Online Appendix

Dynamic Competition and Arbitrage: The Role of Financial Players

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A. Physical Demand's 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 A.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.

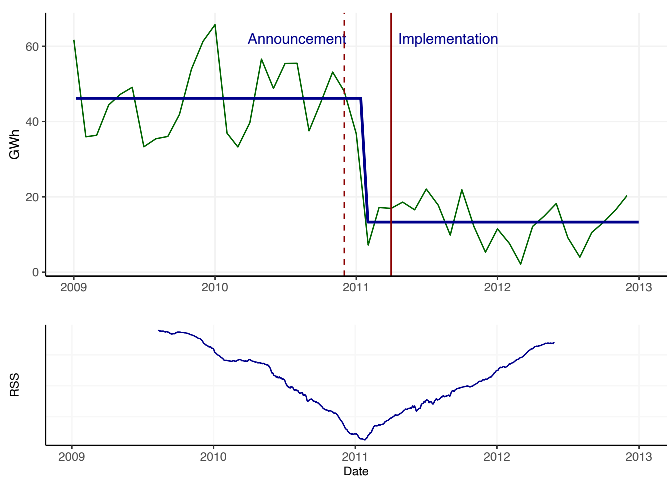


Figure A.1. : **Load Cleared In the Spot Market** The green line shows the monthly average of the daily difference between the quantity cleared in the forward and spot markets. The dashed red line on December 1, 2010 indicates the announcement of the regulatory change; the solid red line on April 1, 2011, its implementation. The structural break occurred on January 26, with a confidence interval between January 20 and February 2.

As Figure A.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.[65]. 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 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.

B. 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

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

FERC, in November 2008 the latter determined that virtual supply had to pay RSG charges.[66] This applied to future virtual 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:

$$\begin{aligned}
\text{RT_RSG_DIST1}_h &= \text{CMC_DIST}_h + \text{DDC_DIST}_h \\
\text{CMC_DIST}_h &= \sum_n \max\left\{\left(MW_n^S - MW_n^D\right) \cdot \text{CCF}_{h,n}, 0\right\} \cdot \text{CMC_RATE}_{h,n} \\
\text{DDC_DIST}_h &= \sum_n \max\left\{\left(MW_n^S - MW_n^D\right), 0\right\} \cdot \text{DDC_RATE}_{h,n}
\end{aligned}$$

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.

C. Structural Break Test Statistics

Financial trading. — 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 the Quandt statistic (Hansen, 2001; Quandt,

[66]This change did not affect physical participants.

1960), and takes values of 965 for total virtual volume, 1134 for virtual supply, and 355 virtual demand.

GENERATORS' SPOT SALES. — The test statistic for the presence of a structural break is 832, which corresponds to a p-value below 1% using the critical values in Andrews (1993).

EXPECTED SPOT PRICE. — The test statistic for the presence of a structural break is 8.63, which corresponds to a p-value of 5% using the critical values in Andrews (1993).

D. 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:

$$\max_{Q_i,S_i} \int_{\underline{p}}^{\overline{p}} \int_{\underline{p}}^{\overline{p}} U\Big(\Pi_i(Q_i,S_i)\Big)\, dH(p^F, Q(p^F); x_i^F)\, dG(p^S, S_i(p^S); x_i^S) \tag{1}$$

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 III.

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

$$\begin{aligned} dH(p^F, Q(p^F); x^F) &= \frac{dH}{dp^F} dp^F = (H_Q Q' + H_P) dp^F \\ dG(p^S, S(p^S); x^S) &= \frac{dG}{dp^S} dp^S = (G_S S' + G_P) dp^S \end{aligned} \tag{2}$$

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:

$$J_Q = \frac{\partial}{\partial p^F} J_{Q'}$$
$$J_S = \frac{\partial}{\partial p^S} J_{S'} \tag{3}$$

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:

$$p^F - p^S = [Q(p^F) - x^F] \frac{H_S}{H_P} \tag{4}$$

$$p^S - c' = [S(p^S) - Q(p^F) - x^S] \frac{G_S}{G_P} \tag{5}$$

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 4, 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.

Hortaçsu 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 $Q_i(p^F, x_i^F) = \alpha_i(p^F) + \beta_i(x_i^F)$. Appendix E 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 E for a proof):

$$p^F - p^S = -[Q^*(p^F) - x^F]\frac{1}{R'(p^F)} \tag{6}$$

$$p^S - c' = -[S^*(p^S) - Q^*(p^F) - x^S]\frac{1}{R'(p^S)} \tag{7}$$

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.

E. 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

$$D^F(p^F) - Q_i - \sum \alpha_j(p^F) < \sum \beta_j(x_j^F) - \epsilon^F \tag{8}$$

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

$$
\frac{H_S}{H_p} = \frac{1}{D'(p) - \sum \alpha'(p)} \tag{9}
$$

Notice that the denominator of the right hand side of equation 9 is the derivative of the ex-post residual demand faced by generator i. For a given realization of ϵ and x_{-i}, the residual demand faced by i is

$$
R(p) = D(p) + \epsilon - \sum_{j \neq i} \alpha_j(p) - \sum_{j \neq i} \beta(x_j) \tag{10}
$$

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 Hortaçsu 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 IV.C. The first column of Table E.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 E.1 show.

Table E.1—: Test of Additive Separability

	(1)	(2)
Residual demand's slope		−0.00000
		(0.00000)
Expected spot price		0.018
		(0.036)
Contract position	−0.002	−0.002
	(0.002)	(0.002)
Observations	758,762	756,536
R^2	0.00004	0.001
Adjusted R^2	−0.015	−0.014

Note: 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.

F. Construction of the Market Definitions

1. Define markets using hierarchical clustering. — Clusters are defined using hierarchical clustering. The process starts with each node in a single cluster, and in each step it joins together the two most similar clusters according to the indicated distance, until there is only one cluster. (Alternatively, it can start with all nodes in one cluster and in each step separate the most dissimilar clusters.) An illustration of this process is presented in Figure J.4. This algorithm requires to specify the linkage, or how to compute the distance between clusters. I chose to use centroid, but results do not change significantly when using complete linkage, single linkage, Ward, or average. Centroid fits as well as the other methods or better. To compute the clusters, I use the function *hclust* from the base R package stats. It requires two parameters: distance measure and method to compute distance between clusters. The distance is the matrix with price correlations and the method is centroid. The correlation matrix is built using the price for all nodes during one hour of one month of the sample, i.e. January 2011 between 6am and 7am. The output is over 2,000 alternative market definitions, so I restrict the

output to up to 50 clusters. Initially I allowed more markets but those definitions did not have a good fit.

2. Market clearing as measure of fit. — For each candidate market definition, I take all bids submitted by physical and financial participants and clear the market. This exercise results in a clearing price and quantity for each market in each candidate market definition. This clearing price is from now referred of as simulated price. When a candidate market does not clear, the simulated price is 0.

3. Price deviation. — This steps computes the difference between the simulated price and the observed price. The observed price is the mean price at the nodes included in the candidate market, weighted by the quantity cleared by physical generators. The difference between the simulated and observed price is then divided by the observed price. This implies that when a market does not clear, the price is set to 0 and thus the deviation is 1. Notice that the fit, measured as the price deviation described above, does not necessarily get better as the number of markets increase, because the market may not clear. In fact, assuming each node is a market will result in most markets not clearing.

4. Selection: first step. — For each hour of each month and year, the price deviation is regressed on a dummy for the market definition using both standard OLS and a quantile regression for the median. The number of observations for each regression is the number of days in the months times the number of markets in each market definition. All market definitions for which the coefficient is not significant at 5% under either OLS or the quantile regression are kept, the rest are discarded. For hours 1, 3, 4, 8, 12, 20, and 22, the null hypothesis of zero difference between the simulated and observed price was always rejected at 5%. For this reason, these hours were excluded from the sample.

5. Selection: second step. — The previous step may result in several market definitions for which the simulated prices are statistically similar to the observed prices. When this happens, I take the market definitions for which the absolute value of the deviation is lower than 0.25, 0.35, or 0.55 in successive order. After this step, there are 4 cases for which the deviation is higher than 0.25 (though statistically zero): hour 2 in September 2011, hour 5 in September 2011, hour 6 in May 2010, and hour 13 in December 2010. Only the latter is part of the main period of analysis.

6. Selection: last step. — As the previous steps still leave more than one market definition for some hours, in this final step I take for each month the

market definition that is more common for that hour. For instance, if in hour 0 of January 2011 the market can be split into between 6 and 17 clusters, I look at what market definitions describe the market well in hour 0 during other months. Splitting the market into 12 separate markets is a suitable market definition for 8 other months, while the other market definitions are suitable during fewer months. I then take the 12 clusters market definition for January 2011 during hour 0. This results in one market definition for each hour of every month and year.

G. Model With Strategic Demand and Supply

This appendix extends the model presented in section III.A 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 ϵ. 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

$$\sum_{j \in Sellers} Q_j(\bar{p}^F) = \sum_{b \in Buyers} D_b(\bar{p}^F) \tag{11}$$

$$\sum_{j \in Sellers} S_j(\bar{p}^S) = l + \epsilon \tag{12}$$

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 ϵ, 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 $\{Q_j(p, x_j^F), j \neq i\}$.

$$H(p, \hat{Q}_i(p); x_i^F) \ \equiv \ \Pr(\tilde{p}^F \leq p \mid x_i^F, \hat{Q}_i) \tag{13}$$

$H(p, \hat{Q}_i(p); x_i^F)$ 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 12, H can be written as

(14)

$$H(p, \hat{Q}(p); x_i^F) = \Pr\Big(\sum_{j \neq i} Q_j(p, x_i^F) + \hat{Q}_i(p) \geq \sum_{d \in Buyers} D_d^F(p, x_d^F) | x_i^F, \hat{Q} \Big)$$

$$= \int_{x_{-i}^F} 1\Big\{ \sum_{j \neq i} Q_j(p, x_i^F) + \hat{Q}_i(p) \geq \sum_{d \in Buyers} D_d^F(p, x_d^F) \Big\} dF^F(x_{-i}^F | x_i^F)$$

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 D)

$$p^F - p^S = [Q(p^F) - x^F] \frac{H_S}{H_P} \tag{15}$$

$$p^S - c' = [S(p^S) - Q(p^F) - x^S] \frac{G_S}{G_P} \tag{16}$$

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 Γ. 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 6 and 7 for sellers and an equivalent one for buyers.

H. 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 $10MW$).[67] 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.

[67]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.

I. Bias in the Contract Position

The estimate of the contract position described in Section IV.C is only valid under the null hypothesis of static Nash equilibrium. This appendix shows that when the null does not hold, the resulting bias in the contract positions leads to underestimating the BRD. To see this, consider the case in which $BRD = \alpha > 0$. Then

$$BRD = p^F - p^S - \frac{Q(p^F) - x^F}{|R'(p^F)|} = \alpha > 0$$

When $p^F = p^S$,

$$\begin{aligned} x^F - Q(p^S) &= \alpha |R'(p^S)| \\ x^F &= Q(p^S) + \alpha |R'(p^S)| \end{aligned}$$

Consequently, estimating the hedging position as $\hat{x}^F = Q(p^S)$ will result in a negative bias, since $\alpha|R'(p^F)| > 0$. This downward bias will result in an upward bias in the BRD, since $\frac{\partial BRD}{\partial x^F} > 0$. An analogous argument shows that when $BRD < 0$, the bias in the forward contract position will lead to underestimating it.

It is not clear that this bias can be corrected, even though the components are observed. For the case of $BRD > 0$, the exercise would lead to moving between overestimating the BRD and underestimating it, with no guarantee of convergence. Nonetheless, it is possible to establish bounds.

J. Additional Figures and Tables

Table J.2—: Supply Bids In the Forward Market

Statistic	N	Mean	Standard Deviation	Min	Max
# bids	730	27,526	988	25,896	28,728
# nodes	730	927	28	883	957
# units	730	1,147	41	1,079	1,197
# firms	730	126	4.8	120	132
Share of bids cleared	730	0.36	0.03	0.29	0.51
Cleared MW	730	1,478,488	196,476	1,079,507	2,028,219
Price taker MWs	730	163,606	24,390	101,316	212,362
Share piecewise linear	730	0.75	0.01	0.73	0.77
Share piecewise linear MW	730	0.82	0.01	0.78	0.86

Note: 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.

Table J.3—: Supply Bids In the Spot Market

Statistic	N	Mean	Standard Deviation	Min	Max
# bids	730	13,037	1,031	10,607	17,071
# nodes	730	525	53	432	776
# units	730	604	65	493	914
# firms	730	100	6.2	88	118
Share of bids cleared	730	0.81	0.02	0.74	0.90
Cleared MW	730	1,460,090	199,253	1,033,536	2,049,684
Price taker MWs	730	123,147	27,014	63,248	196,913
Share piecewise linear	730	0.61	0.03	0.53	0.71
Share piecewise linear MW	302	0.81	0.02	0.74	0.87

Note: 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.

Table J.4—: Demand Bids in the Forward Market

Statistic	N	Mean	Standard Deviatino	Min	Max
Price Takers					
# bids	730	5,762	297.8	5,156	6,299
# nodes	730	228.5	15.7	197	246
# firms	730	96.2	2.4	90	100
Share of bids cleared	730	1.00	0.00	1	1
Cleared MW	730	1,478,659	191,083	1,082,308	2,043,150
Price Sensitive					
# bids	730	962	63.5	772	1,086
# nodes	730	42.30	2.7	33	48
# firms	730	25.20	2.16	18	31
Share of bids cleared	730	0.95	0.03	0.85	1.00
Cleared MW	730	30,992	5,846	17,030	52,089

Note: 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.

Table J.5—: Virtual Demand and Supply Bids (Forward Market)

Statistic	N	Mean	Standard Deviation	Min	Max
Virtual Demand					
# bids	730	20,418	9,506	5,432	47,859
# nodes	730	885	280	321	1,311
# firms	730	56.4	6.71	31	77
Share of bids cleared	730	0.29	0.12	0.06	0.65
Cleared MW	730	86,263	22,058	39,909	161,463
Virtual Supply					
# bids	730	28,210	13,019	7,567	56,089
# nodes	730	1,004	310	352	1,396
# firms	730	50.9	6.34	32	69
Share of bids cleared	730	0.23	0.10	0.05	0.51
Cleared MW	730	60,983	19,354	23,825	128,022

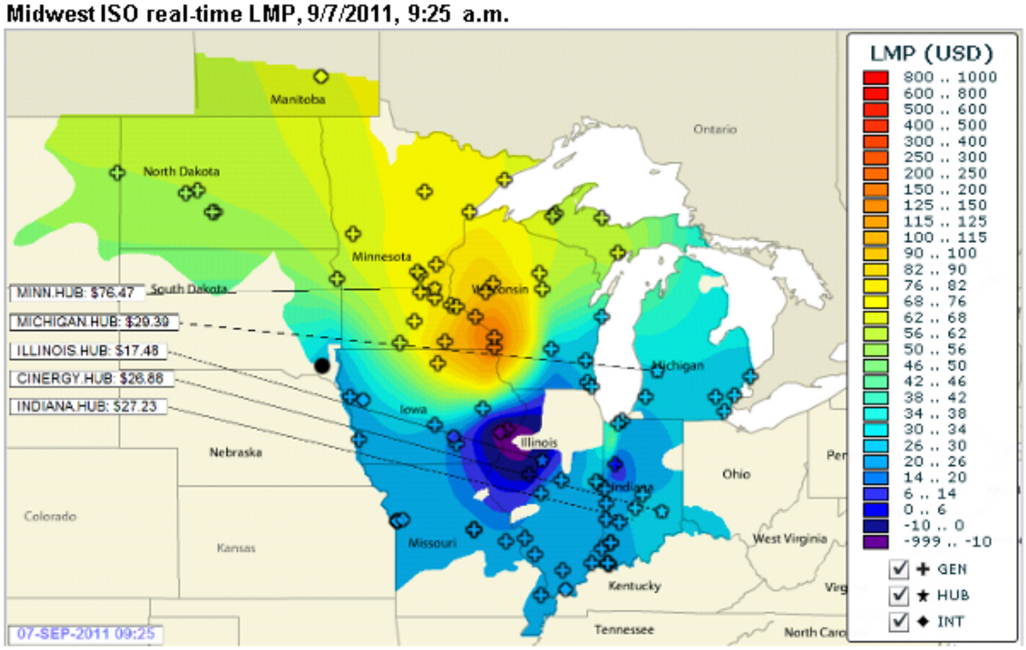
Note: Each variable is computed daily. For instance, the number of bids is the total number of bids submitted each day. The sample goes from January 2010 to December 2011.

Table J.6—: Market Characteristics

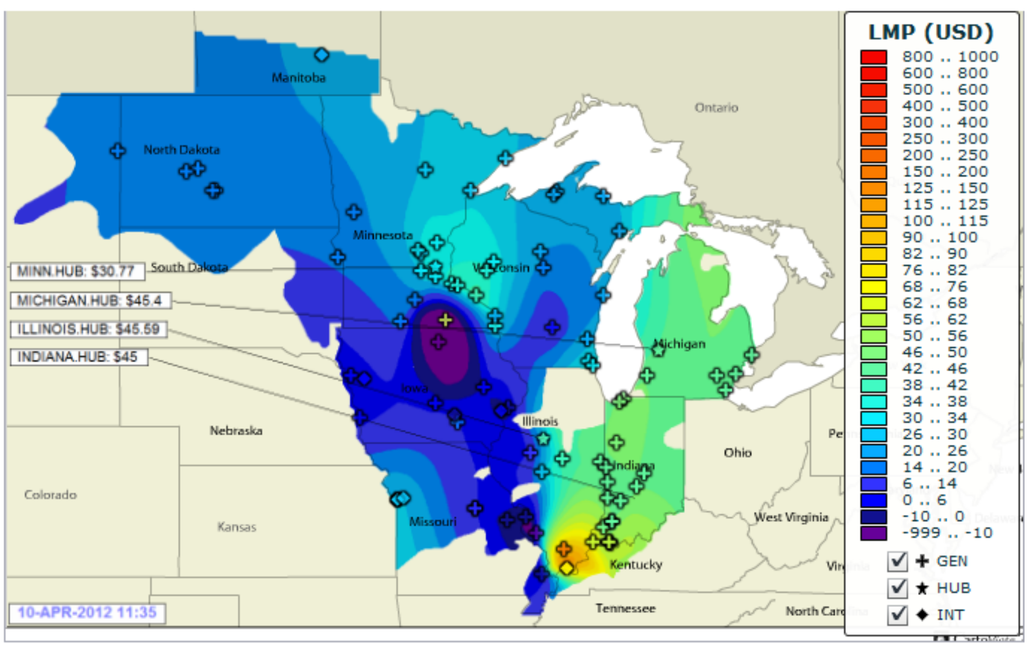
	Dependent variable:		
	HHI	log(# firms)	log(Wind MWh)
Interim	−0.05	−0.42	−0.14
	(0.02)	(0.19)	(0.43)
After	0.02	0.13	0.15
	(0.01)	(0.12)	(0.25)
Mean FE	0.035	0.635	1.245
Observations	384	384	384
R^2	0.20	0.14	0.17

Note: Regression of median market characteristics for each hour of the month and year used in the sample on time period dummies. The regressions include month and hour fixed effects.

Midwest ISO real-time LMP, 9/7/2011, 9:25 a.m.



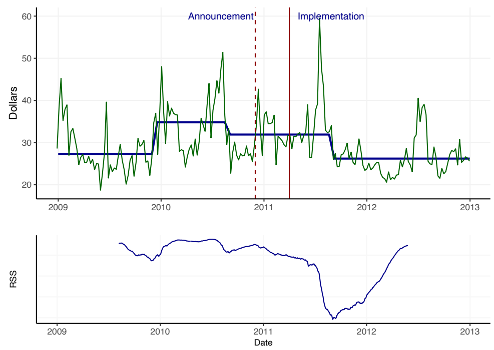
Source: U.S. Energy Information Administration (EIA).



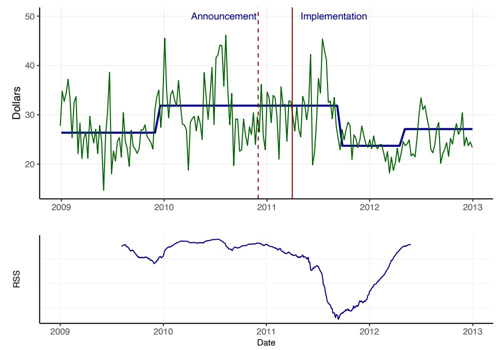
Apr. 10, 2012 - Interval 11:35 EST

Source: EnergyCap, LLC (2021)

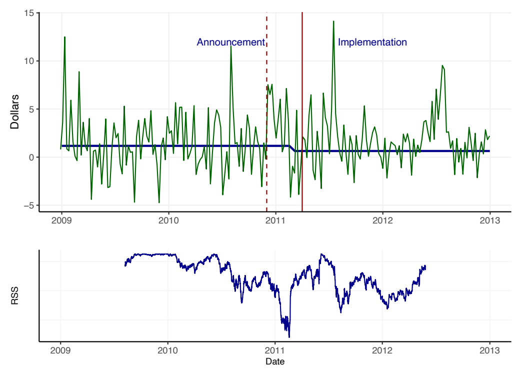
Figure J.2. : **Price Dispersion** Heat map of prices across the MISO market on September 7, 2011 and April 10, 2012. Prices may differ significantly in a given moment, and over time.



(a) Forward Price Over Time



(b) Spot Price Over Time



(c) Forward Premium Over Time

Figure J.3. : **Forward and Spot Prices** The green lines show the weekly median of the quantity weighted hourly forward price, spot price, and forward premium, respectively, while the solid blue line shows the means between break points. The null hypothesis of no structural break is rejected at 1% for the daily series of both prices, with test statistics of 151 for the forward price, and 81 for the spot price. Breaks in the forward price series are dated on 2009-12-06, 2010-08-21, 2011-09-03, and 2012-05-23. Breaks in the spot price series are dated on 2009-11-30, 2011-09-13, and 2012-04-29. For both series, the break on September 2011 is the most robust to changing sample length, and a break in early 2011 is found for shorter samples but it is not very robust. The plots include all breaks detected for the sample between 2009 and 2012. For the forward premium, no break is detected using daily data due to its volatility, but with hourly data the test finds a break on 2011-02-18 (The null of no break is not rejected using daily data -test statistic is 2.5, p-value of 0.66 according to Andrews (1993). With hourly data, the statistic is 11.2 and the p-value 0.01).

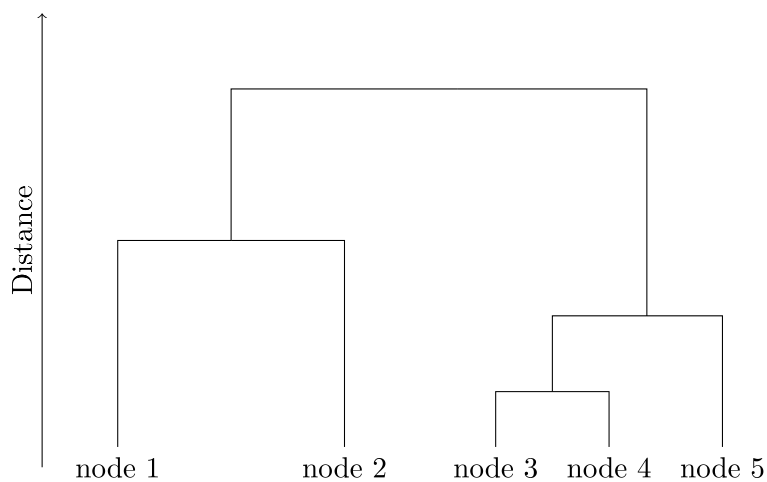
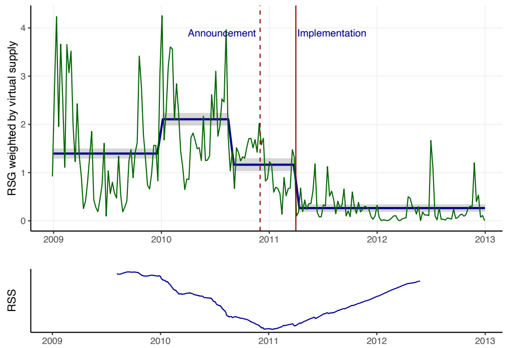
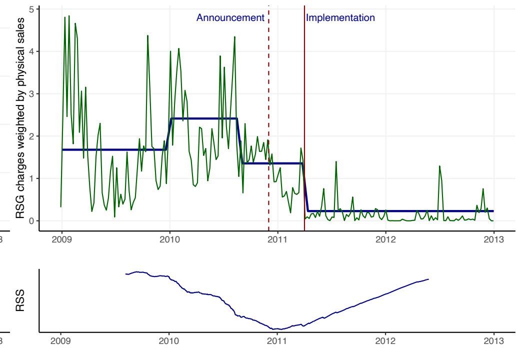


Figure J.4. : **Dendrogram to Illustrate Hierarchical Clustering**



(a) RSG Weighted by Virtual Supply MW



(b) RSG Weighted by Physical Supply MW

Figure J.5. : **RSG Charges Over Time**. The green line shows the weekly median of the hourly mean RSG charges, weighted by virtual supply in the left panel, and physical supply in the right panel. The straight blue line represents the average between break dates. A structural change test using daily data rejects the null of no break (Test statistics are 568 and 729, both resulting in p-values below 1% according to Andrews (1993)) and indicates breaks on 2009-12-27, 2010-08-20, and 2011-04-02 in both cases. The bottom panel indicates the RSS for each date, assuming there is only one break. Since in this case there are multiple breaks, the RSS is lower when several breaks are allowed, but it is not possible to represent this in two dimensions.
Notice that the ex-post series of RSG charges should be interpreted carefully since they may change either because there is new rule of how to compute them, as in April 2011, or because something else in the market increases or decreases total ramping and startup costs. For example, we would expect total RSG charges to go down when spot sales go down in January 2011, because fewer units need to be scheduled last minute. The test does not detect a structural break around this time, but plot of the time series indicates RSG charges slightly went down then.

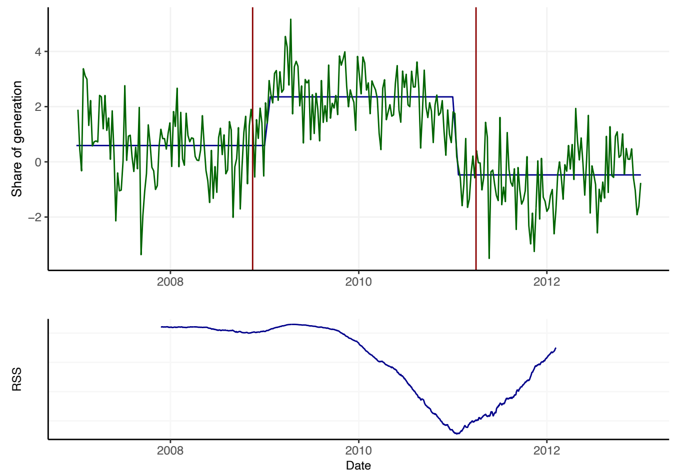


Figure J.6. : **Underbidding** The green line indicates the weekly median of the daily difference between the quantity cleared in the forward and spot markets, which is a measure of generators' underbidding in the forward market. The first vertical red line on November 2008 indicates the date in which RSG charges were first imposed on virtual supply bids, without affecting other players. The second line on April 2011 indicates when these charges were significantly reduced, for both virtual supply and generators. The bottom plot shows the residual sum of squares (RSS) for a model that assumes a structural break in each of the dates in the x-axis, which reaches a minimum on the date of the break when there is a single break. In this case, for the period between January 2007 and December 2012, there are two breaks: one on January 1, 2009, and one on January 10, 2011.

Table J.7—: Additional Specifications

	BRD		Premium	Elasticity	Contracts
	(1)	(2)	(3)	(4)	(5)
Interim	-0.63	−1.98	−2.02	−4.59	−132.59
	(0.28)	(0.34)	(0.82)	(1.60)	(27.66)
After	-0.39	−0.73	-0.82	−6.80	−202.62
	(0.16)	(0.38)	(0.87)	(2.20)	(29.55)
Ngas price		0.87	−1.36	7.46	94.03
		(0.89)	(1.38)	(3.32)	(64.51)
Coal price		−4.38	2.72	−46.19	895.85
		(1.34)	(3.92)	(6.30)	(106.50)
Wind capacity		5.13	-6.97	38.28	−134.62
		(0.95)	(2.56)	(3.93)	(71.06)
Load forecast		16.34	17.56	14.00	413.25
		(3.38)	(4.49)	(15.78)	(171.11)
Actual load		−1.79	6.80	23.86	171.80
		(3.32)	(4.45)	(15.79)	(165.46)
# markets		−0.01			−6.26
		(0.01)			(1.15)
HHI		1.43			1,345.72
		(0.66)			(43.62)
Market size		0.004			410.12
		(0.03)			(2.27)
RT price bias		−0.09	0.85	−0.03	
		(0.004)	(0.01)	(0.003)	
Wind SD		−0.0003			
		(0.0004)			
Wind generation		0.0002			
		(0.0002)			
SD RTprice		−0.03			
		(0.01)			
SD DAprice		−0.06			
		(0.03)			
SD HHI		−3.06			
		(2.80)			
SD Load		−79.89			
		(14.65)			
After July 2011		1.65	3.62	16.06	
		(0.27)	(0.64)	(1.71)	
HHI * Market size		−0.39			−245.04
		(0.11)			(7.77)
Constant		−183.95		−609.24	
		(12.94)		(62.98)	
Hour FE	Y	N	Y	Y	Y
Observations	63,480	63,421	63,480	63,480	63,421
R^2	0.01	0.10	0.85		0.66

Standard errors are clustered a the hour-week level for OLS regressions, and bootstrapped for quantile regressions (elasticity).

Table J.7 presents alternative specifications for the regressions using the BRD (best response deviation) and forward premium as dependent variables. The dependent variable in specifications (1) and (2) use the average BRD in each hour and market, weighted by firm size. In specification (1), I use January

10, 2011, the date of the structural break in generators' behavior as the effective date of the regulatory change. Specification (2) is the same as in Table 2 but here all the coefficients are reported.Columns (3)-(5) present the regressions of the forward premium, including all the coefficients on the controls. Standard errors are clustered a the hour-week level.