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Effects of Changes in Wholesale Electricity Market Structure on Wind Generation in the Midwestern United States

Steve Dahlke

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Colorado School of Mines
Division of Economics and Business
1500 Illinois Street
Golden, CO 80401

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Author(s):
Steve Dahlke
Division of Economics and Business
Colorado School of Mines
Golden, CO 80401
sdahlke@mymail.mines.edu

ABSTRACT
This paper estimates the effect of starting the Midcontinent ISO electricity market in 2005 on wind generation. We find an average increase in wind plant capacity factors of 5.0-6.7% associated with the start of the market, relative to neighboring wind plants not in the market. These results are robust to potentially confounding variation associated with wind speed differences determined by weather. The increased capacity factors are likely attributed to reduced wind plant curtailment from operational improvements associated with starting the market, including improved transmission interconnections and more granular generator dispatch scheduling. We formulate a simulation model that demonstrates this mechanism. While there has been plenty of anecdotal evidence from technical experts and market participants that competitive wholesale markets are beneficial for wind energy, this analysis provides the first statistical evidence to support that claim

JEL **classifications: Q40, Q42**
Keywords: electricity market, renewable energy, wind energy, energy economics, wind generation

1. Introduction

Market restructuring in the U.S. electricity sector began in the mid-1990's as an effort by utility regulators and state legislatures to improve efficiency through increased competition. The first states to restructure were in the northeastern U.S., Texas, and California. Some states introduced competition in wholesale generation and retail distribution of electricity. Others introduced competition only among generation and left their retail sectors as regulated distribution monopolies. Other states considered deregulation until market manipulation by participants in California increased prices and caused large-scale blackouts in 2000 and 2001 (Joskow, 2001). Momentum to deregulate the electricity sector in the U.S. stopped after California's experience. The result today is some electricity markets have competitive wholesale generation and/or retail sectors, while others remain as regulated monopolies. Policy goals for the electricity sector during this initial wave of restructuring were primarily to ensure reliability and efficient, low-cost service. Recently, reducing environmental emissions has grown in importance among policymakers. The effects of differing market structures on renewable generation have largely been unexplored.

One successful aspect of electricity market restructuring was the establishment of independent system operators (ISO's) to manage wholesale electricity markets. ISO's are independent non-profit entities who oversee the high-voltage transmission network, manage the wholesale markets, and schedule generation. Even though momentum to restructure declined after 2000, the benefits realized by ISO-managed markets were such that ISO's have continued to spread to regulated regions. In these regions, ISO's have taken control of generation owned by multiple monopoly utilities to conduct real-time dispatch to minimize costs across the entire region (Sioshansi, 2006). These regions in effect have a hybrid market structure consisting of regulated monopoly utilities operating in a competitive wholesale market. One example of hybrid market restructuring was the launch of the Midcontinent ISO market in 2005.

Prior to this paper, there has been no published statistical assessment of the effect of electricity market restructuring on wind energy production. This is in part because there was little wind generation when major market restructuring took place in the late 1990's and early 2000's, a time which motivated significant economic analysis (see Figure 1 for installed wind capacity in the U.S. over time).

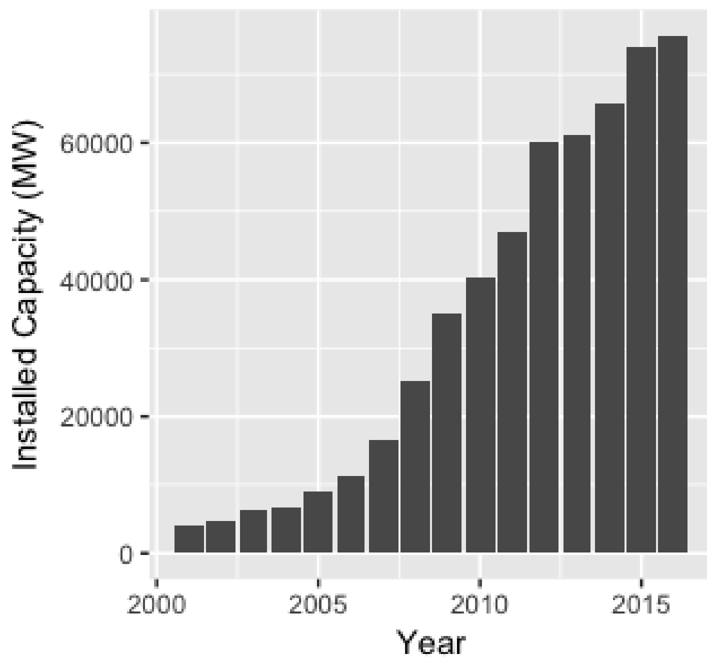

Figure 1 installed wind capacity in the U.S., source: American Wind Energy Association (2016)

In this analysis, we assemble a dataset and build a model that isolates the effect of starting the Midcontinent ISO market on wind electricity production. The MISO market is in a region rich with wind resources, and began operating at a time when there was enough wind production data available to conduct the analysis. We conclude that the MISO market resulted in an increase in monthly average capacity factors of 5.0–6.7% relative to comparable wind plants not in the ISO market. This is a significant increase, equivalent to about $1 million more in annual revenue for a 50-megawatt plant at typical MISO prices. This effect is likely due to wind plants in MISO experiencing improved operations and reduced transmission congestion after the market began.

Previous studies in the literature have identified efficiency gains for power plants in restructured markets. Fabrizio, Rose, & Wolfram (2007) identify reductions in labor and nonfuel expenses of 3-5% for investor-owned power plants. Additionally, Chan, Fell, Lange & Li (2013) find similar levels of input cost reductions for investor-owned coal plants and calculate that restructuring has led to roughly 6.5 million dollars in annual cost savings and up to a 7.6 percent emissions reduction per plant. These studies looked at coal and gas power plants, and focused on the major wave of restructuring which occurred shortly before 2000. The question of how market restructuring impacts renewable energy is important today, as states contemplate further market restructuring to help manage higher penetrations of renewable electricity.

We expect an ISO market to have a beneficial impact on wind generation. Kirby & Milligan, NREL (2008) document anecdotal evidence in support of this hypothesis from market participants, regulators, and other technical experts. They conclude that "of the various utility structures operating in the U.S. today, ISO's provide the best environment for wind generation." They identify two main reasons for this; 1) "they provide electrically and geographically large open markets for wind integration," and 2) "they operate sub-hourly balancing markets," which are ideal for addressing the short-term variability in wind plant output. Both market characteristics decrease the likelihood of wind plant curtailment. First, having wind resources spread across a larger market geography will decrease the variance of total wind generation, lessening the need for curtailment. Second, sub-hourly dispatch intervals are beneficial for wind energy because they reduce the probability for curtailment caused by forecasting errors; for example, it is easier to predict wind production over the 5-minutes intervals typical of ISOs than over hourly intervals.

Furthermore, experience has shown that issues associated with wind plant variability and its effect on ramping of fossil fuel plants are negligible in a competitive market. Kaffine & McBee (2017) look at the effect of wind intermittency on system emissions from fossil fuel ramping in the Southwest Power Pool market. They find a minor increase in emissions, on the order of a few percent relative to the overall emissions savings from wind energy.

2. Background

On April 1, 2005 MISO launched their wholesale energy market and began centrally dispatching power generation throughout the central United States. One effect of this significant reform was to reduce wind curtailments on the system. There are two primary reasons for this. First, the MISO market began centrally dispatching wind generation over a larger geographic region. Aggregating over a larger region has the effect of decreasing the variance of total wind generation, reducing the need to curtail. Second, the MISO market increased the frequency of dispatch for all generators from one hour to five minutes. This improved the system operator's ability to adjust flexible generation to balance random fluctuations in wind, further decreasing wind curtailments.

Curtailment data during this time is not available, but we can indirectly measure the effect on curtailments by looking at the change in generator capacity factors- when a wind plant is curtailed less, its capacity factor will increase. In 2005, the large majority of wind in the MISO region was in either Minnesota or Iowa. Traditionally, utilities in Iowa and Minnesota managed wind generation and other generators to meet demand on their own systems. Once the market began, MISO operators started balancing an aggregated system that included Iowa, Minnesota, and other states in the region. Combining wind plants on a larger system is beneficial to operators and wind plants because it reduces the variance of total wind output. This is because output from wind plants that are farther from each other have experience different wind patterns and thus have a lower correlation of output. Aggregating output from uncorrelated variable wind generation as the MISO market did results in a lower system variance relative to a smaller system with plants that have correlated output. This phenomenon was documented in Ernst (1999).

We can formalize this mechanism with the following model. Consider a system with i interconnected wind plants with total plant capacity denoted by C_i and average plant capacity factor CF_i. Because plant output is largely determined by random variation in wind speeds, we can model potential plant output in each period t as a truncated normally distributed random variable $Y_{it} \sim N(C_i * CF_i,\ \sigma_Y^2)$ where $Y_{it} \in (0, C_i)$. The correlation between any two wind plants $Cor(Y_{it}, Y_{jt})$ is a function of the distance between plants. The correlation is higher when plants are closer together. The variance of the sum of all wind plants $Var(\sum_i Y_{it})$ is larger when then correlation between plants' outputs are higher. This increases the likelihood of curtailment. System demand can also be modeled as a random variable normally distributed truncated to be above zero, $D_t \sim N(\mu_D, \sigma_D^2)$ where $D_t > 0$.[1] When $\sum_i Y_{it} > D_t$, wind output in excess of demand is curtailed and actual wind output is $\sum_i Y_{it} - D_t$. When $\sum_i Y_{it} < D_t$, it is assumed a flexible generator is dispatched to meet the shortfall.

To illustrate with an example, assume two identical wind plants each with a capacity C_i of 100MW and $CF_i = 0.4$, so each plant generates an expected amount of 40 MW each period.

[1] One could add seasonal effects to wind generation and demand without changing the conclusions of this exercise. We omit this for simplicity.

generating amounts Y_{1t} and Y_{2t} in each period. Plant output is random because it is determined by weather, so each plant has an expected output of 40 every period, with a standard deviation assumed to be 15. Since a system operator is primarily concerned with balancing total supply, we can calculate the variance of combined wind generation. If both plants are in the same location (southwest Minnesota, for example) they will experience the same wind speeds, and their output will be correlated. In the case where output is perfectly correlated, the variance of total wind generation on this system will be equal to 900.[2] If we assume the two plants are on a larger system in different locations with different wind patterns (one in Minnesota, the other in Iowa, for example) then the correlation between Y_1 and Y_2 will be lower. In the case with zero correlation the total variance on the system will reduce to 550, lessening the need to curtail.

Now assume electricity demand on this system is 100 MW on average, but can vary randomly with a standard deviation of 10, or $D_t \sim N(100, 10)$. Thus, the expected value of demand each period is 100, and the expected value of total wind output is $E[Y_{1t}] + E[Y_{2t}] = 80$. We will assume flexible generators are available to meet any shortfall in electricity net of wind power. Curtailment of wind will occur when total wind generation exceeds demand.

The charts below in Figure 2 simulate this system over 100 time periods. The thin black line represents combined wind output, and the thick black line is electricity demand. Whenever wind output exceeds demand, the output is curtailed. The chart on the left simulates the wind plants in the same location where output from the two are perfectly correlated. The right chart assumes plants in distant locations, where the wind output is uncorrelated. The variance of

[2]The sum of the variance of two random variables equals the sum of the individual variances plus two times their covariance: $Var(Y_1 + Y_2) = Var(Y_1) + Var(Y_2) + 2Cov(Y_1, Y_2) = 225 + 225 + 2 * 225 = 900$

combined wind output on the right side is lower, resulting in less curtailments. In these two simulations, total curtailments on the left chart are 525 MW per period, or about 6.5% of the total potential wind. Total curtailments on the right chart are 225, or about 3% of total potential wind.

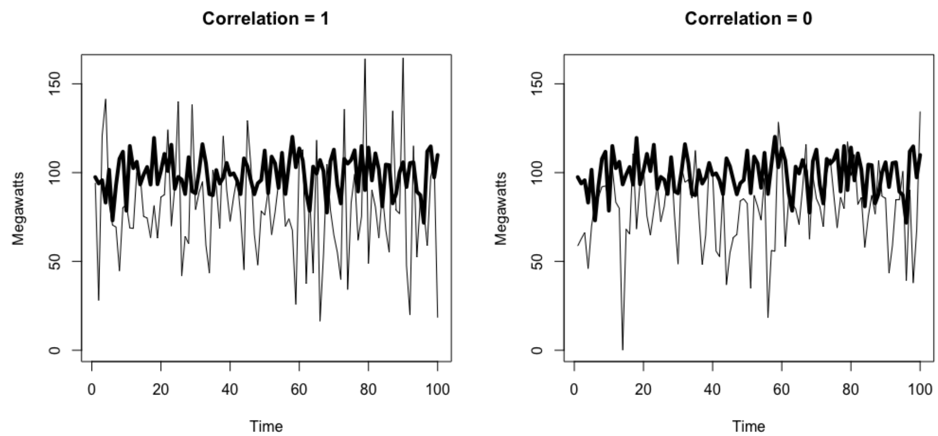

Figure 2 simulated wind plants when output is correlated and uncorrelated. The thin line represents total wind output, the thick line is electricity demand. Curtailment occurs when the thin line exceeds thick line.

Table 1 lists curtailment numbers as the simulation results converge after many periods. As the correlation in output between the plants declines, average curtailments also decline. One can imagine the wind plants correlation decreasing as they are spread out over a larger system.

Correlation, Y_1, Y_2	Curtailment, % of potential output
1	6.31
0.75	5.54
0.5	4.89
0.25	4.03
0	3.21

Table 1 average curtailment as correlation in output decreases. Wind plants on a larger system have lower correlation in their output.

In addition to a larger system, the second reason why the MISO market reduced wind curtailments are because of the transition from hourly to five-minute dispatch intervals. In this example, we assumed that any shortfall in electricity production was met by a flexible generator. An hourly dispatch schedule limits the flexibility by which this generation can respond to changes in wind output, which can vary considerably within an hour. If an operator was unable to lower a generator's output in time to balance a sudden surge in wind output, they would need to curtail the wind. A five-minute dispatch schedule allows an operator to adjust their conventional generation every few minutes to better balance changes in wind output. Furthermore, Milligan et. al (2009) show that forecast error improves as the markets operate closer to real time.

In summary, large, competitive wholesale electricity markets help integrate wind generation because they aggregate wind over a large system and shorten dispatch intervals. The MISO market integrated many individual balancing authorities across the Midwestern United States into one centrally dispatched system. Additionally, the MISO market changed from hourly generation scheduling to 5-minute dispatch periods. The remainder of the paper sets up the process by which we will test for and quantify the expected increase in wind capacity factors because of the MISO market.

3. Data

The data used for this analysis consists of wind plant production data from the Energy Information Administration (via Ventyx), and historical weather data from the National Center for Environmental Information, (NCEI), a department of the National Oceanic and Atmospheric Administration (NOAA). The production data includes detailed monthly information for every power generation facility in the United States larger than 1 megawatt.

The weather data was pulled from NCEI's Quality Controlled Local Climatological Database (QCLCD). From this dataset, we pulled historical monthly average wind speed data from approximately 1000 weather stations spread across the United States and matched each wind farm to the nearest weather station.

4. Empirical Strategy

The outcome we measure is the change in average wind plant capacity factor caused by the start of the MISO energy market, announced to begin operations in April 2005 (Midwest ISO, 2005). The data shows that capacity factors for wind plants in MISO increased by 9% on average in the year following the MISO market launch, reported in Table 2 along with average monthly electricity production.

	Apr 2004 - Mar 2005	Apr 2005 - Mar 2006
Avg capacity factor (%)	24	33
Avg production (MWh/month)	3241	4868

Table 2 production data for wind plants in MISO region before and after MISO market began.

It is likely that other factor(s) caused at least part of this increase in wind generation. The following sections discuss components of the econometric model used to isolate the effect of the MISO market launch on wind generation.

4.1. Treatment and control groups

In our analysis, we designate wind plants in the MISO market region as the treatment group. Wind plants in a neighboring region with similar levels of wind resource make the control group. Figure 3 shows the states whose wind plants are in the treatment and control groups. The black states correspond to the MISO market region when it began in 2005.

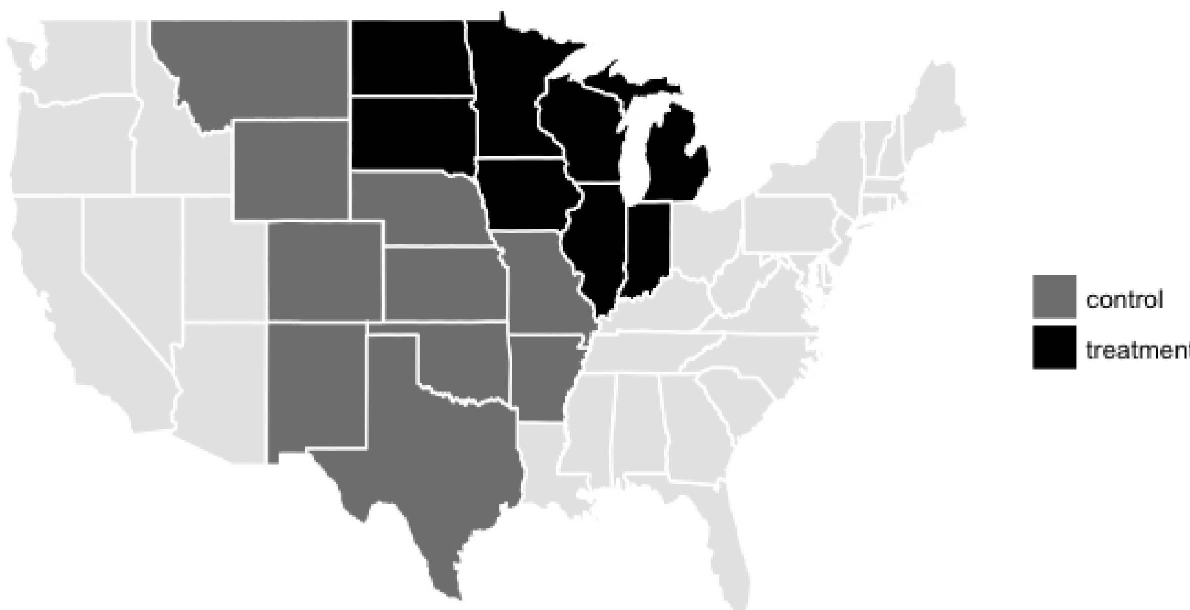

Figure 3 map of states in treatment and control groups

As shown in Table 3 there are more wind plants in the MISO treatment group, and they are smaller on average than plants in the control group. This is likely because states in the upper

Midwest attracted early investment in wind energy, and the early wind plants were smaller. In the MISO group, 60 of the 66 plants are in Minnesota or Iowa; both are states that implemented early policies favorable for renewable energy development. These plants likely use older technology on average compared to plants in the treatment group.

	Treatment group	Control group
Avg capacity factor (%)	24	27
Avg nameplate capacity (MW)	19	69
Number of plants	66	39

Table 3 characteristics of wind plants in treatment and control group prior to MISO market.

Overall, states that joined the MISO market are more likely to have implemented laws more favorable to renewable energy. Four of the eight states in the MISO group voted democrat in at least three of the past four presidential elections spanning 2004-2016. Only two of the ten control group states similarly voted democrat, which is the political party friendlier to renewable energy. Furthermore, six out of the eight states in the treatment group currently have legally binding renewable portfolio standards (RPS) of varying levels,[3] with only 5 out of 10 states in the control group having RPS laws. These laws are designed to stimulate investment in new renewable energy. However, the effect we are testing for is an operational change made to existing wind units from the market change. Furthermore, there is no variation in RPS laws within the treatment group during our sample period from 2004-2006, these laws were passed

[3] Two of these states implemented their RPS after the MISO market began, Minnesota in 2007 and Michigan in 2008.

years before or after our sample period of interest. Therefore, we expect state fixed effects to pick up any differences in states due to RPS.

Table 4 shows the increase in average capacity factors for treatment and control groups for the year before and after the MISO market began. Using a basic difference in differences estimator with these four averages finds a 5% increase in average capacity factor for wind plants in the MISO region due to the MISO market. However, Table 3 shows differences between treatment and control groups that may bias this result. These include differences in wind speeds and plant technology, both over time and across regions. More detail on these issues and methods to address them are provided in the following three sections.

	Pre-treatment	Post-treatment	Difference
Treatment region	22.58	32.71	10.13
Control region	26.21	31.36	5.15

Table 4 change in average capacity factors for plants in treatment and control regions. Standard errors reported in parentheses.

4.2. Wind speeds

Historic wind speeds explain a significant portion of the month-to-month variation in the plant output measured in our data. Regressing average capacity factors on local average wind speed from our sample yields a positive, significant relationship with a slope coefficient of 2.7 and an r-squared of 0.2, suggesting a one mile per hour increase in average monthly wind speed increases wind plant capacity factor by 2.7%. Not accounting for average wind speeds in our model could yield biased treatment effects. For example, if the MISO region had a windier year after the market launch relative to the control group our result would be biased upward. It does turn out to be the case that the second year of our sample period (April 2005 – March 2006) was windier than the previous year in the MISO region, with average wind speeds in the second year of 9.96 miles per hour, compared to 9.72 in the prior year. This suggests that some of the observed 9% increase in average capacity factor for plants in the MISO region can be explained by the weather.

Moreover, the control region was also windier in the year following the start of the MISO market. From April 2004 – March 2005, wind speeds in the control region averaged 10.39 mph, and in the following year averaged 11.15 mph. These values are summarized in Table 5. Since the increase in wind speed is of a greater magnitude in the control region, we expect the 5% difference in differences calculation presented above to be net-negatively biased by historic wind speeds, all else equal.

	Pre-treatment	Post-treatment	Change
Treatment region	9.72	9.96	0.24
Control region	10.39	11.15	0.76

Table 5 average wind speeds (miles per hour) in years before and after start of MISO market.

4.3. Technology improvements over time

Another possible explanation for the observed increase in wind electricity production is from technology and operational improvements. Over time wind plant operators gain experience and implement improvements, such as better forecasting technologies, that increase plant capacity factors. The result is an increase in production over time for wind plants that would have occurred even in the absence of the MISO market. Estimating a linear trend suggest an average improvement in wind capacity factors of 0.33% per year over the last 15 years for all states in our sample. If we assume technology and operational improvements affect the entire wind industry equally, we can model the effect with a general time trend using monthly fixed effects.

4.4. Technology differences between plants

It is possible that technology differences between plants in the treatment and control groups contribute to observed differences in capacity factors. For example, newer vintage plants may have higher efficiencies and operate at higher capacity factors over all time periods. Because plant technology is generally fixed over time, we can account for this with plant fixed effects that control for average differences in capacity factors between plants. This modeling strategy also accounts for differences in capacity factors caused by a plant's location and the wind resource associated with that location. Some wind plants are in windier areas, but fixed effects will control for this since plant location remains fixed over time.

4.5. Model overview

The model components described above are designed to account for the main sources of bias and isolate the effect of starting the MISO market on wind plant capacity factors in the MISO region. Mathematically, the model is represented as:

$$CF_{it} = \gamma * treat_{it} + \beta * windspd_{it} + \alpha_i + \delta_t + \epsilon_{it}$$

Where the i and t subscripts index wind plants and months, respectively. Our sample includes all wind plants in operation per the Energy Information Administration's survey form 923 data, and the time-period spans from April 2004 to March 2006. Additionally:

CF_{it}	is the average capacity factor for plant i in month t.
$treat_{it}$	is a binary indicator variable that changes from 0 to 1 for plants in the MISO region after the market begins in April, 2005.
$windspd_{it}$	is the average wind speed in miles per hour in month t, as recorded in the closest weather station to plant i.
α_i δ_t	are the fixed effect parameters for plant i and month t, respectively.

ϵ_{it} is an error term with an expected value of zero that captures the leftover, random variation in capacity factor not explained by the other model components.

4.6. Model Assumptions

The primary assumption required for a causal interpretation of the treatment effect is that, conditional on the control variables, the slope of the change in capacity factors remains the same between the treatment and control groups, absent the treatment. This parallel trends assumption is fundamentally untestable, since we cannot observe wind production in the MISO region in the counterfactual scenario of no MISO market. Instead, we control for potentially confounding differences in plant technology with fixed effects, and wind speed differences across locations. Figure 10 in the following section provides evidence of relatively similar pre-treatment trends prior to the market. This suggests that conditional on the controls, it is likely this trend would continue in the absence of the MISO market.

5. Results

The model is solved by calculating the values of γ, β, α_i, and δ_t that minimize the total sum of squared errors ($\sum\epsilon_{it}^2$). The value of γ is the treatment effect and is of primary interest for this analysis; it is interpreted as the average percent change in capacity factor for wind plants in the MISO region caused by the start of the MISO market. The γ values are reported in Table 6 in the first row. Treatment effects for four different model specifications are reported as model components are added in each successive column to the right.

	(1)	(2)	(3)	(4)
Treatment effect	5.0*** (1.2)	6.2*** (1.1)	5.9*** (1.1)	6.7*** (2.2)
Wind speeds	No	Yes	Yes	Yes
Monthly FE's	No	No	Yes	Yes
Plant FE's	No	No	No	Yes
Observations	2399	2391	2391	2391
R-squared	0.09	0.18	0.27	0.43

Heteroscedasticity-consistent robust standard errors in parentheses
*** $p < 0.01$

Table 6 model results.

5.1. Interpretation

Each of the four model specifications estimates a positive effect on capacity factors from the MISO market treatment, ranging from 5.0 – 6.7%. The associated heteroscedasticity-robust standard errors are reported in parentheses below the treatment effect estimates. Rows two through four of **Error! Reference source not found.** describe the model specification associated with each column.

The 5% value reported in column 1 is an estimate of the treatment effect based solely off the differences between treatment and control groups, with no additional controls. By design, it is equal to the 5% difference calculation explained at the end of section 4.1. The second column reports the result after controlling for historic monthly wind speeds. The increase in average capacity factor to 6.2% is consistent with the logic explained in section 4.2; since the control region was windier than the treatment region in the year following the market launch, we expect the estimate in column 1 to be negatively biased.

Column 3 adds monthly fixed effects, to control for macro-level time trends, which caused a slight decrease in the estimated treatment effect, to 5.9%. This is consistent with wind plant capacity factors improving over time due to industry-wide technology and operational improvements. In the fourth column we add fixed effects and see an increase in the estimated treatment effect along with an increase in standard errors. The increase in the estimated treatment effect could be explained by the loss of precision associated with the fixed effects model; all the previous estimates fall within the 95% confidence interval of the estimate reported in column 4.

5.2. Robustness checks

These results were calculated based off a data sample limited to one year before and after the MISO market launch, or April 2004 – April 2006. This focused sample was analyzed because the operational benefits to wind were expected to be realized as soon as the market launched, when the centralized and more granular dispatch reforms took place. Analyzing a sample over a longer time range increases the possibility of unobserved confounding factors biasing the results. Nevertheless, increasing the sample size to include wind generation from 1995-2015 and estimating the full fixed effects model yields a treatment coefficient of 3.49 with a standard error of 1.52, significant at the 95% level. This provides evidence of a positive long-term effect, though smaller than the effect in the first year after the market launch.

Firm-level correlation of wind capacity factors might exist if firms that own multiple wind farms have differentiated scheduling strategies for their wind. This could lead to firm-level heteroscedasticity that biases our inference. To address this possibility, we ran the full fixed-effects specification and clustered standard errors at the firm-level; our sample includes 98 firms.

The clustered standard errors increase from 2.2 to 3.3, but the treatment coefficient is still significant at the 95% level.

The treatment and control groups shown in Figure 3 were constructed to balance a need to make the region small enough to minimize geographic heterogeneity, but big enough to include enough plants for sufficient statistical power. The region used was chosen because it spans the central region in the U.S. with a similarly large wind resource. However, some states in the control region are multiple states away from the MISO market, increasing the risk of unobserved factors in the control group biasing the results. The model was re-estimated over a smaller geographic area, including the states near the western edge of the MISO region where the wind resource is greatest- Minnesota, Iowa, Wyoming, Colorado, and Nebraska. This subgroup includes 60 plants in MISO and only 14 plants in the non-MISO control group. Shrinking the size of the region in this way caused the treatment coefficient to increase to 7.06. All the previous sensitivity results are included in Table 7 in Appendix 7.1

Another concern in this analysis is if the stable unit treatment value assumption (SUTVA) holds. If the MISO market affected wind dispatch in the control group then this could bias our estimates. For example, increased dispatch of wind in the MISO footprint could crowd the transmission system of the neighboring region, causing decreased wind dispatch on the other side of the MISO border, and our effect would be biased upwards. To check for possible SUTVA violations we examine more closely the subgroup of wind plants immediately across the border from MISO in Eastern Nebraska, and compare to wind plants farther away from the MISO border in western Nebraska and Wyoming. There appears to be some inconclusive evidence of possible SUTVA issues. More detail is provided in Appendix 7.2.

5.3. Visualizing results

Figure 4 plots average capacity factors by month for wind plants in the treatment and control groups. The chart shows seasonal variation by month, which is controlled for in the model with the wind speed data. The chart also shows a general upward trend shared by both groups, which is controlled for with the time fixed effects. In addition to these sources of variation, the treatment group has lower capacity factors than the control group prior to the market start date, and then higher values after. This is notable since the NOAA data shows the control region was windier in the year following the MISO market launch.

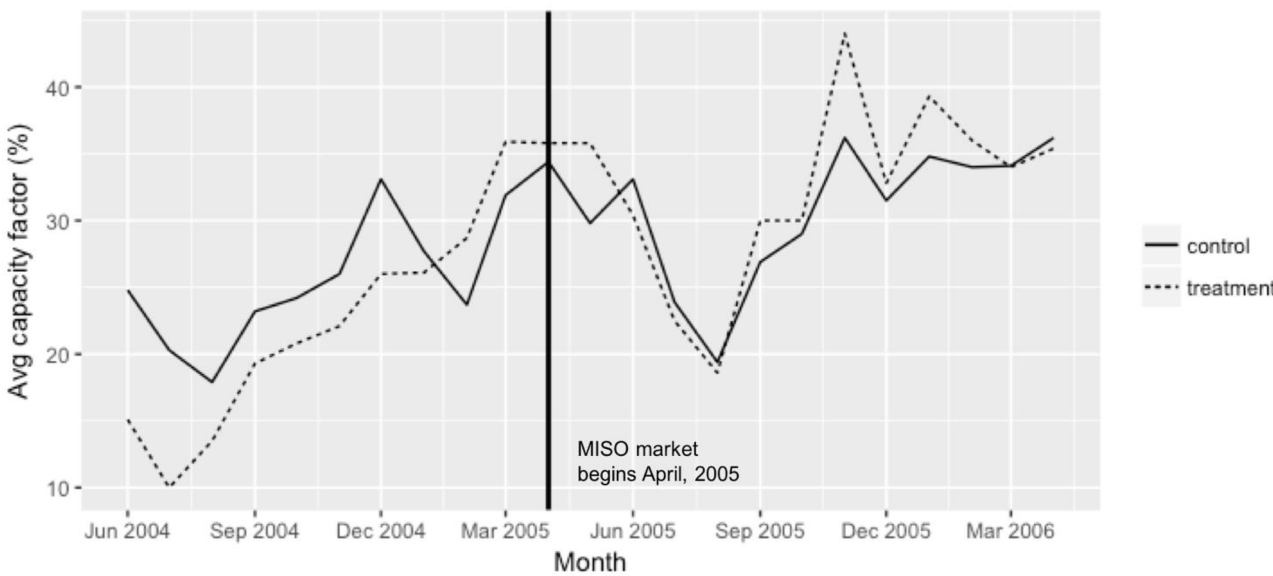

Figure 4 average wind plant capacity factors by region

Figure 5 plots the coefficients of an interaction between the treatment group and year-month indicator variables after accounting for the wind speed and fixed effects controls. Specifically the points represent the estimated γ_t coefficients and their associated standard errors from the following specification:

$$CF_{it} = \gamma_t(treat_{it} * \delta_t) + \beta * windspd_{it} + \alpha_i + \delta_t + \epsilon_{it}$$

Where the first term represents an interaction between the treatment indicator and a set of year-month dummy variables. One insight from the chart is that the improvement in MISO wind plant capacity factors began increasing two or three months prior to the announced start date of the market. An explanation for this is that independent system operators will often perform trial operations a few months before going live with a major market reform. This could have provided operational benefits to wind plants before the official start date in April. Secondly, there is a significant drop in the treatment coefficient in December 2004, immediately before benefits begin to show. This may have been due to plant down-time for work on maintenance, communication, and control equipment necessary to prepare for the operational changes associated with changing dispatch to the independent system operator.

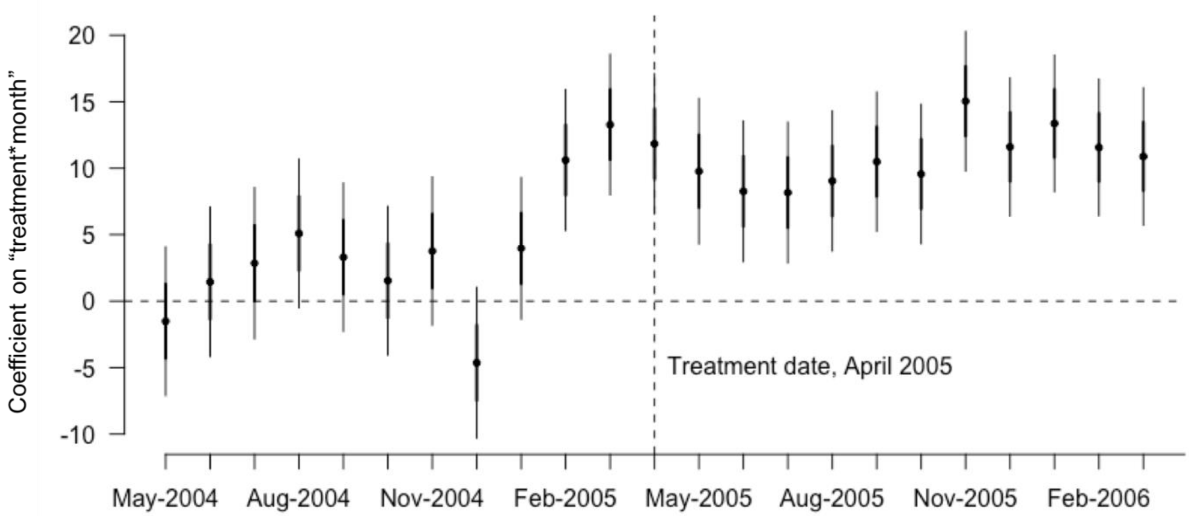

Figure 5 treatment coefficients over time

6. Conclusion

This paper provides statistical evidence supporting the hypothesis that competitive electricity markets managed by independent system operators are beneficial for wind energy. The econometric models employed indicate the start of the MISO market increased capacity factors for wind plants in its region by 5.0 – 6.7%, relative to similar plants not in the market. The econometric model used to estimate these results are robust to multiple potentially confounding variables, including wind speed and technology variation across plants and over time. There is evidence that the MISO market caused a decrease in neighboring non-market wind production, however the bias from this is likely small due to the small number of plants near the market border relative to the total number of plants in the experiment. We demonstrate larger regional integration as one mechanism explaining the effect of market structure on wind generation, although other mechanisms may also be contributing to observed changes in wind generation. Areas of future research involve formalizing other mechanisms such as the impact of more granular dispatch intervals on wind generation, and determining the relative importance of each mechanism. Recent expansions of electricity markets into wind rich areas in the United States provide new opportunities for empirical testing of these hypotheses. This research informs ongoing efforts to expand wholesale electricity markets in part to facilitate integration of renewable energy.

7. Appendix

7.1. Sensitivity results

	Bigger sample: 1995-2015	SE's clustered by firm (98 firms)	Smaller footprint
Treatment effect	3.5** (1.5)	6.7** (3.3)	7.05*** (2.04)
Wind speeds	Yes	Yes	Yes
Monthly FE's	Yes	Yes	Yes
Plant FE's	Yes	Yes	Yes
Observations	39241	2391	1651
R-squared	0.49	0.43	0.48

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7 results of sensitivity tests.

7.2. SUTVA Analysis

This section describes a sensitivity analysis to check for evidence of violation of the stable unit treatment value assumption (SUTVA). It is possible that changes in wind dispatch in the MISO market affected dispatch of wind plants on the other side of the border in the control group, which would bias our treatment estimate. Our approach to test for this problem involves examining capacity factors for the subgroup of wind plants in eastern Nebraska, near the large concentration of wind plants in western Iowa and southwestern Minnesota. These are compared to nearby wind plants that are farther from the border, in western Nebraska and Wyoming. If changes from the MISO market affected plants in the control group we would expect to see a bigger effect in the plants closer to the market border in western Nebraska.

Figure 6 presents the results of the SUTVA sensitivity test. The charts plot deviations from expected capacity factors by month for each control region subgroup. Specifically, these are the coefficients on the δ_t monthly fixed effects term from the model

$$CF_{it} = \delta_t + windspd_{it} + \alpha_i + \epsilon_{it}$$

for the plants in each subgroup. One potentially concerning part of the chart is the dip in capacity factors for the eastern plants in January and February of 2005, an effect that does not show up in the western plants. This drop occurs right as the MISO treatment effect becomes statistically positive, shown previously in Figure 5. One explanation for this could be the increase in wind generation from the MISO market crowding out transmission capacity in the neighboring region, reducing wind output from plants in eastern Nebraska. This would have the effect of positively biasing our treatment coefficient. However, there were only three wind plants operating in Eastern Nebraska during the sample period, compared to 60 plants in Iowa and Minnesota, and this particular effect doesn't show up for the plants in western Nebraska and Wyoming (there were 8 plants in this region at the time).

The small number of plants likely contributes to the wider variability in plant output in the eastern chart, shown by the different scales on the y-axes. Additionally, the drop in eastern Nebraska wind output disappears in March 2005, while the positive deviation in treatment plants is sustained. This gives us confidence that if there was a SUTVA violation it was relatively small, and didn't have a lasting effect beyond a couple months. Furthermore, the main results include the large amount of wind energy operating in Texas as part of the control group, which are far away from the MISO system and wouldn't be affected by changes in wind dispatch in the MISO region.

These charts also show unexplained noise, mostly in late 2005 through early 2006. This could be due to system-specific factors, like a relatively unconstrained transmission system, or an operational change made by WAPA to improve wind dispatch. Since these unexplained deviations are mostly positive, we expect it to negatively bias the treatment effect reported in section 5, and the actual treatment effect could be larger.

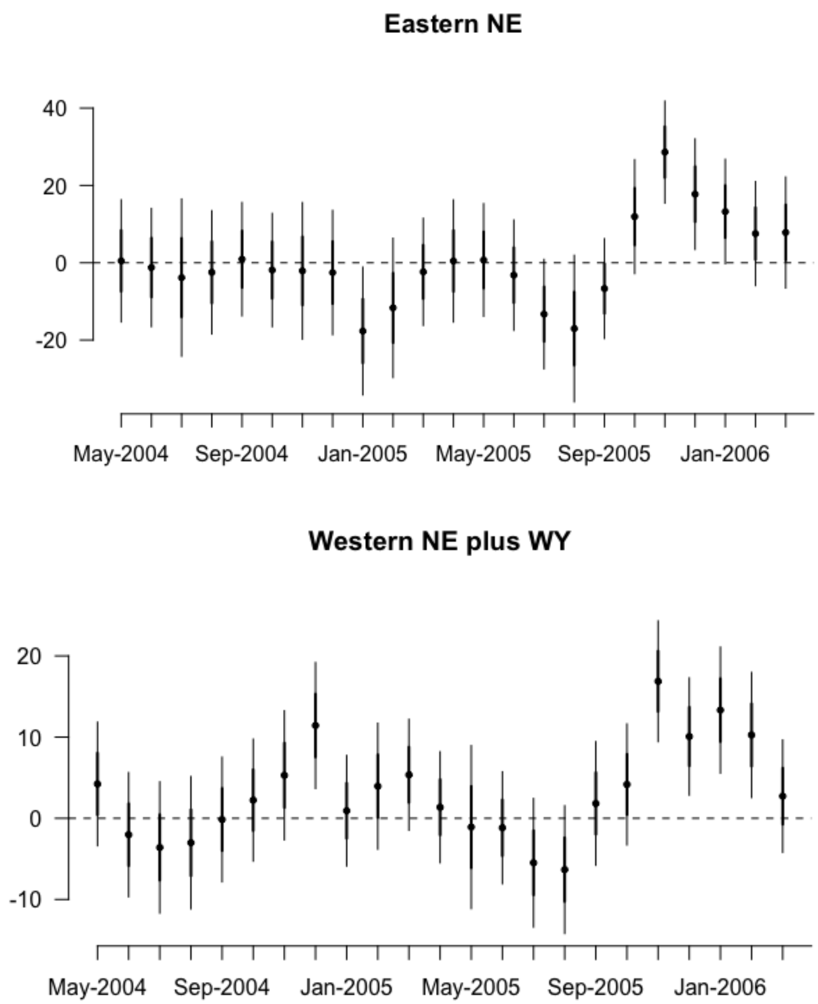

Figure 6 comparison of deviations from expected capacity factor for control regions

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