Does proximity to wind farms affect the value of nearby residential properties? Evidence from Washington and New York States

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Abstract: The rapid growth of wind farms across rural communities in the U.S. has spurred concerns over the effect of wind turbines on residential property values. This paper presents a hedonic regression analysis of property values using a partial panel of properties from two counties in the United States. A total of 24 models are estimated. This paper compares the results of market and county-assessed data, interaction terms, and varying assumptions about the effect of wind turbines. This study finds weak evidence that property values near wind turbines are lower than nearby areas, but given methodological limitations and likely endogeneity bias further research is necessary.

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I. Introduction

For the past decade, wind energy has been the fastest growing source of energy in the United States, increasing by almost 1,700% from 2000 to 2011 (Wind Powering America, 2011). With the expansion of wind farms across many rural landscapes, there have been numerous and persistent cases of opposition to proposed wind farms. While opinion surveys indicate that residents have diverse opinions of nearby wind farms (see Sims *et al.* 2008 p.253), one of the often-cited concerns by those opposed to wind farms is the potentially negative effects of wind turbines on nearby property values. Wind energy's status as an amenity or disamenity is uncertain. Unlike proximity to neighborhood parks or polluting factories, the direct effects of wind turbines on nearby residents are observed to be inconsistent across cases (Cummings 2011). Despite wide concern, very few peer-reviewed economic studies have analyzed these potential effects; in many cases, community groups, national and local government agencies and wind farm developers have commissioned their own studies. Knowledge about the role of wind farms as a disamenity or an amenity will affect emerging zoning ordinances and other forms of state and municipal legislation.

This paper examines the effects of wind farm proximity on property values through a hedonic regression analysis of current market prices and property value assessments, using a cross-section of properties in two counties as well as a panel of properties in one county. The study area consists of wind farms in two sites in the United States: one in Southern Washington State and one in upstate New York. Using geographical data about the location of turbines, property characteristics, proximity to turbines, and property values this paper contributes to the literature by comparing the estimates of market-based (asking and selling prices of properties) and government (county property assessments) property valuation, and further exploring a recently applied technique of parcel-level fixed effects to control for endogeneity bias. Data were obtained through Federal Aviation Administration data on the location of constructed wind farms, publicly available mapping software, county property assessment data and online real estate listings.

Section II describes the problem of measuring the effect of wind farms on property values in the theoretical context of a hedonic regression analysis. Section III introduces previous empirical literature examining the title question. Study areas are introduced in Section IV. Section V presents the conceptual models applied in this paper. Section VI discusses the ideal data to answer the title question and Section VII presents the actual data used in these models. Results are presented in Section VIII. The significance of results in light of study limitations are discussed in Section IX. Section X concludes and discusses policy implications and future research topics.

II. Theoretical background

Hedonic demand theory posits that a property can be thought of as a bundle of characteristics that are known at the time of purchase. In this context, the price of a property is considered a function of property characteristics including the presence of wind turbines which may affect the utility that a potential buyer receives from the property. That is,

[1] Consumer utility = F(property goods, other goods)

[2] Property price = P(property characteristics, location characteristics, other factors)

where property goods include consumption of residential property characteristics; property characteristics include factors such as square footage, number of bedrooms, or number of acres; and location characteristics describe proximity to social amenities such as schools or the type of neighborhood the property is located in. In this case, proximity to the nearest wind turbine is included in location characteristics. Other factors may include regional or macro level factors such as time period or pertinent government policies.

Rosen (1974) was the first to outline hedonic demand theory. Under the assumptions that consumers obtain utility from a bundle of characteristics of a good and that this is reflected in the total price of the good, and that perfect competition exists, Rosen concludes that the population-wide marginal utility of a characteristic, or “implicit price,” can be estimated through a hedonic regression analysis of differentiated goods. Freeman (1979) extended Rosen’s work by applying hedonic demand theory to the problem of estimating the valuation and devaluation of environmental amenities and disamenities. Under the assumptions that the housing market is nearly perfectly competitive, that any market imperfections do not lead to systematic bias, and that all households have identical underlying utility functions, Freeman presents the argument that hedonic regression analysis has significant explanatory power concerning the effect of environmental factors on property values.

Applied to the study of wind farms and property values, the field of real estate economics has built upon the foundation of hedonic demand theory. Hoen *et al.* (2009) outlines area stigma, scenic vista stigma and nuisance stigma as characteristics that may decrease the total value of a property when wind energy moves into an area. That is, potential home buyers may devalue a property because they obtain disutilty from: living in a region or community with turbines (area stigma); from viewing turbines on the landscape from their property (scenic vista stigma); or from directly experiencing noise or sleep disruption from nearby turbines (nuisance stigma).

Note that neither hedonic demand theory nor real estate stigmas account for various non-use effects of wind energy development, including, for example the knowledge of animal habitat destruction during construction or the knowledge of climate change abatement from the project. Furthermore, measurement of the implicit price of living in a turbine-free area does not tell us the socially desirable amount of wind energy, only the disutility that nearby residents may receive from it.

III. Empirical literature

Numerous studies have evaluated the effect of wind turbines on property values through various non-peer reviewed means including expert surveys, homeowner surveys and simple statistical analyses. For example, a study commissioned by a community opposition group and performed by an appraisal firm in Wisconsin in 2009 found as much as a 43% decrease in home prices due to wind turbines based on a survey of real estate agents and simple statistical regression (Kielisch 2009). However, a study by the Renewable Energy Policy Project found positive impacts of wind turbines on property values (Sterzinger *et al.* 2003) but used R^2 as the sole measure of model significance; (for a complete critique of this analysis, see

Hoen 2006 p.17). Because these methods lack sufficient economic rigor, they are excluded from this literature review. For an exhaustive review of all reports on this topic, see Hinman (2010).

A primary question is, are wind turbines environmental disamenities? As stated in Section I, public opinion remains divided. If wind turbines are disamenities, it is useful to compare their effect on nearby property values with that of other disamenities. Table 1 shows how previously studied environmental disamenities compare with one another.

Table 1. Effect of environmental disamenities on nearby property values.

Paper	Type of disamenity	Distance to disamenity, (miles)	Maximum effect on property values
Carroll *et al.* (1996)	chemical plant	2.5	-16%
Dale et a. (1999)	lead smelter	2	-4%
Ready and Abdalla (2005)	landfill	0.45	-12.4%
	confined animal feeding operation	0.3	-6.4%
Hamilton and Schwann (1995)	high-voltage transmission lines	300 feet	-5.7%
Des-Rosiers (2002)	high-voltage transmission lines	50 feet	-14%
Davis (2008)	fossil fuel plants	2	-5%

Adapted from Hoen et al. 2009

It is important to note that wind turbines differ from other types of disamenities. Wind energy development is supported by a large majority of the public in the United States and publicly promoted by climate change activists, state and municipal governments and energy companies, while other citizens may privately feel indifferent or negatively toward wind energy. The experience of residents who live near wind turbines is not uniform as is usually the case with other forms of environmental disamentities; while some residents complain of noise and health effects of large wind turbines (the justification of “nuisance stigma” mentioned above) and others object to the presence of wind turbines on the surrounding landscape, many residents do not report these complaints. Furthermore, wind energy is a highly visible environmental factor. Other public facilities may be easily masked by tree or wall buffers, or their effect may be limited to a very small area.

To date, four hedonic analyses of wind turbines and property values appear in peer-reviewed journals and Heintzelman and Tuttle (2011) are developing a working paper. Table 2 summarizes the findings of previous economic analyses of wind farms' effects on nearby property values.

Table 2. Studies of wind turbines and property values using hedonic regression analysis.

Paper	Study Area	Technique	Sample size	Effect
Hoen *et al.* (2011)[a]	*Ten study areas across the U.S., see below*	*Eight models estimated, see below*	7,459	none
Heintzelman and Tuttle (2011)[a]	Upstate New York	Repeat sales fixed-effects	11,369	negative***
Carter (2011)[b]	Lee County, Illinois	Basic non-linear hedonic price model	1,298	none
Laposa and Mueller (2010)[a]	Northern Colorado	Repeat sales non-linear hedonic price model	2,910	negative* (*authors attribute to national housing crisis*)
Hinman (2010)[b]	McLean County, Illinois	Pooled difference-in-difference estimator	3,851	none
Hoen *et al.* (2009)[c]	*Same as Hoen et al. (2011)*			
Sims, Dent and Oskrochi (2008)[a]	Cornwall, Scotland	Basic linear hedonic price model	201	none
Sims and Dent (2007)[a]	Cornwall, Scotland	Basic linear hedonic price model	1,052	none
Hoen (2006)[b]	Upstate New York	Basic non-linear hedonic price model	280	none

Note: 'a' indicates that a paper appears in a peer-reviewed journal; 'b' indicates that a paper is a thesis or dissertation; 'c' indicates that a study is a government report; '*' indicates significance at the 10% level of confidence; '**' indicates significance at the 5% level of confidence, '***' indicates significance at the 1% level of confidence.

Both Hoen (2006) and Sims and Dent (2007) use small sample sizes and draw on data from near small wind farms with less than 40 turbines each. Sims and Dent, however, have very limited property and location characteristic data and therefore their analysis likely suffers from omitted variable bias. Sims *et al.* (2008) improve upon their previous analysis by including more characteristics but only use data from within a half mile of a wind farm without comparing the prices with those which are further away from the wind farm. Hoen's analysis includes property value data within a 5 mile radius and has more detailed property data, but does not control for endogeneity or omitted variable bias. That is, in these studies it is possible that wind farms are more likely to be built in areas with lower or already declining property values (endogeneity bias) or that variables missing from the regression bias the results (omitted variable).

Laposa and Mueller's (2010) analysis focused on the announcement of a wind energy project in Northern Colorado. The authors analyze properties that were sold in 2000 or 2008 and assign each sale a dummy variable indicating before or after announcement of the wind farm then perform a pooled regression analysis. Several issues exist with this study. First, the authors measure the effect of wind farm announcement on property values and not the actual turbines, which means that the distance from individual turbines cannot be calculated and the results cannot be directly compared with other studies. Second, the announcement of the wind farm construction was nearly perfectly timed with the 2008 financial crisis, which is the authors' justification for ignoring the significant and negative affect of the wind farm announcement on area property values.

The Hoen *et al.* (2009) study, the results of which are published in a peer-reviewed version in Hoen *et al.* (2011), introduced a level of rigor that has not been matched by studies conducted before or since. The authors include data from properties near wind farms in Oregon, Washington, Texas, Oklahoma, Iowa, Wisconsin, Illinois, Pennsylvania and New York and estimated eight models, including a basic hedonic regression analysis, repeat sales analysis, sales volume analysis and five alternative hedonic regression analyses investigating the effect of scenic vista orientation, of varying distance measures, of multiple turbines, and of temporal aspects. This study further corrects for the flaws of past studies by "ground-truthing," or visiting each property to determine the severity of nuisance and scenic impacts of nearby wind turbines. Despite these clear strengths of this study, Hoen *et al.* state that a negative effect on individual properties could have been masked by a larger neutral effect due to the fact that properties up to ten miles away from wind farms are included. Additionally, Hoen *et al.* used a pooled regression analysis of many study areas, meaning that property value effects within one study area may not have been apparent from the national results.

Hinman (2010) and Carter (2011) both use data from nearby counties in central Illinois that were tested in the Hoen *et al.* (2009) analysis. Because Carter continues to rely on basic non-linear hedonic price model, his analysis may suffer from the same sources of property- and regional-level endogeneity bias. Hinman, however, attempts to control for these sources of error through a pooled difference-in-difference hedonic regression, where group-specific (groups being homes within 3 miles and outside of 3 miles from the wind farm) and time-specific effects are incorporated into the regression. Hinman finds evidence that properties with lower property values are indeed more likely to attract wind energy development and that a decrease in property values may be attributable to the anticipation of a wind farm which disappears after construction.

Before Heintzelman and Tuttle's (2011) repeat sales fixed-effects study, the majority of the literature suggested that wind turbines had no effect on nearby property values through nuisance, scenic vista or area stigmas. Heintzelman and Tuttle attribute their unusual results to their use of a repeat sales fixed-effects instrument, which controls for parcel-level endogeneity. The authors also examine the effect of turbines on very nearby properties (within 3 miles), something that Hoen *et al.* (2009) neglect to do. Heintzelman and Tuttle do not "ground-truth" properties to determine the precise effect of different stigmas, instead they use the measure of continuous distance to the nearest turbine in addition to turbine density measures.

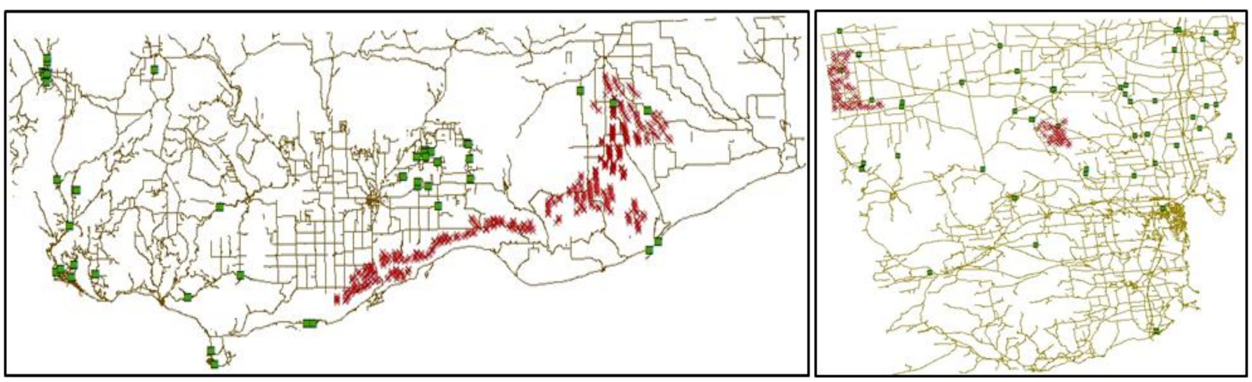
IV. Study Area

This study seeks to compare two geographically dissimilar locations with wind farms using multiple measures of both property values and presence of wind turbines. Due to lack of access to adequate data, this paper cannot precisely replicate Heintzelman and Tuttle's (2011) "successful" analysis which uses a repeat sales fixed effects estimator. The current study does however explore the possibility that proximity to wind turbines interacts with property values differently depending on the region. The differences in the characteristics of these counties are clear from Table 3.

Table 3. Characteristics of study areas.		
	Klickitat County, WA	Clinton County, NY
Area (sq mi)	1,904	1,039
Population (2010)	20,318	81,618
Primary industry	Ranching	Manufacturing, health services
Topography	High desert, mountain forest, river gorge	Deciduous forest, Adirondack mountains, lake shore
Opposed community groups?	No	Yes

This study seeks to measure the effects of two operational wind farms in Clinton County, totaling 119 turbines[1]. In Klickitat County, this study considers 3 operational projects totaling almost 400 individual turbines which were constructed in 2008, 2009 and 2010. The distribution of properties and wind turbines are shown in Figure 1.

Figure 1. Klickitat County (Left) and Clinton County. *Properties are marked with squares and turbines are dark "X"s. Maps not to scale.*



V. Conceptual Model

The current study estimates two types of models. The first set of models use cross section data to regress a measure of property value by a set of property characteristics and a dummy variable indicating if there are wind turbines within a certain distance of the property.

[1] Not all 119 turbines are located within county limits.

As shown in Equations [3] and [4], these models measure if properties with wind turbines within a certain radius are more likely to have higher or lower property values than properties further away from wind turbines. Equation [4] assumes that the effects of wind turbines end within a certain distance. These models use the interaction between a dummy variable indicating if there is a turbine within a specified distance, and the measured distance between a property and the nearest wind turbine to estimate if distance to a wind turbine has an effect on property values within a certain radius.

$$[3] \qquad \ln(value_{ij}) = \beta_0 + \beta X_{ij} + \beta municipality_{ij} + \beta turbine_{ij} + \varepsilon_{ij}$$

$$[4] \qquad \ln(value_{ij}) = \beta_0 + \beta X_{ij} + \beta municipality_{ij} + \beta turbine_{ij} * distance_{ij} + \varepsilon_{ij}$$

where $value_{ij}$ is either the county-assessed 2011 property value or a market-based measure of property value in Clinton or Klickitat, X_{ij} is a vector of property-level control variables, $municipality_{ij}$ is a dummy variable for the township or city where the property is located, and $turbine_{ij}$ is a dummy variable indicating if the property has a wind turbine within ten, five or one miles. The variable $turbine_{ij} * distance_{ij}$ is the distance in meters between a property and the nearest wind turbine if the property is within the radius specified by the $turbine_{ij}$ dummy. We take the natural logarithm of the dependent variable because it is likely that a small change in value for a low-value home is more important than the same change in value for a higher value home.

The second type of model in this paper is a fixed effects regression using panel data. Shown in Equations [5] and [6], this model controls for the unobserved, time invariant property-level characteristics as well as year effects. The primary problem with the previous two types of models is the possibility of endogeneity bias. That is, equations [3] and [4] can only tell us whether properties near wind turbines are valued less than properties which are further away, not if the addition of wind turbines caused property devaluation. A fixed effects model will mitigate the possibility of falsely negative or overly negative effects of wind turbines on property values. The second type of model can be expressed as:

[5] $\ln(\mathit{value}_{ijt}) = \beta_0 + \beta\lambda_t + \beta\pi_{ij} + \beta X_{ijt} + \beta \mathit{turbine}_{tj} + \varepsilon_{itj}$

[6] $\ln(\mathit{value}_{ijt}) = \beta_0 + \beta\lambda_t + \beta\pi_{ij} + \beta X_{ijt}\ \beta \mathit{turbine}_{itj} * \mathit{distance}_{itj} + \varepsilon_{itj}$

where value_{ijt} is the county-assessed property value[2] in a given year *t*, λ_t represents a given year dummy variable, π_{ij} are time-invariant property characteristics, X_{ijt} is a vector of time-variant property characteristics, and $\mathit{turbine}_{ijt}$ is the presence of a wind turbine within a certain radius of a property in a given year.

VI. Ideal Data

The most appropriate data to completely answer this paper's title question would be market-based property value data over time from before and after the construction of nearby wind turbines, properties from many locations and distances, time-variant property characteristics for all time periods, information about the distance to the nearest wind turbine in any given time period, and accurate information about the perception of wind turbines from a given property. Market-based property value data in the format of actual selling prices are important because government assessors may either not reassess a property often enough or they may ignore the effect of the presence of wind turbines and other property characteristics

[2] Time series market data was not available.

on a buyer's willingness to pay for a property. Varied locations are important to ensure that the type of landscape (i.e. farmland versus forest) is not influencing consumers' reactions to wind turbines. Complete time-variant data is important because otherwise the effect of a change in another characteristic might be attributed to the addition of wind turbines.

VII. Actual Data

Data for this study came from several different sources. Property addresses, 2011 characteristics, and 2011 asking price information for Klickitat County came from the real estate site Zillow.com. Property values from 1999 to 2011 came from the Klickitat County government assessor office. For Clinton County, property addresses and 2011 selling prices came from Zillow.com, but characteristic and 2011 property value information came from the Clinton County government assessor office. For both counties, addresses were picked from Zillow.com in order to obtain a distribution of properties from each municipality. Not all listed properties are included in this study's sample. Locations of wind turbines and the dates of their construction, used to calculate the distance from properties to wind turbines, were based on Federal Aviation Administration records and coded into Geographic Information System (GIS) format by KidWind Inc. The addresses obtained through Zillow.com were then coded into GIS format using U.S. Census Bureau address to create an "address locator" which allowed the addresses to be plotted on the same map at the wind turbine locations. ArcMap software was used to measure the distance between selected addresses and the nearest turbine. The GIS file provided by KidWind Inc. also contained the date of construction of the nearest turbine for use in the fixed-effects models.

Due to the inconsistency of the above data sources, this paper estimates several different models. As shown in Table 4, this paper compares the results of models using: market-based and government-assessed property values as dependent variables; dummy variables indicating the existence of wind turbines within ten, five or one miles; and interaction terms assuming the effects of wind turbines end within ten, five or one miles. The comparison of models using market-based versus government data will also lend insight to the validity of results from an exploratory regression using assessed property values in Klickitat County and a dummy variable indicating vacancy.

Table 4. Chart of models estimated. *Experimental variables on top row, dependent variables along left column.*

	Turbine within 10 miles	Turbine within 5 miles	Turbine within 1 mile	Distance away from turbine if within 10 miles	Distance away from turbine if within 5 miles	Distance away from turbine if within 1 mile
2011 values, WA	X	X		X	X	
2011 values, NY	X	X	X	X	X	X
2011 selling price, NY	X	X	X	X	X	X
2011 asking price, WA	X	X		X	X	
1999-2011 values in WA	X	X		X	X	

The property-level control variables used in cross-section models are shown in Table 5. We would expect an increase in any of these variables to have a positive effect on property values. More property value information was available for Clinton County than for Klickitat

County, but for better comparison between the two study areas these were excluded from this model.

Table 5. Property characteristics in cross-section models.		
Variable name	Description	Expected Sign
log_sqft	ln(square feet of home)	Positive
log_area	ln(acreage of property)	Positive
lake_river	Dummy variable for waterfront mentioned in listing	Positive
view	Dummy variable for view mentioned in listing	Positive
fireplace	Dummy variable for fireplace mentioned in listing	Positive
bath	Number of bathrooms	Positive
bed	Number of bedrooms	Positive

Many ideal property-level characteristics (X_{it}), including the condition, age or style of a home were not available for both counties and so were not included in the model. Other characteristics, such as distance to nearest city or nearest major road were accessible only through additional Geographic Information Systems techniques. The acreage and square footage of the home were logged to adjust for heteroskedasticity, and because it makes theoretical sense that a small change in acreage or square feet has a larger impact on the value of a small property than the same size change would for a larger home or property.

In the fixed-effects model, time series county-assessed property value data was only available in Klickitat County. The use of county-assessed property value data increases the likelihood that the property value data will be biased from the true market value. The only time-varying property characteristics available were the vacancy status of the property and the presence of wind turbines within a ten mile or five mile radius. Therefore, time-varying property characteristics, such as if a home suffered storm damage or was remodeled, are omitted from this model. The final form of the fixed effects model then is shown below:

[7] $\ln(value_{ijt}) = \beta_0 + \beta\lambda_t + \beta\pi_{ij} + \beta vacancy_{ijt} + \beta turbine_{tj} + \varepsilon_{itj}$

An additional limitation of the fixed-effects model is that only the nearest turbine in 2011 was examined, so farther away turbines built previously were excluded. That is, if a property had a turbine within five miles in 2011 and had a turbine within ten miles in 2008, the effect of this more distant turbine would not be included in the model. Because the assumptions for a Hausman test were not met (the models were not asymptotic), this equation could not be tested to ensure that a fixed effects model was empirically better than a random effects model. However, because individual properties were observed over time fixed effects is theoretically preferable.

A further difference between the ideal and actual data is the sample sizes and distribution of properties. In both counties N is small and unevenly distributed at varying distances from wind turbines, as shown in Figure 1. Table 6 shows summary statistics for both counties.

Table 6. Summary statistics for Klickitat and Clinton Counties

	Klickitat County, N=57		Clinton County, N=56	
Variable	Mean	St. Dev.	Mean	St. Dev.
Assessed property value ($)	$192,082	$167,616	$107,390	$73,714
Asking or selling price ($)	$261,162	$244,930	$99,011	$66,714
Total property area (sq ft)	413,399	631,890	236,283	350,359
Structure area (sq ft)	1,319	1,288	1,502	626
Waterfront dummy	0.186	0.393	0.16	0.370
View dummy	0.397	0.494	0.12	0.328
Fireplace dummy	0.224	0.421	0.16	0.421
Bedrooms[3]	2	1.685	2.96	1.194
Bathrooms	1.456	1.473	1.49	0.696
Distance to nearest turbine (meters)	98,331	70,361	36,442	25,258

[3] "Bedrooms" was excluded from the Klickitat County models due to a correlation of 0.92 between bedrooms and bathrooms and a variance inflation factor of 12.91 in the base model.

The table above shows that properties in Klickitat County are more expensive, have greater total area, are more likely to report a view, and are on average further away from wind turbines than properties in Clinton County.

VIII. Results

The first results presented are those of the cross-section models, which are subject to endogeneity bias as described above. Table 7 shows the results of models estimated using equations [3] and [4] for Klickitat County using assessed and market property values and all four wind turbine variables. All control variables have the theoretically expected signs, with the exception of number of bathrooms in the county-assessed models but these are very weakly significant across all models and is likely attributable to a small sample size. In all ten models shown, coefficients of the control variables do not switch signs or drastically change magnitude with the addition of the wind turbine variable. Between the groups of assessed value models and market value models, coefficients are roughly equivalent across models. In both groups, properties within ten miles of the turbines have significantly lower values than other properties, shown by large negative coefficients on the ten mile dummy. However, within ten miles there is a weak but significantly positive relationship between proximity to a wind turbine and property values.

The coefficients discussed above, in conjunction with the insignificant but positive coefficients in both models' five mile dummies and distance within five miles, suggests that there are other factors besides proximity to wind turbines that is influencing property values between five and ten miles away from the Klickitat County wind farms. It is unlikely that wind turbines would have a positive impact between five and ten miles and then a negative impact within five miles, despite the fact that properties within five miles are have greater property values in general. While adjusted R-squared statistics remain high between models, additional support for this interpretation comes from the F-tests between all wind turbine models and the base models for both dependent variables. As shown in Table 8, the addition of a 5-mile wind variable does not add any explanatory power to the base model, while the addition of both the ten mile dummy or the ten mile interaction term do. The similarity between the models using dummy variables and interaction terms is likely due to a spefication error, further discussed in Section VIII.

Table 7. Klickitat models controlling for municipality, not shown.

Dependent Variable:	Log of 2011 county-assessed property value					Log of 2011 asking price				
log_sqft	0.13*** (3.607)	0.14*** (3.943)	0.13*** (3.525)	0.14*** (3.962)	0.13*** (3.521)	0.07** (2.106)	0.08*** (2.796)	0.07** (2.067)	0.08*** (2.786)	0.07** (2.063)
log_area	0.0514 (0.934)	0.0592 (1.111)	0.048 (0.863)	0.0599 (1.129)	0.0477 (0.858)	0.0525 (1.023)	0.0611 (1.351)	0.0515 (0.987)	0.0618 (1.363)	0.0513 (0.982)
Fireplace	0.123 (0.686)	0.145 (0.834)	0.134 (0.74)	0.148 (0.854)	0.135 (0.743)	0.326** (2.066)	0.366** (2.621)	0.328** (2.047)	0.369** (2.635)	0.328** (2.05)
View	0.321* (1.775)	0.398** (2.225)	0.306 (1.667)	0.397** (2.23)	0.306 (1.667)	0.387** (2.337)	0.51*** (3.381)	0.383** (2.266)	0.50*** (3.342)	0.382** (2.263)
bath	-0.0087 (-0.092)	-0.0215 (-0.235)	-0.0038 (-0.039)	-0.0221 (-0.241)	-0.0034 (-0.035)	0.161* (1.862)	0.139* (1.826)	0.162* (1.847)	0.139* (1.824)	0.162* (1.851)
lake_river	0.195 (1.263)	0.241 (1.596)	0.171 (1.073)	0.239 (1.59)	0.17 (1.068)	0.19 (1.377)	0.254** (2.067)	0.185 (1.3)	0.249* (2.025)	0.184 (1.293)
ten mile		-0.41* (-1.952)					-0.61*** (-3.453)			
five mile			0.163 (0.689)					0.040 (0.181)		
distance within 10 mi				-0.04* (-2.024)					-0.06*** (-3.431)	
distance within 5 mi					0.017 (0.714)					0.0049 (0.221)
N	57	57	57	57	57	57	57	57	57	57
Adjusted R-squared	0.8152	0.8279	0.8126	0.8291	0.8128	0.7914	0.8379	0.7859	0.8374	0.7860

Table 8. F-tests between base models and wind turbine variable models for Klickitat County.		
Added Wind Turbine Variable	2011 county assessed value	Asking Price as of November 2011
ten mile dummy	3.81*	11.92***
five mile dummy	0.47	0.03
ten mile distance interaction	4.1*	11.77***
five mile distance interaction	0.48	0.05

Similar patterns and issues appeared in the results of the cross section models in Clinton County. Several control variables had theoretically unexpected signs, but these were all insignificant. For the most part control variables have consistent signs and magnitudes across the addition of wind turbine variabeles, with the exception of bedrooms in the selling price models, but this is likely due to a very small number of 25 observations. Here, if a property's acreage increases by 10%, its value might increase by between 1.7 and 1.8% using the estimates of assessed value model, whereas a 10% increase in the square footage of a home might increase between 2.0% and 2.3%. This is a larger elasticity for both square footage and acreage than estimated by Heintzelman and Tuttle, who include Clinton County in their study area but include many other property level characteristics. It is likely that omitted variables which are correlated with square footage and acreage make these variables seem more significant than they truly are. In Clinton County, the sample size of the price dependent variable model is so small that little can be learned from significance levels.

In the county assessed value models the models using the five mile dummy were significant, indicating that properties within five miles of turbines were valued higher than other properties. However, both the ten mile and five mile interaction terms were positive, (though the ten mile dummy is insignificant), which suggests that within these radii properties closer to wind turbines are valued at less than properties which are further away. This relationship breaks down in both groups of models within one mile, as the coefficient is negative on the one mile interaction term. The coefficients on both one mile dummies are negative, suggesting that properties within one mile are valued at less than other properties. Table 10 shows the results of F-tests between all wind tubine models and the two base models, and these confirm that only the models with the five-mile dummies add any significant explanatory power to the base models. As with the Klickitat county models, it is likely that other unobserved geographic factors are responsible for this atheoretical but significant relationship between proximity to turbines and property values. However, the balance of the signs and magnitude of coefficients does suggest that properties near wind turbines may be valued at less than other properties, especially those within one mile of wind turbines.

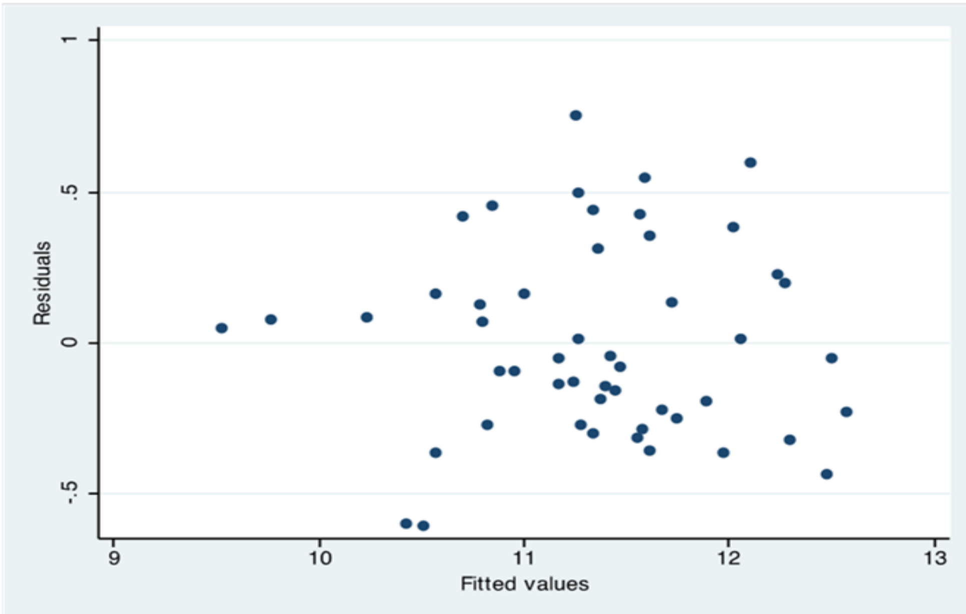
Table 9. Clinton County models controlling for municipality, not shown.														
Dep. Variables:	Log of county assessed value in 2011							Log of selling price in 2011						
log_sqft	0.217**	0.227**	0.214***	0.213**	0.218**	0.208**	0.209**	-0.476	-0.464	-0.675	-0.618	-0.454	-0.785	-0.6
	(2.664)	(2.673)	(2.773)	(2.451)	(2.59)	(2.668)	(2.409)	(-0.962)	(-0.911)	(-1.037)	(-1.211)	(-0.892)	(-1.100)	(-1.206)
log_area	0.18***	0.178***	0.171***	0.18***	0.178***	0.17***	0.180***	0.342***	0.34***	0.349***	0.348***	0.35***	0.351***	0.352***
	(3.897)	(3.855)	(3.938)	(3.829)	(3.839)	(3.922)	(3.852)	(3.671)	(3.591)	(3.576)	(3.751)	(3.603)	(3.619)	(3.828)
fireplace	0.0956	0.0857	0.103	0.095	0.0943	0.103	0.0939	-0.0912	-0.034	-0.176	-0.0475	-0.0518	-0.194	-0.0599
	(0.552)	(0.486)	(0.627)	(0.54)	(0.533)	(0.623)	(0.535)	(-0.208)	(-0.073)	(-0.363)	(-0.109)	(-0.114)	(-0.404)	(-0.139)
view	-0.106	-0.0628	-0.0996	-0.102	-0.1	-0.0956	-0.097	0.212	0.0846	0.254	0.0526	0.0916	0.26	0.016
	(-0.403)	(-0.224)	(-0.401)	(-0.379)	(-0.353)	(-0.382)	(-0.362)	(0.254)	(0.096)	(0.293)	(0.0623)	(0.104)	(0.302)	0.0195)
bath	0.238	0.219	0.245*	0.241	0.235	0.248*	0.245*	0.459	0.473	0.559	0.585	0.467	0.618	0.59
	(1.69)	(1.484)	(1.848)	(1.669)	(1.591)	(1.853)	(1.696)	(1.424)	(1.424)	(1.432)	(1.709)	(1.408)	(1.471)	(1.753)
beds	0.0643	0.0575	0.0256	0.0695	0.0639	0.0355	0.0747	-0.0175	-0.00358	-0.0228	0.0652	-0.0149	-0.0091	0.06
	(0.852)	(0.74)	(0.349)	(0.83)	(0.831)	(0.485)	(0.896)	(-0.128)	(-0.0253)	(-0.161)	(0.417)	(-0.107)	(-0.0646)	(0.414)
lake_river	0.60***	0.66***	0.63***	0.60***	0.61**	0.63***	0.60***	0.66	0.51	0.59	0.73	0.50	0.56	0.75
	(3.104)	(2.864)	(3.438)	(3.058)	(2.648)	(3.413)	(3.065)	(1.198)	(0.842)	(1.00)	(1.332)	(0.812)	(0.962)	(1.38)
ten mile		0.123							-0.315					
		(0.479)							(-0.633)					
five mile			0.379**							0.295				
			(2.251)							(0.496)				
one mile				-0.0407							-0.483			
				(-0.152)							(-1.053)			
distance within 10 mi					0.00157							-0.0309		
					(0.0633)							(-0.638)		
distance within 5 mi						0.0383**							0.0418	
						(2.135)							(0.617)	
distance within 1 mi							-0.0104							-0.0636
							(-0.312)							(-1.170)
N	50	50	50	50	50	50	50	25	25	25	25	25	25	25
Adjusted R Squared	0.6899	0.6827	0.7231	0.6808	0.6806	0.7193	0.6815	0.5806	0.5564	0.5497	0.5847	0.557	0.5556	0.5942

Table 10. F-tests between base models and wind turbine variable models for Clinton County.		
Added Wind Turbine Variable	2011 county assessed value	Selling Price during 2011
ten mile dummy	0.23	0.4
five mile dummy	5.07**	0.25
one mile dummy	0.02	1.11
ten mile distance interaction	0	0.41
five mile distance interaction	4.56**	0.38
one mile distance interaction	0.1	1.37

While the effect of control variables on property values was similar in both Clinton and Klickitat counties, the wind turbine variables differ between the two study areas. In Klickitat County, only the ten mile dummy and interaction term were significant but in Clinton County only the five mile dummy and interaction term were different. If these models had lower risk of omitted variable bias, this difference might be interpreted as wind turbines having different magnitudes of effects in different regions. Given the likelihood that other geographic factors are at play, however, this direct comparison is not possible.

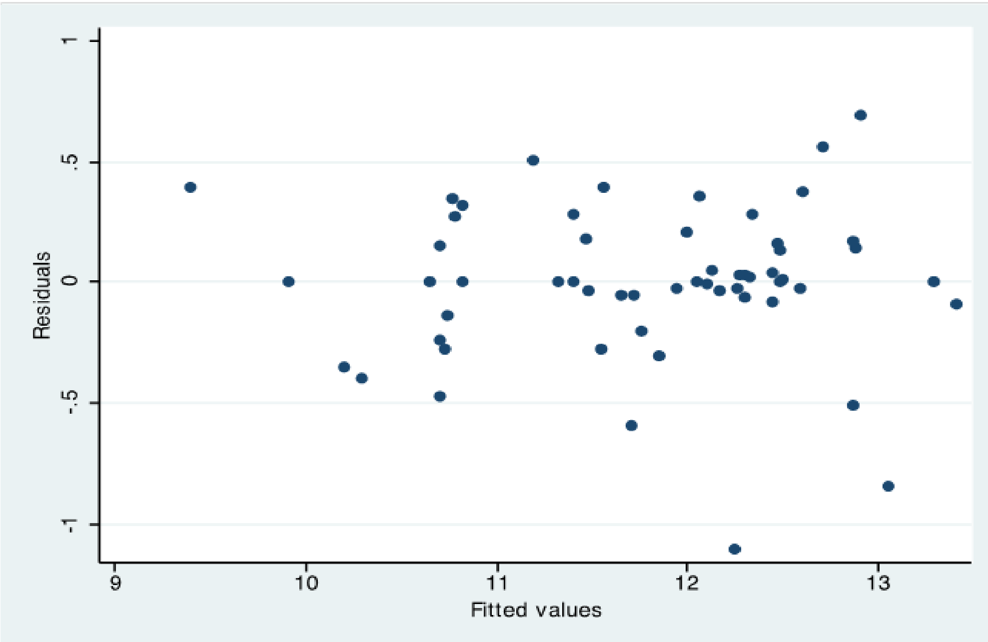
After taking the natural log of the scalar variables in the cross section models and controlling for the municipality where the property was located, residual plots for Clinton County did not reveal any serious systemic error terms. As shown by the example in Figure 2, there was no sign of heteroskedasticity or otherwise clustered error terms. The absence of heteroskedasticity was confirmed by a Breusch-Pagan test with a chi-squared value of 1.92.

Figure 2. Residual versus fitted plot for Clinton County assessed value and five mile dummy wind variable.



In Klickitat County, however, there was some evidence of clustered error terms, as shown in Figure 3. While still not significantly heteroskedastic, a variance inflation factor analysis revealed significant multicollinearity of municipalities, with four municipalities with variance inflation factors above 5. This is likely due in part to the clustered geographic arrangement of properties in the Klickitat County sample compared to the Clinton County sample, which is evident from Figure 1.

Figure 3. Residual versus fitted plot for Klickitat County assessed value and five mile dummy wind variable.

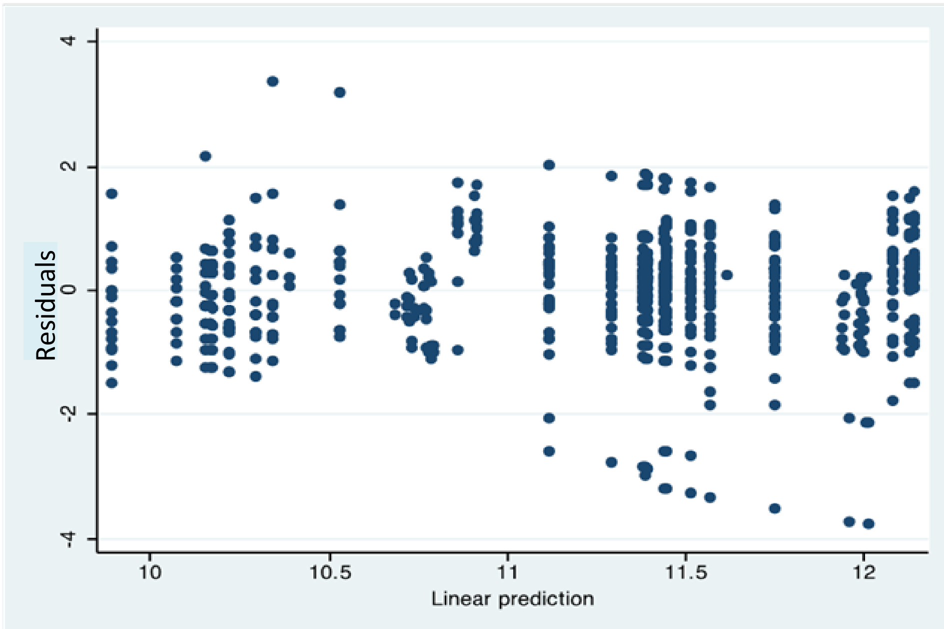


The last group of models estimated were the fixed effects models using incomplete panel data. As with the cross section models, there is little difference in the goodness of fit across models, evidenced by the nearly constant R squared values and consistent signs and magnitudes of the vacancy dummy variable. This model makes more theoretical sense because the five mile dummy and interaction term have a greater significance level and magnitude than the ten mile equivalents. However, the negative signs on the interaction terms still imply that within the specified radius, proximity to wind turbines has a positive influence on nearby property values. It is likely that despite property-level fixed effects, over time, there are omitted time variant factors that are not included in these models but which are simultaneously influencing property values.

Table 11. Results of fixed effects model with year dummies (not shown)				
Dep. variable	Log of county assessed property value			
vacancy	-1.224*** (-14.06)	-1.225*** (-14.12)	-1.223*** (-14.07)	-1.224*** (-14.15)
ten mile	-0.131** (-2.258)			
five mile		-0.210*** (-2.841)		
Distance within 10 miles			-0.0151** (-2.402)	
Distance within 5 miles				-0.0289*** (-3.301)
N	650	650	650	650
R-squared	0.603	0.605	0.604	0.607
Number of properties	56	56	56	56

The two-way scatter plot shown in Figure 4 shows how omitted variables lead to the prediction of unchanging property values for properties which are not near a wind turbine. Additionally, any change in a property's value that occurs the year a wind turbine was built which cannot be attributed to the year itself or a change in vacancy status will be attributed to the construction of wind turbines.

Figure 4. Residual versus fitted plot for Klickitat County fixed effects model using assessed values and ten mile interaction wind variable.



IX. Discussion

The results of this project must be taken in light of several different types of errors. The first and most important group falls under the category of specification errors. While similar equations used in this study have been applied in past peer-reviewed studies, the results could have been compared with alternative specifications, particularly for the wind variables. The wind turbine variables used in this study were relatively blunt instruments in comparison to Heintzelman and Tuttle (2011), who use the inverse log of distance to the nearest wind turbine. In this study, the use of inverse log distance measures could have eased the interpretation of the interaction term coefficients and perhaps given more theoretically consistent results. Hoen *et al.* (2009, 2011) compare the use of several different specifications to demonstrate the robustness of their results, including the use categorical wind variables which indicate an upper and lower bound of distance to the nearest turbine. Applied to this study, the ten mile wind dummy variable could have instead represent properties with a turbine within ten miles but not within five miles. These possibilities were not compared with the chosen specification and could have significantly altered the results.

Another important limitation of this study is the high risk of omitted variable bias across all models. This is especially important in the cross-section models, where variables which are included in past studies, such as the condition of a home, its urban or rural location, the number of days on the real estate market, or its distance from the nearest major road, were not included in this model. In most cases, these additional characteristics were either not publicly available or not accessible given the author's level of GIS programming knowledge. The introduction of municipality dummy variables attempted to control for some omitted variable bias, but there is substantial variation even within municipalities. Omitted variable bias was also an issue in the fixed effects models, where any time varying characteristics were not included.

The fixed effects models are also flawed in their reliance on county-assessed property values as the dependent variables. Even though asking prices likely overvalued Klickitat County properties and the sample size of selling price in Clinton County was too small, it is clear through comparisons of the two groups of models that county and market indicators yield different magnitudes and significance levels of wind variable coefficients. In other words, the use of county-assessed values information was also a blunt measure of property values.

The risk of endogeneity bias invalidates the cross-section models as measures of causation; the results can only be interpreted as showing correlation between lower property values near wind farms. In the fixed effects models, it is possible that if the 2008 housing crisis had a disproportionate effect on rural homes then the construction of wind turbines, which began in 2008 in the Klickitat County sample, could be attributed to wind turbines. The persistent possibility that wind farms are more likely to be built in areas with lower property values must be addressed either by a repeat-sales fixed effects model with complete characteristic information, or use simultaneous equations to instrument for distance to wind farms.

All models also contain significant risk of measurement error. The locations of the properties are estimates based on mailing addresses, so in many large properties it is possible that the actual home or potential home site is further away from or closer to the nearest wind turbine. Using longitude and latitude instead of mailing addresses could better estimate the actual distance of properties from turbines. Furthermore, this paper does not evaluate the perceived impact of wind turbines on properties. It is probable that wind turbines are not visible from many properties within a ten mile radius. This could be ameliorated by estimating the effect on a property by considering turbine density within a certain radius of the property. Further measurement error is possible concerning the date of construction in the fixed effects model. If there was an announcement of proposed wind turbines closer to a property than existing turbines or earlier in time that constructed wind turbine appeared, there could be unmeasured effects of wind turbines stigma. Using an announcement dummy or lagging the dependent variable could fix this problem.

The small sample size of this study is an evident source of error. The source of the addresses used in this paper, a real estate site, also biases the results because there could be a systemic difference between the properties in this sample from the population mean. Namely, properties which have been recently sold or are still are the market may not include homes that are particularly influenced by wind turbine stigma. This problem could be remedied by relying on official records of market data, regardless of which homes are currently for sale or recently sold.

X. Conclusion

This study has presented weak evidence to suggest that property values near wind turbines are on average lower than the surrounding area through negative coefficients on dummy variables indicating proximity to wind turbines. The negative coefficients in the fixed effects models also suggest that values of properties near wind turbines have increased at a slower rate that surrounding properties. However, given the substantial limitations of the methods and data used in this study, no definite conclusions can be drawn about the effect of wind turbines on property values.

After improving upon the limitations described in Section IX, future studies could further explore the potential impact of wind turbines on property values by comparing the influence of wind farms with different configurations, size turbines, ownership structures and different types of regional landscapes. Another line of research might include a search for an appropriate instrumental variable to find a property characteristic which is associated with proximity to wind turbines but not with property values. Studies examining the construction of attitudes toward wind turbines could lend insight into the reasons why wind turbines might have an effect on property values.

An understanding of the possible negative effects of wind turbines is necessary to ensuring the best practices for developers, governments and communities as renewable energy use continues to grow in the United States. Agents can use this information to determine ideal locations for wind turbine facilities and appropriate compensation for nearby residents and property owners.

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