAC standard errors reported.

| | (1) | (2) | (3) |
|---|---|---|---|
| before | $0.270^{***}$ | $0.093^{***}$ | $-0.117^{***}$ |
| | (0.068) | (0.024) | (0.018) |
| interim | $0.073^{*}$ | $-0.029^{**}$ | $0.041^{***}$ |
| | (0.042) | (0.014) | (0.015) |
| log(real-time load) | $3.480^{***}$ | $3.476^{***}$ | |
| | (0.030) | (0.029) | |
| Trend | 0.000 | | |
| | (0.000) | | |
| Fuel price controls | Y | Y | N |
| Observations | 7,100 | 7,100 | 7,100 |
| $R^2$ | 0.917 | 0.917 | 0.017 |
| Adjusted $R^2$ | 0.917 | 0.917 | 0.016 |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | | |

# 9 Conclusion

This paper studies competition and the role of financial players in electricity markets. I examine a regulatory change that exogenously increased virtual trading. I test and reject the null hypothesis of static Nash equilibrium, a standard assumption in both structural industrial organization and event studies. Evidence suggest firms were rather in a cooperative equilibrium that broke as soon as firms learnt about increased competition in the future. My findings highlight the importance of considering potential dynamic incentives in empirical analysis. In this case, assuming static Nash would have lead to conclude that financial traders have no effect on market competitiveness, while I show that they restricted generators' market power and resulted in increased consumer welfare.

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# Online appendix - For online publication

## A Revenue Sufficiency Guarantee (RSG) charges

In the MISO market, some eligible generators are guaranteed the full recovery of their production cost when MISO commits them to produce a quantity that differs from their day-ahead schedule. The production cost has three components: the start-up cost, incurred when the generating units start running, the no-load cost, which is the cost of operating and producing zero MWs, and the marginal cost. Only the latter is covered by the market clearing price (LMP), so the eligible generators need to be compensated for their incurred start-up and no-load costs. This is funded by imposing Revenue Sufficiency Guarantee (RSG) charges on deviations from the day-ahead schedule, *i.e.* on differences between the MWs that a market participant cleared in the day-ahead market and what she produces in the real-time market. As virtual participants do not physically buy or sell energy, the total virtual MWs are considered a deviation and are subject to RSG charges.

MISO's treatment of virtual bidders with respect to the RSG has varied over time in a way that affects incentives. When the market was opened to financial participants in April 2005, virtual transactions were not subject to RSG charges. In April 2006, the FERC issued an order according to which virtual offers had to pay RSG charges retroactively until 2005. This was reversed in October of the same year. After a long discussion between MISO, market participants, and the FERC, in November 2008 the latter determined that virtual supply had to pay RSG charges. This applied to future trades as well as retroactively until April 2006. The discussion about what trades should be subject to the charges and how these should be computed continued until April 2011. During this period, charges were constant across nodes, computed as $\text{RSG}_i = \text{MW}_i^S \cdot \text{RSG\_RATE}$, where i is a bid and MWS are MWs of virtual supply. This means that if a virtual bidder was buying 1 MW at a node, her payoff was just the real-time price minus the day-ahead one. For a virtual participant selling 1 MW in the day-ahead market, the payoff was $p^F - p^S - \text{RSG\_RATE}$. Charges during this period were on average larger than the day-ahead premium (see Tables 1 and 3). On March 2011 the FERC accepted MISO's proposal for a change in the computation of the RSG charges. Since April 1st, 2011, both virtual supply and virtual demand are subject to these charges and their calculation has changed. In addition to a component that is common across nodes, the Day-Ahead Deviation & Headroom Charge or DDC, there is a component that depends on congestion at each specific node called the Constraint Management Charge or CMC. As shown in the formula below, the CMC depends on the sum of deviations weighted by a congestion factor called the Constraint Contribution Factor or CCF which is between -1 and 1. When it is positive, the constraint is relaxed by more demand or less supply, so charges are imposed only on supply; when the factor is negative, only demand has to pay deviation charges. The calculation of the charges for each participant is as follows:

$$\text{RT\_RSG\_DIST1}_h = \text{CMC\_DIST}_h + \text{DDC\_DIST}_h$$

$$\text{CMC\_DIST}_h = \sum_n \max\left\{\left(MW_n^S - MW_n^D\right) \cdot \text{CCF}_{h,n}, 0\right\} \cdot \text{CMC\_RATE}_{h,n}$$

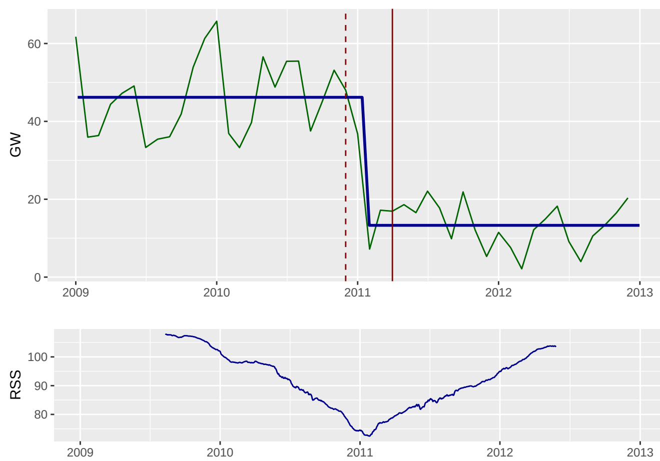
$$\text{DDC\_DIST}_h = \sum_n \max\left\{\left(MW_n^S - MW_n^D\right), 0\right\} \cdot \text{DDC\_RATE}_{h,n}$$

where h is an hour, $MW_n^S$ and $MW_n^D$ are the virtual supply and demand, respectively, cleared by the participant at node $n$ for hour $h$.

# B Physical's demand response to the regulatory change

Generators are able to increase the forward price only if demand does not respond shifting purchases to the spot market. Figure B.1 shows spot purchases in the MISO energy market, which are on average positive before the regulatory change. Although this is consistent with market power on the demand side, it is also what a price-taker buyer facing a forward premium would do to minimize its purchasing cost. A price-taker buyer wants to buy as little as possible in the forward market because the price is lower in the spot market. A buyer with market power restricts its demand in the forward market in order to lower the price. Therefore, in the presence of a forward premium, purchases in the spot market are expected to be positive.

**Figure B.1: Load cleared in the spot market** The green line shows the monthly average of the daily difference between the quantity cleared in the forward and spot markets. The dashed red line on December 1, 2010 indicates the announcement of the regulatory change; the solid red line on April 1, 2011, its implementation. The structural break occurred on January 26, with a confidence interval between January 20 and February.




As Figure B.1 shows, buyers were initially withholding purchases in the forward market, and spot purchases decreased after RSG charges were reduced. I find a structural break in the net purchases time series on January 26, 2011.[34]. This indicates that demand reacted before the change in RSG charges was actually implemented, but after generators did, suggesting demand responded to the generators' reaction and not directly to the regulatory change.

Purchasers' late response, as well as the fact that the forward premium was positive both before and after the regulatory change, which is advantageous for sellers, indicates that the premium was being driven by generators rather than purchasers. This may seem surprising because utilities are large companies

[34] The confidence interval for the break date is between January 20 and February 2.

and are generally expected to have considerable market power. There are a few reasons why demand may not have reacted as much as would be expected. First, many utilities can pass increased costs directly to final consumers, which makes them price insensitive. Second, MISO and the market monitor pay special attention to demand underscheduling. If utilities exerted too much market power by declining to purchase electricity in the overpriced forward market, they could be sanctioned by the authorities. Third, spot purchases are subject to RSG charges, which makes spot sales expensive for buyers. Lastly, demand may be hedged as there are financial instruments available to hedge the risk of spot price volatility, particularly because hedging costs are generally among the costs that regulated utilities are allowed to recover.

# C Derivation of the Euler-Lagrange conditions for the generator's problem

The generator chooses bids in the forward and spot market to maximize expected profits. The generator's problem is the following:

$$\max_{Q_i,S_i} \int_{\underline{p}}^{\overline{p}} \int_{\underline{p}}^{\overline{p}} U\Big(\Pi_i(Q_i,S_i)\Big)\; dH(p^F,Q(p^F);x_i^F)\; dG(p^S,S_i(p^S);x_i^S) \tag{6}$$

where $Q_i = Q_i(p^F, x_i^F)$ and $S_i = S(p^S, x_i^S)$. $G$ and $H$ are the distributions of the clearing price defined in Section 4.

We can rewrite $dH(p^F, Q(p^F); x^F)$ and $dG(p, \hat{S}(p); x^S)$ as:

$$\begin{aligned} dH(p^F,Q(p^F);x^F) &= \frac{dH}{dp^F}dp^F = (H_Q Q' + H_P)dp^F \\ dG(p^S,S(p^S);x^S) &= \frac{dG}{dp^S}dp^S = (G_S S' + G_P)dp^S \end{aligned} \tag{7}$$

Replacing the above and defining the integrand as $J(Q,Q',p^F,S,S',p^S)$, the integrand now becomes

$$J(Q,Q',p^F,S,S',p^S) \equiv U[H_Q Q' + H_P][G_S S' + G_P]$$

where $U = U\Big(p^F Q(p^F) + p^S[S(p^S) - Q(p^F)] - C(S(p^S)) - [p^F - h^F]x^F - [p^s - h^S]x^S\Big)$. The argument is omitted from now on. The Euler-Lagrange equations are:

$$\begin{aligned} J_Q &= \frac{\partial}{\partial p^F} J_{Q'} \\ J_S &= \frac{\partial}{\partial p^S} J_{S'} \end{aligned} \tag{8}$$

Taking derivatives:

$$\begin{aligned} J_Q &= U'[p^F - p^S][H_Q Q' G_S S' + H_Q Q' G_P + H_P G_S S' + H_P G_P] + \\ &\quad U[H_{QQ} Q' G_S S' + H_{QQ} Q' G_P + H_{PQ} G_S S' + H_{PQ} G_P] \\ J_S &= U'[p^S - c'][H_Q Q' G_S S' + H_Q Q' G_P + H_P G_S S' + H_P G_P] + \\ &\quad U[H_Q Q' G_{SS} S' + H_Q Q' G_{PS} + H_P G_{SS} S' + H_P G_{PS}] \\ J_{Q'} &= U[H_Q G_S S' + H_Q G_P] \\ J_{S'} &= U[H_Q Q' G_S + H_P G_S] \end{aligned}$$

$$\begin{aligned} \frac{\partial}{\partial p^F} J_{Q'} &= U'[Q + p^F Q' - p^S Q' - x^F][H_Q G_S S' + H_Q G_P] + \\ &\quad U[H_{QQ} Q' G_S S' + H_{QP} G_S S' + H_{QQ} G_P Q' + H_{QP} G_P] \\ \frac{\partial}{\partial p^S} J_{S'} &= U'[p^S S' + S - Q - c' S' - x^S][H_Q Q' G_S + H_P G_Q] + \\ &\quad U[H_Q Q' G_{SS} S' + H_Q Q' G_{SP} + H_P G_{SS} S' + H_P G_{SP}] \end{aligned}$$

After substituting and canceling terms, the Euler-Lagrange conditions are:

$$p^F - p^S = [Q(p^F) - x^F]\frac{H_S}{H_P} \tag{9}$$

$$p^S - c' = [S(p^S) - Q(p^F) - x^S]\frac{G_S}{G_P} \tag{10}$$

where $H_Q = \frac{dH}{dQ}$, $H_p = \frac{dH}{dp}$, $G_S = \frac{dG}{dS}$, and $G_p = \frac{dS}{dp}$. $H_p$ is the density of the clearing price in the forward market when all firms submit optimal schedules. $H_Q$ is the change in the price distribution caused by a change in the bid submitted by $i$, which can be interpreted as a measure of $i$'s market power. $G_S$ and $G_p$ have equivalent interpretations in the spot market.

Because the forward market is purely financial, generators' sales there have no physical cost. Nonetheless, the spot price is the opportunity cost faced by a generator willing to sell in the forward market, since each unit can be sold in either the spot or the forward market. This becomes clear in Equation 9, which is similar to an oligopolist's first order condition in which the spot price replaces the marginal cost. The forward premium is then a markup with respect to this opportunity cost. Whether the generator wants to have a positive or negative markup will depend on her hedging contract position, because this determines whether the generator is a net seller or a net buyer in the forward market.

A similar trade-off is present in the spot market. The optimal markup for a generator depends on whether she is a net seller or buyer in the spot market, which depends on both her contract position in the spot market and her forward sales. Additionally, the importance of this position is weighted by the firm's ability to affect prices with bids, $G_S$.

Hortacsu and Puller (2008) present a separability condition that allows the optimality conditions to be simplified. Intuitively, the condition is that financial contracts shift the optimal bid, but do not change its slope. Formally, it requires schedules to be additively separable in the two sources of uncertainty, which holds when they can be written as $Q_i(p^F, x_i^F) = \alpha_i(p^F) + \beta_i(x_i^F)$. Figure C.1 in Appendix D shows some bids that seem to satisfy this assumption, as they are parallel shifts of each other. Appendix D presents some empirical evidence backing up this assumption.

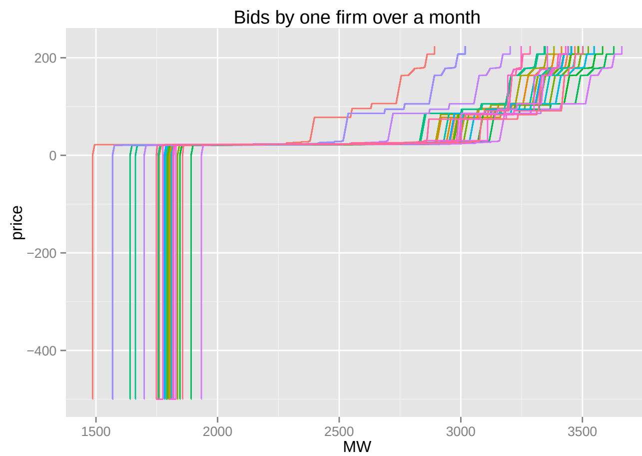
If bids are additively separable, the optimality conditions can be written as directly as a function of the residual demand faced by each firm (see Appendix D for a proof):

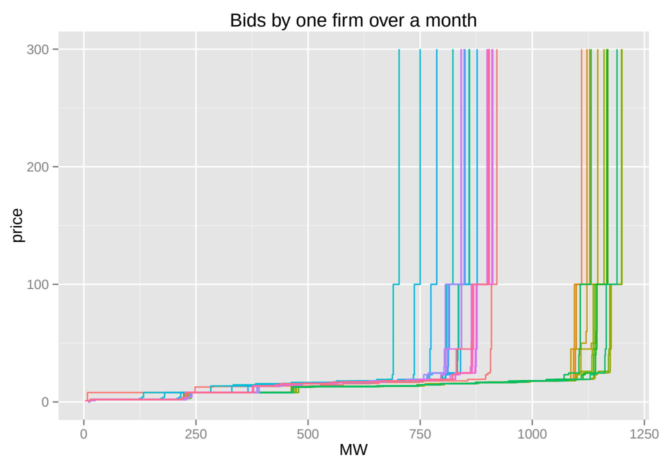
$$p^F - p^S = -[Q^*(p^F) - x^F]\frac{1}{R'(p^F)} \tag{11}$$

$$p^S - c' = -[S^*(p^S) - Q^*(p^F) - x^S]\frac{1}{R'(p^S)} \tag{12}$$

Using the separability assumption to write the optimality conditions in terms of the residual demand makes it much easier to obtain its empirical counterpart. The residual demand within a market can be constructed from the bids, while the distribution of prices is harder to compute.

**Figure C.1: Additive Separability** Differences across the bids for a given firm seem to be parallel shifts.




# D Additive Separability

The empirical strategy in this paper relies on the assumption of additive separability of the optimal bid in the hedging contract position and the price. If schedules are additively separable in the contract position and the price, then the event of excess supply can be written

$$D^F(p^F) - Q_i - \sum \alpha_j(p^F) < \sum \beta_j(x_j^F) - \epsilon^F \tag{13}$$

Define $\theta \equiv \sum \beta_j(x_j^F) - \epsilon^F$, a random variable with distribution $\Gamma(\cdot)$. This variable $\theta$ contains the uncertain components determining the clearing price. Using the definition of $\theta$, $H$ can be rewritten as follows

$$
\begin{aligned}
H(p, \hat{Q}(p); x_i^F) \; &= \Pr\Big(\sum_{j \neq i} Q_j(p, x_i^F) + \hat{Q}_i \geq D^F(p) | x_i^F, \hat{Q}\Big) \\
&\Pr\Big(D^F(p^F) - Q_i - \sum \alpha_j(p^F) < \sum \beta_j(x_j^F) - \epsilon^F\Big) \\
&1 - \Gamma\Big(D^F(p^F) - Q_i - \sum \alpha_j(p^F)\Big)
\end{aligned}
$$

and an equivalent expression holds for $G$. Taking derivatives of this expression and simplifying,

$$
\frac{H_S}{H_p} = \frac{1}{D'(p) - \sum \alpha'(p)} \tag{14}
$$

Notice that the denominator of the right hand side of equation 14 is the derivative of the ex-post residual demand faced by generator $i$. For a given realization of $\epsilon$ and $x_{-i}$, the residual demand faced by $i$ is

$$
R(p) = D(p) + \epsilon - \sum_{j \neq i} \alpha_j(p) - \sum_{j \neq i} \beta(x_j) \tag{15}
$$

therefore its derivative is $D'(p) - \sum \alpha'(p)$. Replacing this in the optimality conditions, they become

$$
\begin{aligned}
p^F - p^S &= -[Q^*(p^F) - x^F] \frac{1}{R'(p^F)} \\
p^S - c' &= -[S^*(p^S) - Q^*(p^F) - x^S] \frac{1}{R'(p^S)}
\end{aligned}
$$

If this assumption holds, changes in the contract position will shift the bid without affecting the slope. I follow Hortacsu and Puller (2008) and use the data to test the assumption. The test evaluates whether the slope of the bids changes with variations in the contract position. Under additive separability, contracts should only cause parallel shifts in the bids, with no effect on the slope.

I fit a linear function to the submitted bids to obtain their slope,;the fit is around 68 percent, a decent approximation. I then regress the slope of the bid on the hedging contract position obtained as explained in Section 6.3. The first column of Table D.1 present the results of this regression, using firm-market fixed effects. The correlation between the slope of a firm's bid and its contract position is not statistically significant, which supports the additive separability assumption.

Because the optimal bid submitted depends on the other players' strategy, I add the slope of the residual demand faced by each firm as a control. I also control for the spot price, since it is the opportunity cost of bidding in the forward market. After controlling for these factors, the forward position is still not significantly correlated with the slope of the bids, as the last three columns of Table D.1 show.

**Table D.1: Test of additive separability** Results from regressing the slope of the bids submitted by producers on their forward contract position. Includes owner-market, month and hour fixed effects. The fact that the correlation between the slope and the contract position is not significant supports the additive separability assumption.

| | (1) | (2) |
|---|---|---|
| Residual demand's slope | | −0.000 |
| | | (0.00000) |
| Expected spot price | | 0.055 |
| | | (0.035) |
| Contract position | −0.003 | −0.002 |
| | (0.002) | (0.002) |
| Observations | 800,597 | 798,301 |
| $R^2$ | 0.0001 | 0.001 |
| Adjusted $R^2$ | −0.014 | −0.014 |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | |

# E Model with strategic demand and supply

This appendix extends the model presented in section 4.1 to include strategic demand. Instead of taking demand given, I model buyers strategically choosing how to distribute their purchases between the spot and the forward markets. Because in wholesale electricity markets most purchases come from utilities serving downstream consumers, I will refer to buyers as utilities. Additionally, I will assume that firms do not hold hedging contracts for the spot price, i.e. $x^S = 0$. The market subindexes are omitted in this section, but the analysis is always done under the assumption of independent separate markets.

**Demand** Unlike generators, utilities' only decision is how to split purchases between the forward and the spot markets. They do not choose how much electricity to buy in the spot market, because final demand is given by households' electricity consumption. Therefore, the spot market is cleared such that there is enough generation to cover the load forecast $L$, which has a deterministic component $l$ and a random component $\epsilon$. In the forward market, each buyer submits a schedule $D(p^F)$ indicating how much she is willing to buy at each price. The difference between the quantity cleared in the forward market and $L$ has to be purchased in the spot market.

Like generators, buyers may have financial contracts that affect their position in the forward market. I denote the contract terms as above: a firm holds a contract for a quantity $x$ at a price $h$. Profits from the hedging contract are computed differently from generators though, because utilities are on the other side of the contract. If the clearing price is larger than $h$, the buyer gets paid the difference; if the clearing price is smaller than $h$, the buyer pays the difference to the other side (a generator).

**Market clearing** The market clearing prices $\bar{p^F}$ and $\bar{p^S}$ are determined by the market clearing conditions below

$$\sum_{j \in Sellers} Q_j(\bar{p}^F) = \sum_{b \in Buyers} D_b(\bar{p}^F) \tag{16}$$

$$\sum_{j \in Sellers} S_j(\bar{p}^S) = l + \epsilon \tag{17}$$

**Generators' uncertainty** As before, each generator $i$ faces uncertainty over the clearing prices $\tilde{p}^F$ and $\tilde{p}^S$, because she does not know what clearing price will result from submitting different schedules. In the spot market, uncertainty comes from the random component of demand, as in the section without strategic demand. In the forward market, it comes from the unknown hedging positions of other firms, which are private information and therefore make the clearing price uncertain. In other words, the generator is uncertain about the residual demand she faces, because residual demand depends on other firms' bidding behavior.

Bidder $i$'s uncertainty in the forward market is represented by $F_x(x_{-i}|x_i)$, the distribution of other firms' contract positions. It is conditional on $i$'s own position because $i$'s position may contain information about others' contracts. Note that this remains a private value setting since $i$'s profits do not depend on its competitors' hedging positions. In the spot market, uncertainty comes from $\epsilon$, which has distribution $F_\epsilon(\epsilon)$.

As above, I define a probability measure over the realizations of the forward clearing price from the perspective of firm $i$, conditional on $i$'s private information about its contract position $x_i^F$, $i$'s submission of a schedule $\hat{Q}_i(p, x_i^F)$, and her competitors playing their equilibrium strategies $\{Q_j(p, x_j^F), j \neq i\}$.

$$H(p, \hat{Q}_i(p); x_i^F) \;\equiv\; \Pr(\tilde{p}^F \leq p \mid x_i^F, \hat{Q}_i) \tag{18}$$

$H(p, \hat{Q}_i(p); x_i^F)$ represents the uncertainty over the forward market clearing price faced by firm $i$. It is the probability, given $i$ 's contract position, that generator $i$ will be paid a price $p$ when she sells a quantity $\hat{Q}_i(p)$ and all other generators submit the equilibrium offer functions. The event $\tilde{p}^F \leq p$ is equivalent to the event of excess supply at price $p$. Using the market clearing condition in Equation 17, $H$ can be written as

$$\begin{aligned} H(p, \hat{Q}(p); x_i^F) &= \Pr\Big(\sum_{j \neq i} Q_j(p, x_i^F) + \hat{Q}_i(p) \geq \sum_{d \in Buyers} D_d^F(p, x_d^F)|x_i^F, \hat{Q}\Big) \\ &= \int_{x_{-i}^F} 1\Big\{\sum_{j \neq i} Q_j(p, x_i^F) + \hat{Q}_i(p) \geq \sum_{d \in Buyers} D_d^F(p, x_d^F)\Big\} dF^F(x_{-i}^F|x_i^F) \end{aligned} \tag{19}$$

**The generator's problem** The problem of the firm is to choose forward and spot bids that maximize its expected profits. As in the case without strategic demand, the generator's expected profits are given by:

$$\max_{Q(p^F),S(p^S)} \int_{\underline{p}}^{\overline{p}} \int_{\underline{p}}^{\overline{p}} U\Big(\Pi(Q(p^F, x^F), S(p^S))\Big)\, dH(p^F, Q(p^F); x^F)\, dG(p^S, S(p^S); x^S)$$

The Euler-Lagrange conditions for the bids that maximize the generator's profits are (proof analogous to the one in Appendix C)

$$p^F - p^S = [Q(p^F) - x^F]\frac{H_S}{H_P} \tag{20}$$

$$p^S - c' = [S(p^S) - Q(p^F) - x^S]\frac{G_S}{G_P} \tag{21}$$

**Additive separability**

If the schedules submitted by both buyers and sellers satisfy additive separability, the optimality conditions can be written in terms of the residual demand or supply. To see this, assume that demand and supply schedules are additively separable and therefore can be written as $D(p) = a(p) + b(x)$ and $Q(p) = \alpha(p) + \beta(x)$. The event of excess supply at price $p$ can then be written

$$\sum_{i\in I^S} \alpha_i(p) + \sum_{i\in I^S} \beta_i(x) \geq \sum_{i\in I^D} a_i(p) + \sum_{i\in I^D} b_i(x)$$
$$\sum_{i\in I^S} \alpha_i(p) - \sum_{i\in I^D} a_i(p) \geq \sum_{i\in I^D} b_i(x) - \sum_{i\in I^S} \beta_i(x)$$

Defining $\theta \equiv \sum_{i\in I^D} b_i(x) - \sum_{i\in I^S} \beta_i(x)$, a random variable with distribution $\Gamma$. Then, the expectation of excess supply from the perspective of a generator is

$$
\begin{aligned}
H(p,\hat{Q}(p);x_i^F) \; &= \Pr\Big(\sum_{j\neq i} Q_j(p,x_i^F)+\hat{Q}_i \geq D^F(p)|x_i^F,\hat{Q}\Big) \\
&\Pr\Big(\sum_{j\in I^D} a_j(p)-Q_i-\sum \alpha_j(p^F) \geq \sum \beta_j(x_j^F)-\sum_{j\in I^D} b_j(x)\Big) \\
&\Gamma\Big(\sum_{j\in I^D} a_j(p)-Q_i-\sum \alpha_j(p^F)\Big)
\end{aligned}
$$

And equivalently for demand. Taking derivatives and simplifying, the optimality conditions can be rewritten as Equations 11 and 12 for sellers and an equivalent one for buyers.

# F Market-clearing algorithm

In the MISO market, generators submitted schedules consist of more information that the 10 steps of the bid. They additionally indicate the maximum and minimum quantity that they can produce economically, and under an emergency, as well as whether they act as price-takers. Additionally, they may indicate that the unit is already working, so it must run during that hour but they do not need to pay the start costs. They also provide technical information about the plant like the maximum and minimum temperatures, ramping times and costs, and the number of hours in a row a unit needs to run. The effect of these cost complementarities has been studied by Reguant (2014)

MISO only publishes some of the information provided by the generators at each moment. The main part missing are the complementarities between hours that the market authority must consider when clearing the market. As a simplification, I do not consider this when I clear the markets either, but this does not seem to cause great divergence between my simulated market clearing quantities and prices, and those observed in the data.

I include the step function submitted by each bidder, as well as whether they are price-takers. Additionally, I adjust some bids to reflex other parameters. For instance, a good number of run-of-river and wind units submit offers for $999MW$

in the second step, even though their capacity, as represented by the economic and emergency maxima, is below this (usually around $10MW$).[35] As keeping this would alter the market clearing results, I modify the bids to reflect the unit's capacity. I generally restrict every step to be below the specified economic maximum. Additionally, when a bid specifies a quantity in the first step, but no prices, I assume they are willing to pay any price for that quantity.

[35]The economic minimum and maximum are part of the bids submitted by generators, and indicate the minimum and maximum quantity that it is profitable to produce. They may be willing to produce more under emergency conditions.

# G Additional figures and tables

**Figure G.1: Price dispersion** Heat map of prices across the MISO market on September 7, 2011 and April 10, 2012. Prices may differ significantly in a given moment, and over time. Source: MISO

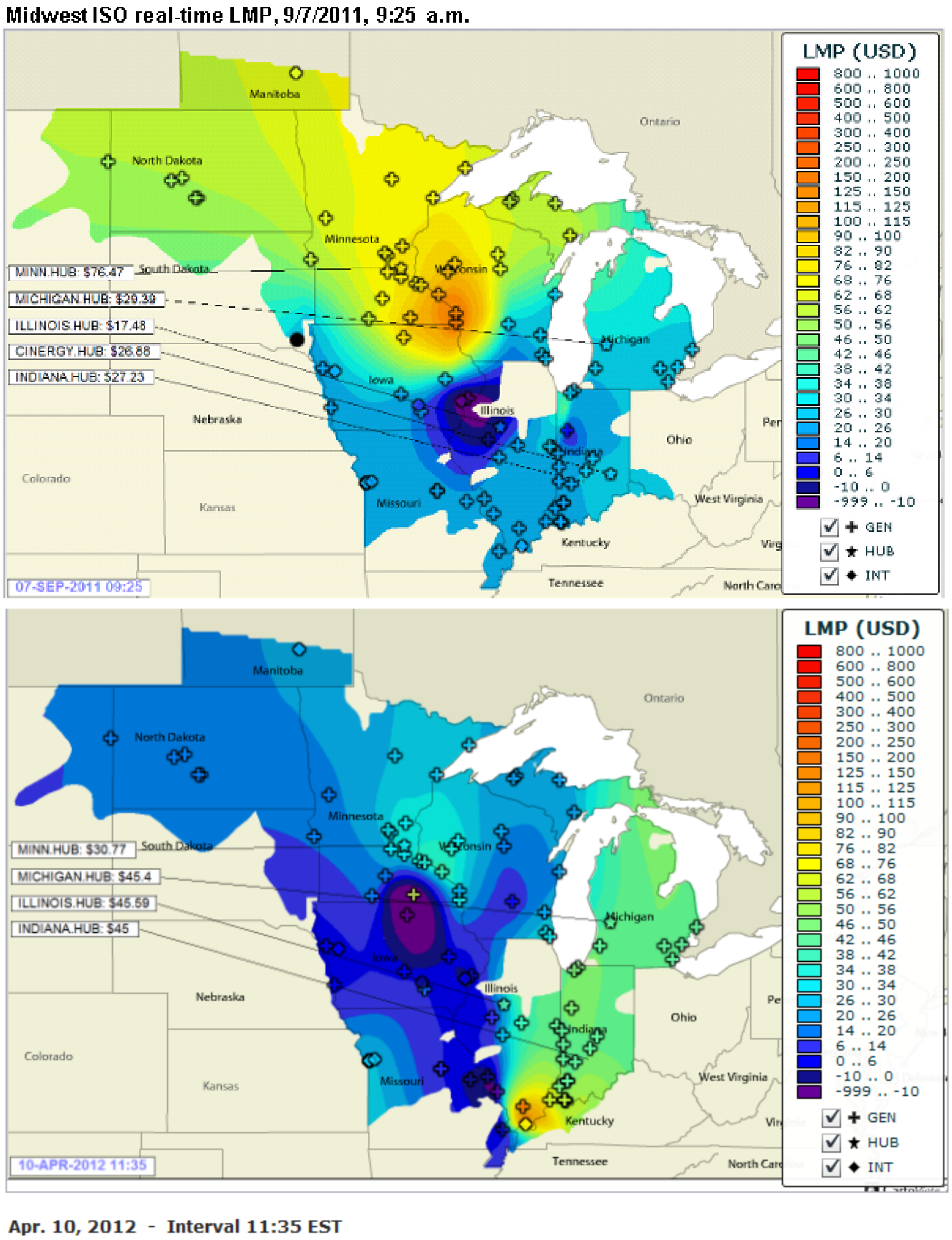
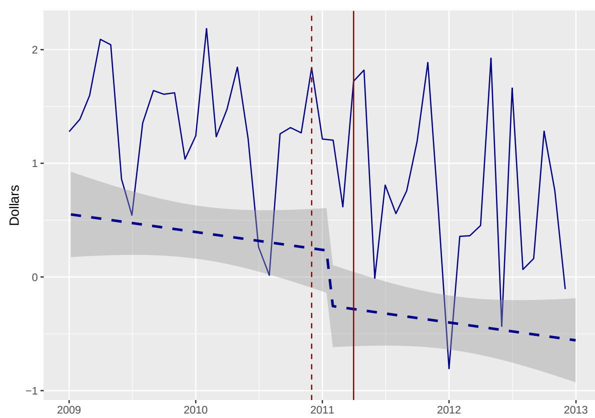


**Figure G.2:** Forward premium over time. The solid line shows the monthly average of the daily forward premium. Since the premium is so volatile, the plotted premium is a residual of a regression of the forward premium on monthly fixed effects, wind production, and actual demand. The dashed solid lines shows a regression line that includes a trend and a dummy for the two periods. The dashed vertical line on December 1, 2010 indicates the announcement of the regulatory change; the solid vertical line on January 16, 2011 shows the data in which there is a structural break for generators' behavior.

**(a)** OLS




**(b)** Robust regression

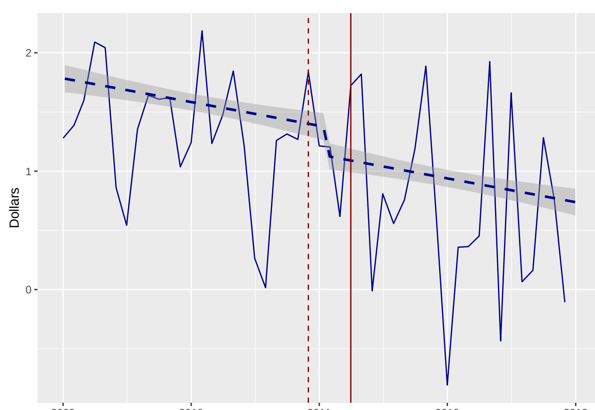


**Figure G.3:** Forward and spot prices. The dashed line shows the monthly average of the forward price over time, the solid line shows the same for the spot price.

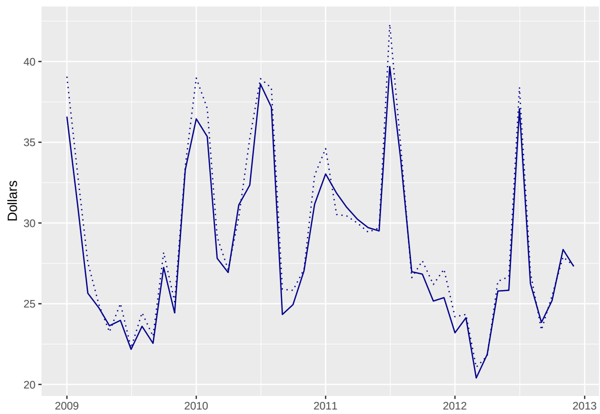



**Table G.1: Supply bids in the forward market** Each variable is computed daily. For instance, the number of bids is the total number of bids submitted each day. The sample goes from January 2010 to December 2011.

| Statistic | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| # bids | 730 | 20,717 | 1,036 | 18,861 | 21,886 |
| # nodes | 730 | 927 | 28.2 | 883 | 957 |
| # units | 730 | 1,147 | 41.172 | 1,079 | 1,197 |
| # firms | 730 | 126 | 4.78 | 120 | 132 |
| Percentage of bids cleared | 730 | 0.361 | 0.035 | 0.288 | 0.511 |
| Cleared MW | 730 | 1,214,775 | 162,234 | 849,110 | 1,672,726 |
| Price taker MWs | 730 | 163,606 | 24,390 | 101,316 | 212,362 |
| Percent piecewise linear | 730 | 0.75 | 0.012 | 0.72 | 0.77 |
| MW piecewise linear | 730 | 0.82 | 0.013 | 0.78 | 0.86 |

**Table G.2: Supply bids in the spot market** Each variable is computed daily. For instance, the number of bids is the total number of bids submitted each day. The sample goes from January 2010 to December 2011.

| Statistic | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| # bids | 730 | 13,037 | 1,031 | 10,607 | 17,071 |
| # nodes | 730 | 525.2 | 53.4 | 432 | 776 |
| # units | 730 | 603.9 | 65.1 | 493 | 914 |
| # firms | 730 | 100.3 | 6.24 | 88 | 118 |
| Percentage of bids cleared | 730 | 0.72 | 0.027 | 0.62 | 0.79 |
| Cleared MW | 730 | 1,447,665 | 189,301 | 1,075,636 | 1,977,326.000 |
| Price taker MWs | 730 | 123,147 | 27,014 | 63,248 | 196,913 |
| Percentage bids piecewise linear | 73 | 0.62 | 0.03 | 0.53 | 0.71 |
| Percentage MW piecewise linear | 730 | 0.81 | 0.02 | 0.74 | 0.86 |

**Table G.3: Summary statistics for demand bids** Each variable is computed daily. For instance, the number of bids is the total number of bids submitted each day. The sample goes from January 2010 to December 2011.

| Statistic | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| Price takers | | | | | |
| # bids | 730 | 5,762 | 297.8 | 5,156 | 6,299 |
| # nodes | 730 | 228.6 | 15.7 | 197 | 246 |
| # bidders | 730 | 96.2 | 2.4 | 90 | 100 |
| Percentage of bids cleared | 730 | 1.000 | 0.000 | 1 | 1 |
| Cleared MW | 730 | 1,478,659 | 191,083 | 1,082,308 | 2,043,150 |
| Price sensitive | | | | | |
| # bids | 730 | 1,015 | 63.5 | 792 | 1,152 |
| # nodes | 730 | 42.3 | 2.7 | 33 | 48 |
| # bidders | 730 | 25.2 | 2.16 | 18 | 31 |
| Percentage of bids cleared | 730 | 0.9 | 0.031 | 0.78 | 0.99 |
| Cleared MW | 730 | 30,992 | 5,846 | 17,030 | 52,089 |

**Table G.4: Virtual bids summary stats** Each variable is computed daily. For instance, the number of bids is the total number of bids submitted each day. The sample goes from January 2010 to December 2011.

| Statistic | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| Virtual Demand | | | | | |
| # bids | 730 | 53,556 | 18,873 | 15,240 | 97,824 |
| # nodes | 730 | 874 | 274.9 | 318 | 1,280 |
| # bidders | 730 | 56.4 | 6.71 | 31 | 77 |
| Percentage of bids cleared | 730 | 0.102 | 0.038 | 0.028 | 0.228 |
| Cleared MW | 730 | 86,263 | 22,058 | 39,909 | 161,463 |
| Virtual Supply | | | | | |
| # bids | 730 | 62,313 | 22,024 | 16,080 | 117,384 |
| # nodes | 730 | 993.6 | 309.4 | 351 | 1,378 |
| # bidders | 730 | 50.9 | 6.34 | 32 | 69 |
| Percentage of bids cleared | 730 | 0.095 | 0.032 | 0.034 | 0.197 |
| Cleared MW | 730 | 60,983 | 19,354 | 23,825 | 128,022 |

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