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The Effect of Wholesale Electricity Market Restructuring on Wind Generation in the Midwest

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January 2017

Acknowledgements

This report was made possible with support from the Heising-Simons Foundation.

The report authors would also like to thank Mike Gregerson and Brendan Jordan at the Great Plains Institute for their review of the report.

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Abstract

This paper estimates the effect of having a competitive wholesale electricity market on wind plant generation for the Midcontinent Independent System Operator (MISO) electricity market. This question is of interest today as states consider expanding competitive wholesale markets as a strategy to manage growing levels of wind and solar energy. Using publically available data, we build an econometric model that estimates the effect of the MISO real-time market on wind energy production. We find the market resulted in an increase of average wind plant capacity factors by 5.0 - 6.7%, relative to neighboring wind plants not in the market. The model statistically controls for potentially confounding variables, including wind speed differences determined by weather and plant technology differences. The increased capacity factors are likely attributed to reduced wind plant curtailment associated with operational benefits specific to an ISO market. These benefits include greater regional interconnection of the transmission system, and shorter intervals for generator dispatch scheduling. While technical experts and market participants have shared anecdotal evidence that ISO markets are beneficial for wind energy, this analysis provides the first statistical evidence to support that claim.

Background

Market restructuring in the U.S. electricity sector began in the mid-1990s as an effort by utility regulators and state legislatures to lower prices through competition. The restructuring involved deregulating monopoly electricity producers and introducing new competition in the electric generation sector. The first states to do this were in the northeastern U.S., Texas, and California. Some states introduced competition both in wholesale generation and retail distribution of electricity, while others introduced competition only among generation and left their retail sectors as regulated monopolies. Additional states considered deregulation until market manipulation by new competitors in California increased prices and caused multiple large-scale blackouts in 2000 and 2001. Momentum to deregulate the electricity markets have competitive generation and/or retail while others still operate as full regulated monopolies.

One successful aspect of electricity market restructuring was the establishment of independent system operators (ISO's) to manage wholesale electricity markets. These are independent non-profit entities who oversee the high-voltage transmission network, manage the markets, and schedule generation. Even though states stopped restructuring after 2000, the benefits realized by ISOmanaged markets were such that ISO's continued to spread to monopolyregulated regions. In some regulated regions, ISO's have taken control of incumbent utilities' generation to conduct real-time dispatch, minimizing costs across the balancing regions of multiple utilities. This occurred with the launch of the Midwest ISO market in 2005.

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Previous studies in the economic 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 coal investor-owned 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 focused on coal and gas-fired power plants, and looked at the major wave of market restructuring which occurred prior to 2000. The somewhat different question of the effect of market restructuring on renewable energy is important today, as states contemplate further market restructuring to help manage higher penetrations of renewable electricity. Current efforts by states are taking place in the western U.S.

We expect an ISO market to have a beneficial impact on wind generation. Kirby & Milligan, NREL (2008) document supporting anecdotal evidence from market participants, regulators, and other technical experts. They conclude that "of the various utility structures operating in the U.S. today, ISOs and RTOs provide the best environment for wind generation." The two main reasons for this, they cite, are that they 1) "provide electrically and geographically large open markets for wind integration," and 2) "they operate sub-hourly balancing markets," which are ideal for addressing the variability in wind plant output. Both of these market characteristics decrease the likelihood of wind plant curtailment. First, a larger market provides more demand centers and transmission capacity to move wind energy during times when local demand is low and wind production is high. Second, sub-hourly dispatch intervals are beneficial for wind energy because they reduce the probability for curtailment from a forecasting error; it is easier to predict wind production over 5-minute intervals than over hourly intervals. A wind integration study by the Minnesota Department of Commerce and other stakeholders in 2006 came to a similar conclusion.

To our knowledge 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 analysis among economists (see Figure 1 for installed wind capacity in the U.S over time). It is also because there are significant confounding variable issues that can mask the true effect of market restructuring on wind production. Possible confounding sources of variation include differences in historical wind speeds & weather over time and across regions, as well as general improvements in wind technology over time. A study from Spees and Lave (2007) from Carnegie Mellon University attempted to estimate the effect of RTO membership on wind plant investment, and found a small negative correlation between wind development and RTO membership. However they wrote they "have no explanation as to why this would be true." One potential issue could have been a

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shortage of data, since they did not have data to look at the MISO or Southwest Power Pool markets.



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 Midwest ISO market in 2005 on wind electricity production. The MISO market is located in a region rich with wind resources, and began operating at a time when there was enough wind production data to motivate a statistical analysis. We conclude that launching the MISO market caused an increase of capacity factors by 5.0 - 6.7% on average relative to comparable wind plants not in an ISO market.

Setting up the analysis

The outcome we aimed to measure is the change in wind capacity factors caused by the start of the MISO energy market in April 2005. To begin we collected plant-level monthly generation data maintained by the Energy Information Administration. A simple analysis could involve comparing the average capacity factors for wind plants in MISO before and after the market began. In fact, doing this shows a large bump of 9% in average capacity factors for wind plants the market began. These values are reported in Figure 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

Figure 2 production data for wind plants in the MISO region before and after the MISO market began

These statistics appear promising, but we cannot conclude that the MISO market caused a 9% average improvement in wind capacity factors. It is likely that other factor(s) caused at least part this change. It would be useful to know the counterfactual scenario; that is, make a best-guess as to what the average change in wind capacity factors for these plants would have been if the MISO market did not start. Next, we present the components of our econometric model designed to build this counterfactual scenario and control for confounding variables.

Treatment and control groups

In econometric analyses, it is common practice to set up a model that treats the outcome as the result of a quasi-natural experiment. Real lab experiments often are characterized by two groups of participants; the experimental treatment is randomly assigned to one group, and the rest are left as a control group for comparison. We will make use of this strategy for our analysis, designating wind plants in the MISO 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 were put in each group. The red states correspond to the MISO market region when it started in 2005.



Figure 3 map of states in treatment and control groups

In an ideal experiment, the treatment and control groups would exhibit similar characteristics. Unfortunately, the real world is messier than a controlled lab.

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As shown in Figure 4, there are more wind plants in 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 states that were early to implement policies favorable for renewable energy development. These plants likely use older technology on average compared to plants in the treatment group. The econometric model is designed to account for these differences and minimize the possibility of biased results.

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

Figure 4 characteristics of wind plants in treatment and control groups prior to MISO market

The control group is useful for comparison as a counterfactual scenario. In other words, if plants in the treatment and control groups are similar, then the change in capacity factors in the control region provides a good approximation of how capacity factors in MISO would have changed if the MISO market never started. Thus, the difference between the changes in treatment and control groups provides a rough estimate of the effect of the MISO market. It turns out that average capacity factors for plants in the control group changed from 27% to 31% over the same time, an improvement of 4%. Subtracting this from the observed 9% improvement among MISO plants (Figure 2) leads to the conclusion that the MISO market caused a 5% increase in average capacity factors. However, there are differences in the characteristics of our treatment and control groups that should be factored into the model before making such a conclusion. 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.

Wind speeds

Historic wind speeds explain a large portion of the month-to-month variation in the plant output measured in our data. If this is not accounted for it is possible the results would be biased. 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. To account for this potential issue, we collected county-level monthly

weather data from the National Oceanic and Atmospheric Administration (NOAA). It does turn out to be the case that the second year of our sample period (April 2005 – May 2006) was windier than the previous year in the MISO region, with average wind speeds of 9.96 and 9.72 miles per hour, respectively. Therefore, it is possible at least some of the observed improvement in capacity factors was caused by the weather. Fortunately, the NOAA data allows us to control for this confounding effect by adding a wind speed parameter to the multiple regression model.

Technology improvements over time

Another possible explanation for an increase in wind electricity production is 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. If we assume technology and operational improvements affect the entire wind industry equally, we can model the effect with a general time trend describing all wind production in our data (not just those in the MISO market). Estimating a linear trend over our dataset suggests an average improvement in wind capacity factors of 0.33% per year over the last 15 years, likely explained by improvements in wind turbine technology and better location siting. In the econometric model, we estimate the time trend by including an indicator variable for every month, allowing a more flexible form. Doing this allows for the possibility that wind production technology accelerated more rapidly in some periods compared to others.

Technology differences between plants

It is possible that technology differences between plants contribute to observed differences in capacity factors. For example, newer plants may have higher average capacity factors at all time periods, which could cause part of the observed differences between treatment and control groups. Evidence of technology differences across regions was presented in Figure 4. Because plant technology is generally fixed over time, these differences can be modeled with "fixed effects." A fixed effects model in this context includes separate parameters for each wind plant that remain fixed over time. These parameters account for the average differences in capacity factors between each plant, helping to keep plant technology differences from biasing our results.

Econometric model

Model overview

The model components and data described in the bBackground section are combined in a multiple linear regression framework to make the best possible estimate of our parameter of interest- the change in wind plant capacity factors resulting from the start of the MISO market. Mathematically, the model is compactly represented as:

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

Where the i and t subscripts index the wind plants and months, respectively, in our sample of data. This 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 month *t* measured in the zipcode locale of plant *i*.
- $\alpha_i \quad \delta_t$ is the fixed effect parameter for plant *i*, and the time trend for month *t*, respectively.
- ϵ_{it} is an error term with average value of zero that captures the leftover, random variation in capacity factor not explained by the other model components.

The model is solved by calculating the values of γ , β , α_i , and δ_t which minimize the total sum of squared errors ($\sum_{it} \epsilon_{it}^2$). The value of γ (also known as the "treatment effect") is of primary interest; it is interpreted as the average percent change in capacity factor for wind plants in the MISO region caused by the start of the electricity market. The γ values are reported in Figure 5 as the entries in the first row. The model is deconstructed and four different treatment effects are reported in the table, model components are added in each successive column to the right. This shows how the potentially confounding variables discussed in the econometric model section affect our result.

	(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
Time trends	No	No	Yes	Yes
Fixed effects	No	No	No	Yes
Observations	2399	2391	2391	2391
R-squared	0.09	0.18	0.27	0.43

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Robust standard errors in parentheses

*** p < 0.01

Figure 5 model results

Explanation of results

First and most importantly, each of the four model specifications estimate a positive effect on capacity factors from the MISO market treatment, ranging from 5.0 - 6.7%. In other words, the model estimates that the MISO market resulted in an increase in wind plant capacity factors by 5.0 - 6.7%, relative to non-MISO plants. Confidence intervals are calculated based off the leftover variation in the data, providing us an indication of how well our sample estimates reflect the true population parameter. The associated standard errors are reported in parentheses below the estimate. The three-stars convention (***) indicates a confidence level of 99% (that we estimated a positive effect with a probability greater than 99%). Rows two through four describe the model specification associated with each column. "Observations" indicates the number of data points used to estimate the model. Finally, "R-squared" is a measurement that describes how well the model fits the data. The increase in R-squared as model components are added indicates a better model construction that explains more of the variation in plant capacity factors.

The 5% value reported in column 1 is an estimate of the treatment effect based 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 Treatment and control groups subsection. The second column reports the result after adding wind speed data. The increase in average capacity factor to 6.2% initially was counterintuitive; earlier we reported that it was windier in the MISO region after the market launch, averaging 9.96 mph in the year following the market launch compared 9.72 the prior year. Thus, we initially expected that controlling for wind speeds would reduce the treatment effect. This wasn't the case because it turns out the control group region was also windier in the year after the MISO market began, by a greater amount than in the MISO region. From April 2004 – March 2005 (the year before the MISO market), wind speeds in the control region averaged 10.4 mph. The following year they averaged 11.1

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mph. Since the treatment effect is calculated relative to the control group, a windier second year in the control region counteracted the positive bias we expected, and caused the initial estimate in column 1 to be net-negatively biased.

Column 3 shows the result after indicator variables for each month were added to control for all sector-level time trends. Adding the time trend caused a slight decrease in the treatment effect, to 5.9%. This is consistent with wind plant capacity factors improving over time across both treatment and control regions due to industry-wide technology and operational improvements. In the fourth column, we add fixed effects and see an increase in the treatment effect. This result would be expected if individual plant technologies (or some other time-invariant factor) caused higher capacity factors in the control region. This is possible; earlier in Figure 4 we showed that wind plants in the control region were larger, indicative of better technology. This result could also be explained by a loss of statistical precision associated with the fixed effects model, represented by the larger standard error in column 5. This is plausible since all the previous treatment effect estimates fall within the 95% confidence interval for the fixed effects estimate.

Visualizing results

Figure 6 plots average capacity factors by month for wind plants in the treatment and control groups. The chart shows seasonal variation, which is controlled for in the model with the wind speed parameter. The chart also shows a general upward trend shared by both groups, which is controlled for with the technology time trend. Despite these sources of variation, if you squint your eyes you can see the treatment group has lower capacity factors relative to the control group before the MISO market, and then relatively higher values after. This is notable since the NOAA data shows that the control region was windier than the MISO region in the year following the market launch (explained in the previous section).



Figure 6 average wind plant capacity factors by region and month

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Figure 7 provides a way of visualizing the model results. It plots the estimated treatment effect for months before and after the MISO market start date.¹ These data points represent the model output after wind speeds and technology differences are statistically controlled for. One insight from this chart is that the improvement in wind capacity factors began one or two months before the MISO start date. One possible explanation is that independent system operators will often run trial operations if possible before a major reform such as starting a real-time market. This could have caused wind plants to realize operational benefits of the ISO market prior to the actual start date. A second takeaway from this chart is the significant dip in capacity factor for January 2005 immediately prior to the large increase. This may have been due to plant down-time for work on maintenance or communications & controls to prepare for changes associated with ISO market dispatch.



Figure 7 treatment coefficients from fixed effect model, monthly

¹ Specifically, each point in the plot is the coefficient on an indicator variable for the MISO region interacted with the corresponding month, estimated with the rest of the controls and specifications for the fixed effects model. For graphical simplicity we omit the associated confidence intervals, however the coefficients are significantly different from zero at a 99% confidence level for the months following the market launch. The average difference in the plotted points before and after the treatment date roughly estimates the value calculated in column 4 of Figure 5. This makes sense if the corresponding change in coefficients for the counterfactual scenario remain relatively constant, which is indeed the case. The values represented on the y-axis are not intuitive; technically, since the points are output from a multiple regression model they are interpreted as the average unexplained deviation in wind plant capacity factor for plants in the MISO region, after accounting for the local wind speed in that month, its individual fixed effect, and the overall technology time trend.

Conclusion

This paper is among the first to provide statistical evidence supporting the hypothesis that competitive electricity markets managed by independent system operators are beneficial for wind energy. It concludes that the start of the MISO market increased capacity factors for wind plants in its region by 5.0 - 6.7%, relative to similar plants around the country. The econometric model used to estimate the results are robust to multiple potentially confounding variables. These include controlling for changes in wind speeds caused by different weather patterns across regions and over time. The model also controls for differences in wind plant technology vintage between plants, and industry-wide technology improvements over time.

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Glossary of terms

Capacity factor: The ratio between total g capacity and actual production. For wind plants, this factor is typically much lower than one, since wind generation is variable and depends on local wind speeds.

Competitive wholesale electricity market: The market in which wholesale electricity is transacted between producers and retailers, managed under an independent system operator (ISO), also sometimes referred to as a regional transmission operator (RTO). ISO's operate real-time energy markets in which electricity is scheduled and traded in near real-time, enhancing competition relative to the traditional regulatory structure. Some regions in the United States still operate under a traditional regulatory model in which a single vertically integrated utility retain control over generation and the transmission network.

Confounding variable: A variable that is correlated with both variables of interest in a statistical model. If a confounding variable is omitted from the model, it prevents interpretation of a causal effect from the correlation between variables of interest.

Retail distribution: The process by which electricity providers sell and distribute electricity to consumers.

Wholesale generation: Electricity that is generated and sold to retail electricity providers via the transmission network.

Wind plant curtailment: When a wind generator is forced to shut down by the system operator due to reliability or economic problems, often caused by the uncertainty associated with its generation.