The External Costs Of Wind Farm Development On the High Plains: Are Developers Making An Effort To Minimize These Costs?

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Introduction

With the increased wind energy capacity in the United States there is increased concern for how wind farms are being developed. Groups such as the American Bird Conservancy, the National Audubon Society, Inc., and Ducks Unlimited have information on their websites regarding the interaction between bird populations and wind farms. Additionally, the development of a wind farm (building roads, mixing concrete, etc.) may have negative impacts on the local ecosystem. Finally, there is some concern that wind farms create noise and visual pollution that must be borne by those that live, or utilize land, near a wind farm.
Recently, the United States Fish & Wildlife Service (US FWS) announced that it expects finalization of its “Land-Based Wind Turbine Guidelines”, which was submitted to the Secretary of the Interior in March of 2010.\(^1\) The guidelines would be voluntary, but would provide developers with the appropriate information to be able to proceed with the utmost care to minimize the impact on the environment. The benefits of a clean (in terms of greenhouse gas emissions) and renewable energy resource could have easily overshadowed the less high-profile environmental concerns that have been brought to light by these groups. And while existing wind farm developers have not had access to the US FWS guidelines, other groups (such as the American Bird Conservancy\(^2\)), have provided feedback to the wind energy industry over the years.

This research evaluates the extent to which, if any, the location of existing wind farm developments has been influenced by the potential negative externalities generated by the wind farm. Included in this analysis are noise and visual pollution, impact on migratory waterfowl, impact on birds of prey, and impact on the threatened Prairie Chicken and Sage Grouse. The study area has been restricted to the Great Plains of the United States.

**Methodology**

It is assumed that the objective of wind power facility developers is to maximize profits, and that the objective is revealed in the choice of location. Here, the development of these facilities is observed as having occurred in a particular county (the number of turbines installed), allowing for the relative importance of county-varying characteristics to be observed. These characteristics include average land value, average wind speeds, electric transmission capability, and regional characteristics. Additionally, as the question put forth by this research is whether or not the external costs of wind power facility

\(^1\) [http://www.fws.gov/habitatconservation/windpower/Wind_Turbine_Guidelines_Advisory_Committee_Recommendations_Secretary.pdf](http://www.fws.gov/habitatconservation/windpower/Wind_Turbine_Guidelines_Advisory_Committee_Recommendations_Secretary.pdf)

The observed number of turbines within a county represents count data. As such, the empirical methodology must be suitable for the analysis of count data. The Poisson regression is suitable for this type of analysis, with specific application to firm location decisions (Guimarães, Figueirdo, & Woodward, 2003). In particular, Guimarães et al. (2003) show that the Poisson regression is particularly well suited to analysis of large choice sets, as is the case here.

Due to the large choice set, and a relatively small number of wind power facilities within that set, the data exhibits an excess zeros problem. Gurmu & Trivedi (1996) identify the “excess zeros” problem as one of the limitations of the standard Poisson regression. One solution, as presented by Lambert (1996), is the zero-inflated Poisson (ZIP) regression. However, our data exhibits a second limitation for the use of a Poisson regression, that of overdispersion, even after accounting for the excess zeros. Overdispersion in the Poisson regression may lead to biased estimates. A standard solution to this challenge is to use an overdispersed Poisson model such as the negative binomial regression (Gurmu & Trivedi, 1996). In order to account for both the overdispersion and excess zeros in the data, a zero-inflated negative binomial (ZINB) regression will be employed. Examples of its use can be found in Minami, Lennert-Cody, Gao, & Román-Verdesoto (2007), Sheu, Hu, Keeler, Ong, & Sung (2004), and Yau, Wang, & Lee (2003).

The zero-inflated regressions (ZIP and ZINB) assume that the zeros in the data exist for two distinct reasons. Observations of zero in the perfect state exist because they are truly zeros. In other words, they lack the characteristics that would make them a viable choice. Observations of zero in the imperfect state exist because they are part of the choice set that may be chosen, but happen to have not
been. The count takes a value of zero in the perfect state, and greater than or equal to zero in the imperfect state. Specifically, the probability function for the ZINB regression model is of the form:

\[
f(y_i|B_i, G_i, \beta_i, \gamma_i, \theta) = \begin{cases} 
  p_i + (1 - p_i)q(0|\mu_i, \theta) & \text{for } y_i = 0 \\
  (1 - p_i)q(y_i|\mu_i, \theta) & \text{for } y_i = 1, 2, \ldots
\end{cases}
\]  

(1)

where \(B_i\) is a row vector of imperfect state covariates for the \(i^{th}\) observation, \(G_i\) is a row vector of the perfect state covariates for the \(i^{th}\) observation, \(\beta\) and \(\gamma\) are the parameter estimates for the imperfect and perfect states respectively, and \(\theta\) is the mean. The estimates are obtained by maximizing the log-likelihood function \(L(\beta, \gamma, \theta|y, B, G) = \sum_{i=1}^{n} \log f(y_i|B_i, G_i, \beta, \gamma, \theta)\) with respect to \(\beta\), \(\gamma\), and \(\theta\) (Minami et al., 2007).

Two statistical tests were implemented to determine that the ZINB regression model was appropriate. First, a likelihood-ratio test is performed to test the ZINB regression model against a ZIP regression model. A statistically significant test result indicates that the data demonstrates overdispersion and the ZINB regression model is preferred. Second, Vuong’s test (Vuong, 1989) is used to test the ZINB regression model against the negative binomial (NB) regression model. Statistical significance of Vuong’s test is an indication that there are excess zeros in the data, and that the zero-inflated model is preferred to the standard NB model.

Data

The data used in this study have been acquired from numerous sources. The model is evaluated at the county level, therefore all data has been assigned a geographic identifier (Federal Information Processing Standard (FIPS) county code). Additionally, the analysis is restricted to the counties which comprise the Great Plains physiographic region of the United States. This restriction represents the central flyway for migratory birds, as well as some homogeneity in avian habitat, agricultural production, and population.
The Great Plains include portions of the states of Colorado, Kansas, Montana, Nebraska, New Mexico, North Dakota, Oklahoma, South Dakota, Texas, and Wyoming.

Wind farm development data was obtained from the American Wind Energy Association (AWEA\(^3\)). This data includes the location (latitude and longitude) of the development, the number of units (turbines) installed, and the nameplate capacity of the electricity production facility in MW (1,000 kW). There are a total of 115 observed wind farms in the study area, with an average of 131 turbines per wind farm and an average nameplate capacity of 181 MW, or 1.37 MW/turbine. The number of turbines observed, rather than nameplate capacity, in a county serves as the dependent variable in the empirical model. The number of turbines better represent the external impact of the facility on birds and humans, with an estimated 2.8 square miles being disturbed by the average wind farm development in this study (Denholm et al., 2009).

The remaining data, all assigned county geographic identifiers, is considered as being part of one of two sets of explanatory variables. First, those variables which would be part of the wind farm developer’s profit maximization function are considered. These include wind quality, electric transmission availability, average land value, state-level renewable portfolio standards (RPS), the irrigated share of agriculture, and the power market in which the county lies. The remaining variables of interest represent the previously identified potential external costs associated with wind farm developments. Included in this set are population density, crop density, the irrigated share of agriculture, extent of lakes and wetlands, and sensitive habitat for the greater sage grouse and prairie chicken.

The availability of quality wind is a necessary condition for wind farm development. Average wind speed data was acquired from two sources. The West Texas A&M University Alternative Energy Institute provided data for the state of Texas, and the rest of the data was downloaded from the National

\(^{3}\) http://archive.awea.org/projects/
Renewable Energy Laboratory (NREL\textsuperscript{4}). This GIS data provides annual average wind power classes (WPCs) at 50 meters altitude with a resolution of 200m (1000m for ND, SD, and TX) cells. There are seven WPCs, calculated based upon the power density associated with varying wind speeds. Average annual wind speeds exceeding 6.5 m/s at a height of 80m (WPC of 2 or greater at 50m) are considered sufficient for the development of utility-scale wind farms (DOE windpoweringamerica\textsuperscript{5}). While a WPC of 2 is sufficient, it is hypothesized that wind power facility developers will seek out higher quality wind resources. Therefore, a dummy variable taking a value of one if the county contained at least 2 square miles of WPC of 3 or greater (value of zero if not) was created.

Wind energy facilities must also have access to the electric grid in order to sell the generated electricity. The development of wind farms is dependent upon the existence of electric transmission lines (Milligan, 2007). In particular, the extent of development within a county is constrained by the carrying capacity of the grid. A GIS line file containing the location of transmission lines in the United States, credited to NREL, was obtained.\textsuperscript{6} The file contains line segments representing the varying carrying capacities of the transmission lines. For each county, a measure of the availability of carrying capacity was created by summing the kV-capacity available.

In order to account for policy-related differences between states, and general public sentiment about alternative energy production in their state, the renewable portfolio standard (RPS) for each state has been assigned to the observed counties. Renewable portfolio standards establish a requirement for an increased production of electricity using renewable energy resources, such as wind, solar, and geothermal. The state-level RPS standards were obtained from the Database of State Incentives for Renewables & Efficiency.\textsuperscript{7} The standards in the study region range from zero to twenty percent of electricity production. Additionally, some of the standards are voluntary. A dummy variable for mandatory RPS has been

\textsuperscript{4} http://www.nrel.gov/gis/data_analysis.html
\textsuperscript{5} http://www.windpoweringamerica.gov/wind_maps.asp
\textsuperscript{6} Downloaded from: http://www.mapcruzin.com/renewable-energy-us-electric-transmission-shapefiles.htm
\textsuperscript{7} Downloaded from: http://www.dsireusa.org/rpsdata/index.cfm
included to account for the difference that a mandatory standard might have on development compared to one that is voluntary.

Electricity isn’t necessarily sold in the same state that it is produced in, so the electric power market that each county resides in is included. The data for electric power markets was acquired from the Federal Energy Regulatory Commission (FERC) website. Dummy variables were created for each of the five electric power markets that overlap with the Great Plains region. The included markets are the Electric Reliability Council of Texas (ERCOT), the Midwest Independent System Operator (MISO), Northwest, Southwest Power Pool (SPP), and Southwest.

Wind farm development is hypothesized to be more likely to occur, all else equal, where tracts of land are less expensive. The average value per acre of cropland in a county was obtained from the United States Department of Agriculture National Agricultural Statistics Service (USDA NASS) Quick Stats database. Additionally, it is hypothesized that the fixed costs associated with large-scale irrigation projects represent access to resources making that land less available for wind farm projects. Irrigated acreage data was also acquired from the USDA NASS database, and was used to calculate the share of cropland that is under irrigation within each county. Irrigation is also representative of intensive agricultural production, which represents less desirable bird habitat. A third included variable related to agricultural production is the share of the county area that is cropland. Existing cropland is suitable for wind power facilities, and, as indicated above, areas of intensive agricultural production are desirable in reducing the impact on avian populations.

Two additional variables are included in the model in order to capture the potential impact on bird species by wind power facilities. First, migratory waterfowl and other birds use lakes and wetlands throughout the Great Plains. Of particular interest are the playa lakes which dot the physical landscape of the Great Plains, covering the western half of Kansas and Nebraska, the eastern half of Colorado and New

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8 [http://www.ferc.gov/market-oversight/mkt-electric/overview.asp](http://www.ferc.gov/market-oversight/mkt-electric/overview.asp)
Mexico, the Oklahoma panhandle and much of northeastern Texas. In addition to the playa lakes, numerous other lakes and rivers are part of the region. Playa lake data (geospatial location and size) was obtained from the Playa Lakes Joint Venture. Additional lake data was obtained from the National Weather Service geodata catalog. These two shapefiles were used to calculate the total area of bodies of water as a share of county area.

The second avian habitat variable that is used accounts for the Lesser Prairie Chicken, Greater Prairie Chicken, and Greater Sage Grouse. The Lesser Prairie Chicken and Greater Sage Grouse are both listed on the US Fish & Wildlife Service’s “Review of Native Species That are Candidates for Listing as Endangered or Threatened”. The Greater Prairie Chicken (Tympanuchus cupido) has extinct and endangered subspecies, with the remaining subspecies being threatened (Robb & Schroeder, 2005). The Great Plains region is home for much of the remaining population of these birds, and their habitat is potentially threatened by the disturbance associated with wind farm development. A GIS shapefile was obtained for the current know range of each of the three species. The Greater Sage Grouse data was obtained from the United States Geological Survey (USGS) SAGEMAP database, the Lesser Prairie Chicken data was downloaded from the Kansas Biological Survey, and the Greater Prairie Chicken data was acquired from NatureServe. A dummy variable was created for each county to indicate whether that county is currently within the range of one of the three birds.

Finally, the question of visual and noise pollution resulting from wind power facility development is addressed with the inclusion of population density (population per square mile) at the county level.

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9 Downloaded from: http://www.pljv.org/cms/playa-county-maps-data-layer
10 Downloaded from: http://www.nws.noaa.gov/geodata/catalog/hydro/html/lakes.htm
12 Downloaded from: http://sagemap.wr.usgs.gov/
13 Downloaded from: http://kars.ku.edu/geonetwork/srv/en/main.home
County population data was obtained from the US Census Bureau. The reported population of each county was divided by the area of the county in square miles to obtain the population density measure.

Results

Table 1 shows the results from the ZINB regression model. It is first important to note the statistical test results for model fit at the bottom of the table. Both the likelihood-ratio test (against a ZIP to test for oversdispersion) and Vuong’s test (against the standard NB to test for excess zeros) are statistically significant. The ZINB regression model is a better fit to this data than either the standard NB regression model or the ZIP regression model. It should also be noted that we observe 425 counties in the model, with 55 positive counts and 370 zero observations.

The logistic model, which evaluates the perfect state, is shown in the bottom half of Table 1. The variables included in this portion of the model are hypothesized to aid in predicting the counties that will exhibit a certain zero. Only three of the parameters are significant in this portion of the model: *high wind*, *percent irrigated*, and *grouse/prairie chicken*. As hypothesized, a county which possesses average wind speeds that exceed the minimum suitable standard for generating electricity at a wind power facility is less likely to be a certain zero count than a poor wind counterpart. Specifically, all else equal, a ‘high wind’ county is 0.2 times less likely to be a certain zero.

It is also consistent with the initial hypotheses that an increase in *percent irrigated* increases the probability that a county well certainly have a zero count of wind turbines. This is a particularly interesting result when considering the question of impact on avian populations. It was stated previously that areas of intensive agriculture represent less suitable bird habitat, and would therefore serve as preferred locations for wind power facility development. These results imply that a one percent increase in the amount of cropland that is irrigated increases the odds of a county being zero for wind turbine
counts by 1.022. In other words, less irrigated agriculture in a county (potentially better bird habitats) increases the likelihood of wind farm development when all other variables are unchanged.

### Negative Binomial Regression

|                    | Estimate | Robust SE | z   | P>|z| |
|--------------------|----------|-----------|-----|-----|
| high wind (d)     | 0.2728   | 0.54951   | 0.50 | 0.620 |
| RPS                | 0.0580   | 0.02422   | 2.39 | 0.017 |
| electric capacity  | 0.0005   | 0.00018   | 2.72 | 0.007 |
| value per acre     | 0.0005   | 0.00049   | 1.06 | 0.288 |
| percent cropland   | -0.0066  | 0.00738   | -0.89| 0.375 |
| percent irrigated  | -0.0014  | 0.00348   | -0.41| 0.684 |
| grouse/prairie chicken (d) | 0.5467   | 0.39525   | 1.38 | 0.167 |
| percent water      | 0.3089   | 0.23003   | 1.34 | 0.179 |
| population density | 0.0001   | 0.00080   | 0.17 | 0.867 |
| MISO (d)           | -3.1034  | 0.59248   | -5.24| 0.000 |
| Northwest (d)      | -1.9689  | 0.48523   | -4.06| 0.000 |
| SPP (d)            | -1.3444  | 0.40853   | -3.29| 0.001 |
| Southwest (d)      | -1.7418  | 0.57419   | -3.03| 0.002 |
| _cons              | 4.5725   | 0.49702   | 9.20 | 0.000 |

### Logistic Regression for Zero Inflation

|                    | Estimate | Robust SE | z   | P>|z| |
|--------------------|----------|-----------|-----|-----|
| high wind (d)     | -1.4632  | 0.58980   | -2.48| 0.013 |
| RPS                | 0.0114   | 0.02212   | 0.52 | 0.607 |
| electric capacity  | -0.0002  | 0.00014   | -1.45| 0.146 |
| value per acre     | -0.0003  | 0.00066   | -0.40| 0.693 |
| percent cropland   | 0.0000   | 0.00606   | 0.00 | 0.998 |
| percent irrigated  | 0.0224   | 0.01204   | 1.86 | 0.063 |
| grouse/prairie chicken (d) | 0.9912   | 0.31649   | 3.13 | 0.002 |
| percent water      | 0.0425   | 0.16009   | 0.27 | 0.791 |
| population density | -0.0001  | 0.00114   | -0.11| 0.913 |
| _cons              | 2.5068   | 0.57334   | 4.37 | 0.000 |

Likelihood-ratio test: chibar2(01) = 3731.52  Pr>=chibar2 = 0.0000
Vuong test: $z = 2.94$  Pr>$z = 0.0016$

Table 1: Zero-Inflated Negative Binomial Regression Model
On the other hand, the Greater Sage Grouse, Greater Prairie Chicken, and Lesser Prairie Chicken habitats increase the odds that a county will be a certain zero in turbine counts. A county that falls within one of these three habitats is 2.69 times more likely, holding all other variables constant, to have zero turbines. This doesn’t imply that developers have necessarily chosen to avoid these regions. In fact, it could be the case that the current range of these birds represents the influence of wind farm development. It is not the place of this researcher to draw those conclusions, but rather to state that those counties that are home to this group of birds with fragile populations are more likely to not have experienced wind farm development than other counties in the Great Plains, all else equal.

For those counties that are not in the perfect state (count of turbines “certainly” zero), the top portion of Table 1 contains results which allow for the prediction of the turbine count. Two of the primary variables, electric capacity and RPS, are statistically significant. Additionally, each one of the power market dummy variables is significant. ERCOT was left out of the model to avoid multicollinearity, so each of the remaining power market dummy variables can be interpreted as a comparison to ERCOT. For example, a county in MISO is expected to have 0.049 times fewer turbines installed than a county in ERCOT, all else being equal. This result can be explained, in part, by the fact that the Great Plains region and ERCOT power market overlap primarily in the counties of Texas that exhibit large scale wind power facility development. Additionally, Texas has three times as many MW of wind power installed as the next state.

The availability of electric transmission lines in a county is statistically significant in predicting the count of turbines in this model. An increase in county capacity of one mile of 115kv transmission line increases the turbine count by one, holding all else constant. This is consistent with the initial hypothesis that the extent of wind power facility development would be increasing in electric transmission line capacity. The renewable portfolio standards are also significant in this model. The model predicts that a county that has a standard for renewable production that is one percent higher than another, all else equal, will have a 1.06 higher count of turbines.
Finally, it is important to discuss the variables that were not statistically significant in this model, particularly those that are related to the question of whether or not wind farm developments are occurring in areas that minimize external costs. Population density is not statistically significant in either portion of the model. This suggests that on the Great Plains, at the county level, that population doesn’t play a significant role in determining wind power facility development locations. Additionally, percent water doesn’t provide any additional information in predicting the count of turbines. This variable is meant to represent the habitat for waterfowl that make the Great Plains either their temporary or permanent homes.

Discussion

The intent of this work is to identify the potential relationship between wind power facility development and avian and human populations in the Great Plains region of the United States. The available data for this study presented many challenges in answering the research question, and great care has been taken to not overstate the findings of this work. However, given these limitations, the results of this research suggest that it is unlikely that avian and human populations (at least at a county level aggregation) are determining factors in wind farm development. It would unfortunately require data at a greater resolution than that which was used in this study, and that data would increase the sample size (and number of excess zeros) tremendously.

Future research on this topic should include an expansion to regions beyond the Great Plains as well as an increase in the number of bird species that are evaluated. Additionally, externalities experienced by humans would be better evaluated with spatial econometric techniques that could also allow for line of sight measures. An evaluation of the economic impact on hunting ranches would provide an estimate of external costs borne by some humans. Finally, data on the developer, electricity purchaser, and prior land use could provide further answers to these questions.
References


