PLEASANT RIDGE EXHIBIT 35

Values in the Wind: A Hedonic Analysis of Wind Power Facilities

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ABSTRACT. *The siting of wind facilities is extremely controversial. This paper uses data on 11,331 property transactions over nine years in northern New York State to explore the effects of new wind facilities on property values. We use a fixed-effects framework to control for omitted variables and endogeneity biases. We find that nearby wind facilities significantly reduce property values in two of the three counties studied. These results indicate that existing compensation to local homeowners/communities may not be sufficient to prevent a loss of property values.* (JEL Q51, Q53)

I. INTRODUCTION

Increased focus on the impending effects of climate change has resulted in pressure to develop additional renewable power supplies, including solar, wind, geothermal, and other sources. While renewable power provides several environmental advantages to traditional fossil fuel supplies, there remain significant obstacles to large-scale development of these resources. First, most renewable energy sources are not yet cost-competitive with traditional sources. Second, many potential renewable sources are located in areas with limited transmission capacity, so that, in addition to the costs of individual projects, large-scale development would also require major infrastructure investments. Finally, renewable power projects are often subject to local resistance.

Wind power is, by far, the fastest growing energy source for electricity generation in the United States, capacity and net generation having increased by more than 1,348% and 1,164%, respectively, between 2000 and 2009. No other sources of electricity have even doubled in capacity over that period. This sort of growth for wind energy is expected to continue into the future, although not at quite those high rates.[1] If additional steps are taken to combat global climate change, the demand for wind energy would only increase relative to these forecasts.

There are many outspoken critics who focus on the potential negative impacts of wind projects. These critics point to the endangerment of wildlife including bats, migratory birds, and even terrestrial mammals. Some critics also point to detrimental human health effects including abnormal heartbeat, insomnia, headaches, tinnitus, nausea, visual blurring, and panic attacks.[2] There are also concerns about the aesthetics of these facilities. One oft-quoted critic, Hans-Joachim Mengel, a professor of political science at the Free University, Berlin, has likened wind turbines to "the worst desecration of our countryside since it was laid waste in the 30 Years War nearly 400 years ago."[3] If wind turbines are perceived to have this manner of impact on local areas, they would have a strong negative impact on local property values.

[1] Data on the recent and future expected growth of wind energy are derived from the Energy Information Administration of the U.S. Department of Energy (www.eia.doe.gov).

[2] These symptoms are described by Nina Pierpont in her book on the topic, *Wind Turbine Syndrome* (Santa Fe, NM: K-Selected Books, 2009).

[3] Renee Mickelburgh et al., "Huge protests by voters force the continent's governments to rethink so-called green energy," *Sunday Telegraph* (London), April 4, 2004, 28.

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As regards the noise impacts of these facilities, consider that estimated sound levels for a typical turbine at a distance of 1,500 feet are 50 dBA, equivalent to a normal indoor home sound level (Colby et al. 2009). Typically, distances between wind turbines and receptors are regulated at the local level. The New York State Energy Research and Development Authority (NYSERDA) recommends turbine setbacks of 1,000 feet from the nearest residence (Daniels 2005). These setbacks focus on general safety considerations such as turbine collapse instead of specific health impacts associated with noise or vibration. The National Environmental Protection Act and comparable New York State Environmental Quality Review legislation prescribe a general assessment process that does not define specific turbine setback requirements. Viewshed impacts are more far reaching but vary widely by property and depend on land cover and property elevations.

As a result of these potential effects, the siting of wind facilities is extremely controversial, and debate about siting has caused delays and cancellations for some proposed installations. Perhaps the most famous case is that of Cape Wind in Massachusetts. First proposed in 2001, this project, approved by the U.S. Department of Interior in April 2010, calls for the construction of 130 turbines, each with a maximum blade height of 440 feet, approximately 5 miles off the shore of Cape Cod between Cape Cod and Nantucket. In response, local activists have organized the "Alliance to Protect Nantucket Sound" to fight the proposal through the courts and other avenues. This is despite the fact that the primary local impact is expected to be the impacted view from waterfront properties.[4] In the case of terrestrial projects, the opposition can be even stronger. In Cape Vincent, New York, in Jefferson County, wind developers have been working since 2006 to construct two separate facilities that include 147 turbines. Cape Vincent is bordered to the north by the St. Lawrence River and Lake Ontario, within view of an 86-turbine wind farm on Wolf Island in Ontario, Canada, and within a short drive to the largest wind farm in New York State. The response to the proposal has been spirited, with both pro- and anti-wind factions fighting to determine its fate. In October of 2010, a lawsuit was filed to nullify a town planning board's approval of a final environmental impact statement; the meeting at which it was approved had been disrupted by vocal protestors.[5] Recent reports in the popular media suggest that such controversy over wind turbines is widespread.[6]

At the individual level, property owners willing to permit the construction of turbines or transmission facilities on their property receive direct payments from the developer as negotiated through easement agreements. In terms of community benefits, wind developers claim that their projects create jobs and increase tax revenues by way of payment in lieu of taxes (PILOT) programs. PILOT programs are a significant revenue source that can help offset overall town and school tax rates for all residents. These host community benefits are not unlike those made to communities that have permitted the construction of landfills within their municipal boundaries. In the case of Cape Vincent, a town-appointed committee evaluated the economic impacts of the proposed facility and concluded that 3.9% of property owners would benefit directly from easement payments made by the developers.[7] Easement payments are negotiated with individual land owners and are not publically available, so the magnitude and actual economic benefit to these property owners was not quantified. PILOT agreements between the developers and the town were estimated at $8,000 per turbine, or $1.17 million per year. In the opinion of some Cape Vincent property owners, local officials are negotiating PILOT agreements to the benefit of the

[4] See the U.S. Department of Interior Cape Wind fact sheet (www.doi.gov/news/doinews/upload/Fact-Sheet-Cape-Wind-with-SOL-edits-04-28-10.pdf) for details on the regulatory process surrounding the project.

[5] "WPEG sues Cape Vincent; Petition asks judge to nullify approval of impact statement," *Watertown Daily Times*, October 28, 2010.

[6] "Not on my beach, please," *The Economist*, August 19, 2010.

[7] *Cape Vincent Wind Turbine Development Economic Impact: Final Report,* submitted by Wind Turbine Economic Impact Committee, Town of Cape Vincent, New York, October 7, 2010.

municipality, individual property owners are negotiating individual easement agreements to offset their respective property impacts, and property owners in close proximity to turbines are left with no market leverage to offset the impacts that they believe turbines will have on their property values. This is the externality problem that is at the heart of the issue.

In moving forward with wind power development then, it is important to understand the costs that such development might impose. Unlike traditional energy sources, where external/environmental costs are spread over a large geographic area through the transport of pollutants, the costs of wind development are largely, but not exclusively, borne by local residents. Only local residents are likely to be negatively affected by any health impacts and are the people who would be most impacted by aesthetic damages, either visual or audible. These impacts are likely to be capitalized into property values, and as a consequence, property values are likely to be a reasonable measuring stick of the imposed external costs of wind development.

The literature that attempts to measure these costs is surprisingly thin. To our knowledge, there are only two peer-reviewed hedonic analyses that examine the impact of wind power facilities on property values. Sims, Dent, and Oskrochi (2008) and Sims and Dent (2007) use small samples of homes near relatively small wind facilities near Cornwall, U.K., and find no significant effect of turbines on property values. The first of these studies has very limited data on homes, just home "type" and price, and uses a cross-sectional approach. In addition, there is a quarry adjacent to the wind turbines, and other covarying property attributes, which makes identification of the wind turbine effect very difficult. They actually do find a significant negative effect from proximity to the turbines, but based on conversations with selling agents, attribute this instead to the condition and type of the homes. The second study uses a very small sample of only 201 homes, all within the same subdivision, and a cross-sectional approach. They focus specifically on whether homes can view the turbines and have very limited data on home attributes. Moreover, given the small geographic scope of the analysis, it is unlikely that there was sufficient variation in the sample to identify any effect; all of the homes were within 1 mile of the turbines.

In 2003, Sterzinger, Beck, and Kostiuk released a report through the Renewable Energy Policy Project (REPP) that used a series of 10 case studies to compare price trends between turbine viewsheds and comparable nearby regions and found, in general, that turbines did not appear to be harming property values. This analysis, however, was not a true hedonic analysis. Instead, for each project, they identified treated property transactions as being within a 5-mile radius of the home and a group of comparable control transactions outside of that range. They then calculated monthly average prices, regressed these average prices on time to establish trends, and then compared these trends between treatment and control groups. They did not control for individual home characteristics or any other coincident factors.

Hoen (2006) also focuses on the view of wind turbines and collects data for homes within 5 miles of turbines in Madison County, New York. His sample is also small, 280 transactions spread over 9.5 years, and he uses a cross-sectional approach. He fails to find a significant impact from homes being within viewing range of the turbines. Hoen et al. (2009) use a larger sample of 7,500 homes spread over 24 different regions across the country from Washington to Texas to New York that contain wind facilities and again find no significant effect. They look at transactions within 10 miles of wind facilities and use a variety of approaches, including repeat sales. However, they limit themselves to discontinuous measures of proximity based on having turbines within 1 mile, between 1 and 5 miles, or outside of 5 miles, or a similar set of measures of the impact on scenic view, and they again find no adverse impacts from wind turbines. In addition, by including so many disparate regions within one sample they may be missing effects that would be significant in one region or another.

There is also a small literature using stated preference approaches to value wind turbine disamenities. Groothuis, Groothuis, and Whitehead (2008) asked survey respondents about the impact of locating wind turbines on western North Carolina ridgetops and found that on average, households are willing to accept annual compensation of $23 to allow for wind turbines, although retirees moving into the area require greater compensation. Similarly, Krueger, Parsons, and Firestone (2011) surveyed Delaware residents about offshore wind turbines and find that residents would be harmed by between $0 and $80 annually, depending on where the turbines are located and whether the resident lives on the shore or inland.

This paper improves upon this literature using data on 11,331 arm's-length residential and agricultural property transactions between 2000 and 2009 in Clinton, Franklin, and Lewis Counties in northern New York to explore the effects of relatively new wind facilities. We use fixed-effects analysis to control for the omitted variables and endogeneity biases common in hedonic analyses, including the previous literature on the impacts of wind turbines. We find that nearby wind facilities significantly reduce property values in two of the three counties we study. We find evidence of endogeneity bias in the use of fixed-effects models with relatively large geographic groupings (census block groups or census blocks) that appears to be controlled for in a repeat sales approach.

II. BACKGROUND AND STUDY AREA

New York State is a leader in wind power development. In 1999, New York had 0 MW of installed wind capacity but by 2009 had 14 existing facilities with a combined capacity of nearly 1,300 MW, ranking it in the top 10 of states in terms of installed capacity.[8] New York also appears to have more potential for terrestrial wind development than any other state on the East Coast.[9] This is borne out by the fact that there are an additional 28 wind projects in various stages of proposal, approval, or installation in the state.[10]

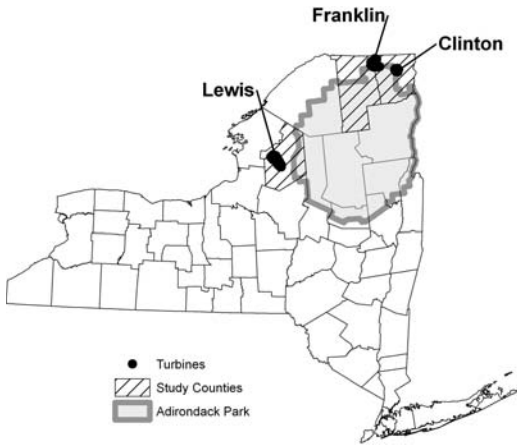

FIGURE 1
Study Area

New York has also been badly affected by the environmental impacts of traditional energy sources. The Adirondack Park, in particular, has been severely impacted by acid deposition and methyl mercury pollution (Banzhaf et al. 2006). In that sense, the state has much to gain from transitioning away from fossil sources of energy and toward renewable sources like wind. New York, however, has relatively little potential to develop solar, geothermal, or other renewable sources. Existing wind developments are spread throughout the state, with clusters in the far west, the far north, and in the northern finger lakes region. The largest projects, however, are in what is often referred to as "the North Country," and are in the three counties—Clinton, Franklin, and Lewis—which make up our study area, shown in Figure 1, along with the outline of the Adirondack Park and the location of the wind turbines in this area.

Northern New York is dominated by the presence of the Adirondack Park. The Adirondack Park was established in 1892 by the state of New York to protect valuable natural resources. Containing 6.1 million acres,

[8] U.S. Department of Energy (www.windpoweringamerica.gov/wind_installed_capacity.asp).

[9] U.S. Department of Energy (www.windpoweringamerica.gov/wind_maps.asp).

[10] New York State Department of Environmental Conservation (www.dec.ny.gov/docs/permits_ej_operations_pdf/windstatuscty.pdf).

TABLE 1
Study Area Wind Facilities

Facility	County	Capacity (MW)	Turbines	Startup Year
Maple Ridge	Lewis	320	194	2006
Noble Chateaugay	Franklin	106.5	71	2009
Noble Belmont	Franklin	21	14	N/A
Noble Altona	Clinton	97.5	65	2009
Noble Clinton	Clinton	100.5	67	2008
Noble Ellenburg	Clinton	81	54	2008

TABLE 2
Study Area Demographics

Geographic Area	2008 Median Income ($)	2000 Population Density (ppl/sq mi)	2008 Median Value Owner-Occupied Homes ($)
United States	52,029	86.8	119,600
New York State	55,980	401.9	148,700
Clinton County	49,988	76.9	84,200
Franklin County	40,643	31.4	62,600
Lewis County	41,837	21.1	63,600

Source: U.S. Census.

30,000 miles of rivers and streams, and over 3,000 lakes, the Adirondack Park is the largest publically protected area in the United States and is larger than Yellowstone, Everglades, Glacier, and Grand Canyon National Park combined. Approximately 43% of the Park is publically owned and constitutionally protected to remain "forever wild" forest preserve. The remaining acreage is made up of private land holdings. There are no wind facilities within the borders of the park, but as you can see in Figure 1, the facilities in our study are very close. There are six wind farms in our study area, as summarized in Table 1.[11]

Table 2 presents a comparison of the counties in our study area to the New York State and U.S. averages for population density, per capita income, and home prices. As that table shows, our study area is a very rural, lightly populated area of small towns and villages that is also less affluent than the state average. The largest population center in our study area is Plattsburgh, New York, with a 2000 population of about 18,000.

III. DATA AND METHODOLOGY

Data

Our data consists of a nearly complete sample of 11,331 residential and agricultural property transactions in the Clinton, Franklin, and Lewis Counties from 2000 to 2009. Of these there are 1,938 from Lewis, 3,251 from Franklin, and 6,142 from Clinton. Each observation constitutes an arm's-length property sale in one of the three counties between 2000 and 2009. Parcels that transacted more than once provide a greater likelihood of observing specific effects from the turbines on sales prior to and after installation. In total, 3,969 transactions occurred for 1,903 parcels that sold more than once during the study period.[12]

[11] The Final Environmental Impact Statement for the Noble Belmont project in Franklin County was completed in conjunction with the Noble Chateaugay project. Construction for the combined project consisting of 85 turbines was initiated in 2008. While 71 turbines were brought online in 2009, site work for the additional 14 turbines was completed but the turbines themselves were never installed. Since the turbine bases are visible from orthoimagery and the project environmental review was completed as a single project, these locations have been included in our analysis.

[12] In our repeat sales sample there are 3,251 transactions of parcels that sold twice, 649 that sold three times, 55 that sold four times, and 14 that sold five times. All of these that

Transacted parcels were mapped with a geographic information system (GIS) to enable us to calculate relevant geographic variables for use in the regressions. Turbine locations were obtained from two different sources. In Lewis County, a GIS shape file was provided by the county, which contained 194 turbines. According to published information on the Maple Ridge wind project, there are 195 turbines at the facility (Maple Ridge Wind Farm). Noble Environmental Power would not provide any information on their turbine locations, so 2009 orthoimagery was utilized to create a GIS shapefile with the turbine locations in Franklin and Clinton Counties.

Turbine locations in combination with several other datasets were merged using ESRI ArcView GIS software (ESRI 2011) and STATA data analysis and statistical software (StataCorp 2009) to form the final dataset. Transacted parcels were mapped with a GIS to determine the distance to the nearest turbine. Distances are used as a proxy to estimate the nuisance effects of the turbines (i.e., viewscapes, noise impacts, perceived health effects). The distance to turbines was exported from the GIS and combined with the other parcel-level details in STATA. Table 3 summarizes the datasets that were used in the analysis and their sources. Table 4 provides summary statistics for many of the variables included in our analysis.

Unfortunately, we have relatively few transactions that are very close to the turbines. In the full sample data there are 461 transactions within 3 miles of a turbine, with 92 in Clinton County, 118 in Franklin County, and 251 in Lewis County. In the repeat sales data, there are 142 transactions within 3 miles of a turbine: 41 in Clinton County, 34 in Franklin County, and 67 in Lewis County. Table 5 presents a count of transactions at various distances from turbines by county for each of our two datasets.

sold four or more times were hand-checked to make sure they seemed reasonable (no multiple sales in the same month, big jumps in price, etc.), and some were eliminated. We also eliminated all transactions that sold more often than this because it appeared that they were parcels that had been subdivided.

TABLE 3
Data Sources

Description of Dataset	Source
Turbine locations, Lewis County	Lewis County
Turbine locations, Clinton/Franklin Counties	2009 orthoimagery
2000–2009 property sales	New York State Office of Real Property Services
2009 parcel layer	Clinton, Franklin, and Lewis Counties
2009 parcel-level details	New York State Office of Real Property Services
80-meter wind potential	AWS Truepower
Census blocks	New York State GIS Clearinghouse
Elevations	Cornell University Geospatial Information Repository
Land cover	U.S. Geological Survey
Streets	New York State GIS Clearinghouse

Methodology

Our analytical approach to estimating the effects of wind turbines on property values is that of a repeat sales fixed-effects hedonic analysis.[13] We are attempting to estimate the "treatment" effect of a parcel's proximity to a wind turbine. There are a number of difficulties in measuring the effect of turbines. First and foremost, there is a question of when a turbine should be said to exist. The obvious answer is that turbines exist only after the date on which they become operational. However, there is a long approval process associated with development of these projects, and local homeowners presumably will have some information about where turbines will be located some years before they actually become operational. To deal with this issue, we run our regressions with three different assumptions about the date of existence: the date the draft environmental impact statement (EIS) was submitted to the New York State Department of Environmental Conservation, the date the final environmental impact statement was approved, and the date at which the turbines became operational.

[13] For a summary and background on the use of hedonic analysis see Taylor (2003) or Freeman (2003).

TABLE 4
Summary Statistics by County

	Clinton		Franklin		Lewis	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Sale price ($)	122,645	83,603	120,466	354,556	81,740	63,207
Building age (years)	37	41	49	109	50	42
Living area (sq Ft)	1,609	611	1,447	643	1,538	690
Lot size (acres)	5.9	39.3	6.8	25.6	9.0	27.2
Distance to nearest major road (feet)	1,549	2,493	1,861	3,189	6,094	6,628
Value of included personal property ($)	63	965	324	6,995	204	2,678
Buyer from local area	0.913	0.282	0.790	0.407	0.684	0.465
Home in established village	0.049	0.215	0.395	0.489	0.261	0.439
Full bathrooms	1.615	0.647	1.312	0.618	1.287	0.630
Half bathrooms	0.332	0.495	0.226	0.441	0.229	0.431
Bedrooms	3.134	0.936	2.829	1.051	2.929	1.140
Fireplaces	0.306	0.544	0.245	0.484	0.167	0.416
Excellent-grade building quality	0	0	0	0	0.0005	0.023
Good-grade building quality	0.031	0.173	0.019	0.137	0.013	0.112
Average-grade building quality	0.833	0.373	0.584	0.493	0.639	0.480
Economy-grade building quality	0.136	0.342	0.381	0.486	0.317	0.465
Minimum-grade building quality	0.001	0.028	0.016	0.127	0.031	0.174
Single family	0.859	0.348	0.755	0.430	0.677	0.468
Single family plus apartment	0.001	0.025	0	0	0	0
Estate	0.0002	0.013	0.003	0.058	0	0
Seasonal residence	0.032	0.175	0.111	0.314	0.181	0.385
Multifamily property	0.054	0.226	0.046	0.209	0.043	0.203
Acreage/residence with agricultural uses	0.043	0.202	0.054	0.226	0.054	0.225
Mobile home(s)	0.0003	0.018	0.002	0.039	0.006	0.075
Other residential classes	0.007	0.081	0.012	0.107	0.011	0.106
Primarily agricultural use	0.005	0.071	0.018	0.135	0.029	0.168
Percent of parcel forested	0.202	0.324	0.269	0.353	0.319	0.371
Percent of parcel open water	0.011	0.077	0.031	0.127	0.024	0.123
Percent of parcel fields/grass	0.160	0.293	0.139	0.277	0.292	0.356
Percent of parcel wetlands	0.041	0.147	0.068	0.172	0.067	0.170
Percent of parcel developed	0.444	0.448	0.226	0.369	0.134	0.293
Percent of parcel open	0.141	0.256	0.268	0.344	0.164	0.290
Observations	6,142		3,251		1,938	

TABLE 5
Count of Transactions with Turbines in Specified Ranges

	Full Sample Dataset				Repeat Sales Dataset			
Range	Clinton	Franklin	Lewis	Total	Clinton	Franklin	Lewis	Total
0–0.5 mile	6	4	15	25	3	2	3	8
0.5–1 mile	11	23	25	59	6	6	7	19
1–1.5 miles	14	25	32	71	7	6	7	20
1.5–2 miles	19	27	42	88	8	7	11	26
2–3 miles	42	39	137	218	17	13	39	69
Total	92	118	251	461	41	34	67	142

Given the uncertain and possibly diverse physical/aesthetic impacts of turbines, it is difficult to know how to measure proximity. Is it distance to the turbine, whether or not the turbine can be seen, whether or not the turbine can be heard/felt, or all of the above? For all of these factors, it is reasonable to suspect that distance would work as a proxy measure. That is, homes closer to turbines will be more likely to see the turbines and more likely to hear or feel vibrations from the turbines. In Clinton and Franklin Counties, the turbines are located in a broad river valley (the St. Lawrence) with only small hills that are unlikely to obstruct turbine views; in Lewis County the turbines are on top of a large plateau. In our regions then, proximity should be a good measure of impacts. So, all of the measures that we employ are distance based, starting with the simplest: the inverse of the distance to the nearest turbine.[14] This inverse distance measure is also calculated with the date of the turbines' existence in mind. So, distance will decrease (inverse distance will increase) for all parcels after new turbines come into existence. Specifically, at the beginning of our sample period there are no commercial turbines in the study counties. However, there are turbines outside of the study counties that are counted as the "nearest" turbines for the purposes of measuring distance. The distances to these turbines are approximated by measuring the distance from these facilities to the centroid of each of the study counties. As new facilities are built, both inside and outside the study area, these distances are updated. At the time that the Lewis County facility final EIS is submitted, those become the closest turbines for the entire sample area. When the facilities in Clinton and Franklin Counties come online distances are again updated. Because, initially, the nearest turbines are out of the sample area, we also ran the analysis assuming that the nearest turbine was infinitely far away. The results of this specification however do not change significantly from those reported below.[15]

In addition to the relatively simple distance measure, which imposes a particular functional form on the distance effects, we also include a series of distance dummies that indicate the range in which the nearest turbine lies. This approach allows for nonlinear, and nonmonotonic, impacts to be measured. These variables also change over time as new turbines are sited, which is necessary to implement a fixed-effects approach. Table 6 presents summary statistics for various measures of the effect of wind turbines.

We also include a number of other covariates. These include distance to the nearest major road, the value of any personal property included in the transaction, whether the home is in a "village," which would imply higher taxes but also higher services and proximity to retail stores and restaurants, in addition to standard home characteristics including number of bedrooms, bathrooms, half baths, the square footage of the house, the age of the home, and the size of the lot.

Parcel-level land cover data tells us the share of each parcel in a number of different land cover categories (woodland, pasture, crops, water, etc.). To capture possible information asymmetries between buyers and sellers we include a dummy variable for whether the buyer was already a local resident or moving in from outside of the North Country. This is particularly important since there is good reason to believe that local residents would have more information about the future location of turbines, and about any associated disamenities than someone less familiar with the area. Finally, we include a series of relatively subjective measures of construction quality and property classification (mobile homes, primary agriculture, whether the home is winterized, etc.) that come from the New York State Office of Real Property Services assessment database.

Empirical Issues

There are three main empirical issues that we have to deal with in accurately estimating the effects of wind developments on property values through a hedonic analysis: omitted variables, endogeneity, and spatial dependence/autocorrelation. As Greenstone and Gayer (2009), Parmeter and Pope (2011), and others lay out, omitted variables bias is a major concern in any hedonic analysis. Put simply, there are almost innumerable factors that codetermine the price of a property, and many or most of these factors are unobservable to the researcher. If any of the unobserved fac-

[14] We measure the linear distance rather than road network distance since the effects are not a matter of travel to or from the turbines, but instead simple proximity.

[15] For Clinton and Franklin Counties, in fact, there is virtually no effect of this change. For Lewis County, making this change makes the effects of proximity more negative and more significant.

TABLE 6
Summary Statistics for Wind Turbine Variables

	Clinton			Franklin			Lewis		
Variable	Mean	Std. Dev.	Max.	Mean	Std. Dev.	Max.	Mean	Std. Dev.	Max.
Distance to nearest turbine (miles, date of sale)	95.2	60.5	140.0	98.3	60.0	148.0	25.7	25.2	64.0
Distance to nearest turbine (miles, in 2009)	11.1	4.3	28.9	22.8	14.6	53.5	9.6	6.2	26.7
Nearest turbine is within 0.5 mile	0.0010	0.0312	1	0.0012	0.0351	1	0.0077	0.0877	1
Nearest turbine is in the range 0.5–1 mile	0.0008	0.0285	1	0.0058	0.0762	1	0.0052	0.0717	1
Nearest turbine is in the range 1–1.5 miles	0.0005	0.0221	1	0.0009	0.0304	1	0.0036	0.0600	1
Nearest turbine is in the range 1.5–2 miles	0.0008	0.0285	1	0.0006	0.0248	1	0.0052	0.0717	1
Nearest turbine is in the range 2–3 miles	0.0037	0.0611	1	0.0055	0.0742	1	0.0490	0.2160	1
Nearest turbine is in the range 3–5 miles	0.0111	0.1046	1	0.0102	0.1003	1	0.1362	0.3431	1
Nearest turbine is in the range 5–10 miles	0.1044	0.3058	1	0.0163	0.1267	1	0.2363	0.4249	1
Number of turbines between 0 and 0.5 mile	0.008	0.279	16	0.009	0.311	16	0.042	0.514	10
Number of turbines between 0.5 and 1 mile	0.028	0.686	23	0.038	0.561	15	0.113	1.120	21
Number of turbines between 1 and 1.5 miles	0.046	0.987	36	0.056	0.800	23	0.209	1.711	25
Number of turbines between 1.5 and 2 miles	0.062	1.250	43	0.071	0.985	34	0.298	2.091	29
Number of turbines between 2 and 3 miles	0.133	2.387	87	0.242	2.574	60	1.096	5.532	50
At least 1 turbine between 0 and 0.5 mile	0.001	0.037	1	0.002	0.039	1	0.010	0.100	1
At least 1 turbine between 0.5 and 1 mile	0.002	0.048	1	0.007	0.081	1	0.016	0.127	1
At least 1 turbine between 1 and 1.5 miles	0.003	0.054	1	0.007	0.084	1	0.020	0.142	1
At least 1 turbine between 1.5 and 2 miles	0.004	0.061	1	0.008	0.090	1	0.029	0.167	1
At least 1 turbine between 2 and 3 miles	0.009	0.094	1	0.013	0.113	1	0.071	0.257	1

tors are also correlated with included factors, then the resulting coefficient estimates will be biased. Equally concerning in attempting to accurately estimate the effects of a discrete change in landscape, like the construction of a wind turbine, is endogeneity bias. This bias has a similar effect as omitted variables bias but a slightly different cause. Endogeneity bias enters when the values of the dependent and one or more independent variables are codetermined. In the case of hedonic models, if property values determine the location of some facility, and that facility also impacts property values, we have endogeneity bias. In our case we do need to be concerned about this since it is likely that, ceteris paribus, wind turbines will be sited on lower-value, cheaper land. Then, if this is not corrected, we might falsely conclude that wind turbines negatively impact property values or, at least, overstate any negative impacts, simply because wind turbines are placed on cheaper land. This selection effect would cause us to confuse correlation with causation.

As developed by Greenstone and Gayer (2009), Parmeter and Pope (2011), and Kuminoff, Parmeter, and Pope (2010), spatial fixed-effects analysis can be a solution to both of these problems in hedonic analysis. Fixed effects work by including a set of spatial dummy variables in the regression that correspond to groupings of the observations. In this way, any static features of the groups that affect property values will implicitly be controlled for by these dummy variables. Essentially, we are allowing for group-specific constant terms. So, many otherwise omitted effects that occur at the level of the groups (the fixed-effects scale) will now no longer be omitted. Similarly, if, within groups, the occurrence of the variables of interest (the placement of wind turbines, in our case) is random, we will have controlled for endogeneity bias as well.[16]

The geographic scale of the fixed effects, or the size of the groups, is a critical issue. The smaller the geographic scale of the fixed effects, the tighter the controls will be for endogeneity and omitted variables biases. Following this logic, the cleanest analysis would be using repeat sales where the fixed effects are implemented at the parcel level.[17] There are trade-offs, however. The first arises since variation in the remaining observable explanatory variables can be observed only within the groups, a smaller geographic scale means less variation and less power with which to estimate these remaining coefficients. That is, if we are interested in the distance from each parcel to the nearest major road, the statistical power to measure this comes only from variation in this distance within the scope of the fixed effects (i.e., the census block). Presumably, since homes within a census block are all close to each other, they will all be a similar distance to the nearest road, and thus there is limited variation with which to measure this effect. In a repeat sales analysis, since parcel location and most other characteristics are assumed to be fixed, one can only estimate the effects of time-variant factors. The second trade-off is that, in general, repeat sales are relatively rare, and so to implement such an analysis, one will be forced to ignore a large percentage of all observations. This also brings to light the possibility of a sample selection bias if those homes that sell more than once are not representative of the general population of parcels. In this paper, we experiment with these trade-offs by using three different levels of fixed-effects analysis: census block group, census block, and repeat sales analysis.[18] To give a sense of the scale of these different approaches, consider that in our study area there are 92,960 total parcels, 1,997 census blocks, and 17 census block groups, which implies that, on average, there are 46.55 parcels per block and 5,468.24 parcels per block group. The average census block has an area of just under 2 square miles, and the average census block group about 232 square miles.[19] We conduct all of our analysis at the county level. That is, we do not pool our datasets from the three counties in the study area but instead run each specification separately for each county.[20]

Finally, we have to be concerned about spatial dependence and spatial autocorrelation. There is no doubt that homes that are close to each other affect each other's prices (spatial dependence) and that unobserved factors for one home are likely to be correlated with unobserved factors for nearby homes (spatial autocorrelation or spatial error dependence). These factors could bias our coefficient and standard error estimates if not

[16] For a thorough treatment of fixed-effects analysis, see Wooldridge (2002).

[17] Repeat sales analysis was first developed by Bailey, Muth, and Nourse (1963) in the context of creating real estate price indices. Palmquist's (1982) is the first application to environmental economics. There are many examples since then including those of Parsons (1992) and Gayer, Hamilton, and Viscusi (2002).

[18] To save space, results for the census block group analyses are not presented.

[19] We also attempted an instrumental variables approach to this problem using two instruments: the wind potential of each parcel and the elevation of each parcel. The first was strongly correlated with the location of turbines, but also correlated with property values—parcels that are exposed to higher winds are less desirable. The second instrument was not correlated with property values in our sample, but was not a strong predictor of the location of turbines. For these reasons, we abandoned this approach.

[20] F-tests did not support pooling in the block and block group-level fixed-effects analyses because coefficient estimates were significantly different across counties. Pooling of Franklin and Lewis Counties was supported in the repeat sales analysis, but, for simplicity, we have chosen to conduct separate analyses throughout.

corrected. We correct for these issues using fixed effects, again, for the first and error clustering for the second. The fixed-effects analysis is akin to employing a spatial lag model with a spatial weights matrix of ones for pairs of parcels within the same geographic area, the scale of the fixed effects, and zeros for pairs of parcels in different areas. Likewise, the error clustering allows for correlation of error terms for parcels within an area and assumes independence only across areas (Cameron and Trivedi 2010). This is akin to employing a spatial error model with the spatial weights matrix as just described above to control for spatial autocorrelation.[21] In this way it also controls for heteroskedasticity (Wooldridge 2002).

Formally, we estimate two regression equations. The first uses census block or block group fixed effects:

$$\ln p_{ijt} = \lambda_t + \alpha_j + \mathbf{z}_{ijt}\boldsymbol{\beta} + \mathbf{x}_{ijt}\boldsymbol{\delta} + \eta_{jt} + \epsilon_{ijt}, \quad [1]$$

where p_{ijt} represents the price of property i in group j at time t; λ_t represents the set of time dummy variables; α_j represents the group fixed effects; $\mathbf{z}_{ijt}$ represents the treatment variables—the different measures of the existence/proximity of turbines at the time of sale; $\mathbf{x}_{ijt}$ represents the set of other explanatory variables; and η_{jt} and ϵ_{ijt} represent group- and individual-level error terms, respectively. This specification is adapted from Heintzelman (2010a, 2010b) and follows from Bertrand, Duflo, and Mullainathan (2004) and Parmeter and Pope (2011).

Following again from Bertrand, Duflo, and Mullainathan (2004), the second regression equation uses the repeat sales approach, which is an adaptation of the model above:

$$\ln p_{it} = \lambda_t + \alpha_i + \mathbf{z}_{it}\boldsymbol{\beta} + \epsilon_{ijt}, \quad [2]$$

where λ_t represents annual and seasonal dummies, α_i represents parcel fixed effects, $\mathbf{z}_{it}$ represents a vector of time-varying parcel-level characteristics, and ϵ_{ijt} is the error term. In effect, this analysis regresses the change in ln(price) on the change in any time-variant factors. In our case these time-varying factors ($\mathbf{z}_{it}$) are the variety of measures of the proximity of the parcel to wind turbines. Allowing for error clustering at the parcel level allows error terms to be correlated for different transactions of the same parcel.

IV. RESULTS

We first present results for the census block fixed-effects analysis. Table 7 shows results for two models for each of the three counties. Model 1 includes only the log of the inverse distance to the nearest turbine, while Model 2 instead includes a set of dummy variables indicating the range in which the nearest turbine is located.[22] All of the results presented here assume that turbines exist at the date the final EIS is issued. This accounts for the fact that local residents and most other participants in real estate markets will be aware of at least the approximate location of turbines before they are actually constructed. In fact, most of the turbine locations would be known, if not publically, well before this, since developers typically negotiate with individual landowners before moving forward with regulatory approvals. Our results are quite robust to adjusting the date of existence forward to the date of the draft EIS. If we adjust this date backward to the date of the permit being issued ,the results are qualitatively similar, but we lose significance—likely because we then have even fewer postturbine transactions in the treatment group.

First, notice that the covariate results are largely as would be predicted. Homeowners in this region prefer larger homes, with more bathrooms and fireplaces, and homes of higher quality grades. In two of three counties, homeowners also take into account the value of included property, while the age of the

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[21] Spatial autocorrelation, when applied at the property level in a repeat sales analysis, is similar to serial correlation in that the error term in one transaction is likely to be correlated with the error term in a transaction of the same property at a different date.

[22] In other specifications, we also included a combination of dummy and count variables describing the number of turbines in various ranges up to 3 miles from the parcel. These variables, however, were highly collinear with each other and so estimates were largely insignificant and inconsistent.

TABLE 7
Regression Results (Coefficient Estimates): Census Block Fixed Effects

	Clinton		Franklin		Lewis	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
ln(Inverse distance to nearest turbine)	−0.052***	—	−0.111***	—	0.036	—
Nearest turbine is within 0.5 mile	—	−0.223	—	−0.288*	—	0.389
Nearest turbine is in the range 0.5–1 mile	—	0.380*	—	−0.417***	—	−0.909
Nearest turbine is in the range 1–1.5 miles	—	−0.282**	—	−0.492	—	−0.559
Nearest turbine is in the range 1.5–2 miles	—	−1.086*	—	0.137	—	0.031
Nearest turbine is in the range 2–3 miles	—	−0.001	—	0.242*	—	0.213*
Nearest turbine is in the range 3–5 miles	—	−0.048	—	−0.230	—	0.070
Nearest turbine is in the range 5–10 miles	—	−0.054	—	−0.116	—	−0.021
Distance to nearest major road (feet)	0.000	0.000	−0.000***	−0.000***	−0.000	−0.000
Value of included personal property ($)	0.000	0.000	0.000***	0.000***	0.000**	0.000**
Buyer from local area	−0.088***	−0.090***	−0.199***	−0.204***	−0.054	−0.053
Home in established village	−0.384***	−0.385***	0.192**	0.201***	−0.079	−0.097
ln(Lot size)	0.002	0.002	0.085***	0.086***	0.052	0.055
Living area (sq ft)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Building age (years)	−0.002***	−0.002***	−0.002***	−0.002***	0.002	0.002
Building age squared	0.000***	0.000***	0.000***	0.000***	−0.000**	−0.000**
Full bathrooms	0.057***	0.057***	0.157***	0.162***	0.119**	0.114**
Half bathrooms	0.125***	0.125***	0.184***	0.189***	0.183***	0.184***
Bedrooms	−0.007	−0.007	0.018	0.015	0.002	0.003
Fireplaces	0.124***	0.124***	0.268***	0.270***	0.140***	0.142***
Excellent-grade building quality	—	—	—	—	0.150	0.094
Good-grade building quality	0.197***	0.194***	0.082	0.095	−0.136	−0.127
Economy-grade building quality	−0.160***	−0.156***	−0.325***	−0.323***	−0.301***	−0.303***
Minimum-grade building quality	−0.680*	−0.664*	−0.588***	−0.587***	−0.706***	−0.705***
Single family plus apartment	−0.743*	−0.756*	—	—	—	—
Estate	0.407***	0.406***	0.819**	0.813**	—	—
Seasonal residences	−0.169**	−0.171**	0.160	0.155	−0.153*	−0.157*
Multifamily properties	−0.178***	−0.180***	−0.271***	−0.275***	−0.323***	−0.336***
Acreage/residences with agricultural uses	−0.041	−0.051	−0.368***	−0.372***	0.057	0.054
Mobile home(s)	−0.282***	−0.299***	−1.504***	−1.482***	−0.736	−0.752
Other residential classes	0.349***	0.339***	−0.206	−0.207	0.201	0.199
Primarily agricultural use	−0.193	−0.167	0.110	0.101	−0.248	−0.292
Percent of parcel forested	−0.106*	−0.107*	0.038	0.035	0.105	0.116
Percent of parcel open water	0.601***	0.599***	1.509***	1.515***	0.684***	0.699***
Percent of parcel fields/grass	−0.086	−0.083	−0.163**	−0.175**	0.056	0.069
Percent of parcel wetlands	0.165**	0.165**	0.237*	0.234*	0.261*	0.294**
Percent of parcel developed	0.142***	0.139***	−0.186***	−0.187***	−0.056	−0.054
Constant	10.387***	10.653***	9.877***	10.445***	10.246***	10.108***
Number of observations	6,142	6,143	3,251	3,251	1,938	1,938
Adjusted R^2	0.277	0.277	0.331	0.328	0.229	0.235
Year and month dummies	Yes	Yes	Yes	Yes	Yes	Yes
Clustered errors	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

home has a generally negative impact on price. The effect of being in a village varies by county, having a negative effect in Lewis (insignificant) and Clinton Counties and a positive impact in Franklin County. Lot size is a significant factor only in Franklin County in the census block fixed-effects model but is positive and significant in the unreported block group model. It also becomes significant in alternative specifications that exclude the village variable but are not reported here.[23] In all counties, local buyers pay somewhat less for homes than others. This result may have to do with asymmetric information but may also be related to preferences or sociodemographics. Residents appear to not value additional bedrooms, but since we are controlling for house size, this result is likely because, ceteris paribus, more bedrooms means smaller bedrooms (or fewer and/or smaller other rooms). Properties with multiple units, including apartments, or mobile homes on a parcel reduce the price, while "estates" receive a premium.[24] Seasonal homes have a negative and significant coefficient in two of three counties. Seasonal homes are generally homes deemed unsuitable for habitation during the winter months. Not surprisingly, parcels with more dedicated agricultural land are priced lower, controlling for acreage, and homes with open water or wetlands are more valuable. These measures are partially proxying for a home having waterfront.

The Model 1 results imply that proximity to wind turbines has a negative impact on property values in Clinton and Franklin Counties.[25] These proximity results are also robust to the inclusion of more detail about the location and density of nearby turbines.[26] The results of Model 2 are largely, but not entirely, consistent with those of Model 1. In Clinton and Franklin Counties we see negative impacts for having the nearest turbine within most zones representing proximity of less than 10 miles.[27] However, there are two significant estimates that imply a positive impact: between 0.5 and 1 mile away for Clinton County and between 2 and 3 miles away for Franklin County. In Lewis County, the only significant impact is a positive one at the range of 2–3 miles. These results are largely robust to changes in the size of the zones. When we include dummies for <1 mile, 1–2 miles, 2–3 miles, 3–5 miles, and 5–10 miles, the positive result in Clinton County goes away, but those in Lewis and Franklin Counties remain.[28] Importantly, as illustrated in Table 5, we have relatively few observations for which the nearest turbine is within the ranges identified in these dummy variables. The implication of this is that it is relatively difficult to identify these effects. Given the small numbers, it is also possible that individual observations are having an undue impact on the estimates.

Table 8 presents results from the estimation of equation [2] using parcel-level fixed effects. Here we see similarly negative and significant impacts of proximity to the nearest turbine in Clinton County, negative but insignificant impacts in Franklin County, and a positive but insignificant result in Lewis County. In both Clinton and Franklin Counties the estimated coefficients are somewhat smaller in magnitude in the repeat sales model than they were in the census block model, which is consistent with an endogeneity bias. The insignificance of the impacts in Franklin County is likely caused by the relatively small number of observations, as the estimates presented for the ln(inverse distance) variable have p-values in the range of 0.123 to 0.142, which is approaching significance. In Lewis

[23] These two variables are negatively correlated in our sample. The correlation coefficient is -0.2854.

[24] Estates are defined according to NYSORPS as "a residential property of not less than 5 acres with a luxurious residence and auxiliary buildings."

[25] The interpretation of the coefficient value is somewhat complicated and is discussed in more detail below.

[26] We also run a series of specifications including other continuous distance measures, as well as dummy and count variables representing geographic ranges up to 3 miles from a parcel. The results of the other distance specifications, while not reported here, are broadly consistent with the results of the log of the inverse distance estimation (Model 1) in that turbines do not seem to impact property values in Lewis County but have largely negative and significant impacts in Clinton and Franklin Counties. The dummy and count variable results suffer from multicollinearity and are difficult to interpret.

[27] Implicitly, the omitted category is those parcels with the nearest turbine being more than 10 miles away.

[28] These results are not reported in detail for space considerations.

TABLE 8
Regression Results (Coefficient Estimates): Repeat Sales

	Clinton		Franklin		Lewis	
Variable	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
ln(Inverse distance to nearest turbine)	−0.040**	—	−0.044	—	0.034	—
Nearest turbine is within 0.5 mile	—	−0.109	—	−0.065	—	0.435
Nearest turbine is in the range 0.5–1 mile	—	−0.059	—	−0.027	—	−0.050
Nearest turbine is in the range 1–1.5 miles	—	0.038	—	—	—	0.740***
Nearest turbine is in the range 1.5–2 miles	—	0.103	—	−0.302**	—	0.420*
Nearest turbine is in the range 2–3 miles	—	−0.106*	—	−0.036	—	−0.180
Nearest turbine is in the range 3–5 miles	—	−0.166***	—	−0.095	—	−0.008
Nearest turbine is in the range 5–10 miles	—	0.070	—	−0.019	—	−0.011
Buyer from local area	−0.057	−0.059	−0.046	−0.044	−0.150*	−0.163**
Constant	10.955***	11.162***	10.231***	10.458***	10.504***	10.389***
Number of observations	2,259	2,259	1,077	1,077	633	633
Adjusted R^2	0.2	0.199	0.233	0.229	0.284	0.297
Year and month dummies	Yes	Yes	Yes	Yes	Yes	Yes
Clustered errors	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

County, the proximity measure is again positive but highly insignificant. The Model 2 results are largely negative and sometimes significant in Clinton and Franklin Counties, while the only significant results in Lewis County are positive. Adjusting the specification of the dummy variables as above makes no substantial difference in the repeat sales model. Local buyers still pay less than others, but this effect is significant only in Lewis County.

V. DISCUSSION

Overall, the results of this study are mixed as regards the effect of wind turbines on property values. In Clinton and Franklin Counties, proximity to turbines has a usually negative and often significant impact on property values, while, in Lewis County, turbines appear to have had little effect and, in some specifications, a positive effect. One possible interpretation, since the Lewis County turbines are older, is that the impacts of turbines decay over time so that the impacts we see in Clinton and Franklin Counties may be short-run impacts. To test this, we re-ran the Lewis County analyses having cut out any transactions after 2006 to restrict ourselves to the short-run. These results were not supportive of this interpretation as, if anything, the short-term impacts in Lewis County appeared to be more positive. Another possible interpretation is that there is something about the design or placement of the facilities in Lewis versus Clinton/Franklin Counties which has reduced or eliminated the negative impact on property values. It may also be heterogeneity in consumer preferences in the various counties that drives this dichotomy.

When turbines do impact values, the magnitude of this effect depends on how close a home is to a turbine. For Model 1, since we are using a log-log specification, the estimated coefficient on the log of the inverse distance measure represents the elasticity of price with respect to the inverse of the distance to the nearest turbine. So, a coefficient of $-\beta$ implies that a 1% increase in the inverse distance (a decrease in distance to the nearest turbine) decreases the sale price by β%. Inverse distance declines as distance increases, so this

TABLE 9
Estimated Percentage Price Declines Using Model 1, Selected Distances

Distance to Nearest Turbine (miles)	Clinton County		Franklin County	
	Repeat Sales	Census Block	Repeat Sales	Census Block
	$\beta = -0.040$	$\beta = -0.052$	$\beta = -0.044$	$\beta = -0.111$
Initial Distance = 25 miles				
0.1	19.82	27.80	21.57	45.82
0.25	16.82	23.79	18.34	40.02
0.5	14.49	20.61	15.81	35.22
1	12.08	17.30	13.21	30.04
2	9.61	13.84	10.52	24.45
3	8.13	11.76	8.91	20.97
Initial Distance = 15 miles				
0.1	18.16	22.94	19.79	42.66
0.25	15.11	19.18	16.49	36.52
0.5	12.72	16.21	13.90	31.44
1	10.27	13.14	11.23	25.96
2	7.74	9.95	8.48	20.04
3	6.23	8.03	6.84	16.36
Initial Distance = 5 miles				
0.1	14.49	18.41	15.81	35.22
0.25	11.29	14.43	12.35	28.29
0.5	8.80	11.28	9.64	22.55
1	6.23	8.03	6.84	16.36
2	3.60	4.65	3.95	9.67
3	2.02	2.62	2.22	5.51

tells us that the impacts of wind turbines similarly decay. Using the estimated coefficients above, we calculate the percentage change in price from a given change in distance. These results are presented in Table 9 for Clinton and Franklin Counties using estimated β's from Model 1 at both fixed-effects levels.[29] The double log/inverse distance specification enforces that the relationship between percentage price declines and distance be convex. To test for the robustness of this assumption we also tried quadratic and cubic distance specifications, which would allow for a concave rather than convex relationship. The quadratic specification confirmed the convex shape of the relationship since the linear term was positive and significant and the quadratic term was negative and significant. The quadratic and cubic terms in the cubic specification were not significant.[30]

From the repeat sales model we see that the construction of turbines such that for a given home in Clinton County the nearest turbine is now only 0.5 mile away results in a 8.8% to 14.49% decline in sales price, depending on the initial distance to the nearest turbine. For Franklin County, this range is 9.64% to 15.81%. For the average properties in these two counties, this implies a loss in value of between $10,793 and $19,046. Obviously, at larger distances, these effects decline. At a range of 3 miles the effects are between about 2% and 8%, or between $2,500 and $9,800.

Table 9 also shows that the predicted impacts are more severe when based on the census block model. In the case of Franklin

[29] These results, being based on Model 1 in the tables, do not take into account the dummy or count variables estimates, since these are so inconsistent and suspect because of the collinearity.

[30] We also tested log-linear inverse distance and log-linear distance specifications, and the results were consistent with those reported here. There was no evidence that these alternative specifications provided a better fit to the data.

TABLE 10
Estimated Percentage Price Changes Using Model 2

	Repeat Sales			Full Sample		
	Clinton	Franklin	Lewis	Clinton	Franklin	Lewis
Nearest turbine is within 0.5 mile	− 10.37	− 6.33	54.53	− 19.98	− 25.02	47.48
Nearest turbine is in the range 0.5–1 mile	− 5.73	− 2.63	− 4.88	46.29	− 34.07	− 59.71
Nearest turbine is in the range 1–1.5 miles	3.87	—	109.50	− 24.60	− 38.85	− 42.83
Nearest turbine is in the range 1.5–2 miles	10.87	− 26.10	52.17	− 66.25	14.73	3.15
Nearest turbine is in the range 2–3 miles	− 10.06	− 3.58	− 16.45	− 0.08	27.44	23.79
Nearest turbine is in the range 3–5 miles	− 15.29	− 9.06	− 0.75	− 4.71	− 20.56	7.26
Nearest turbine is in the range 5–10 miles	7.30	− 1.90	− 1.08	− 5.22	− 10.94	− 2.08

County, we see declines of up to 35% at a distance of 0.5 mile. These results are indicative of endogeneity bias at this larger fixed-effects scale. This is because we expect the endogeneity to take the form of turbines being located, all else equal, on lower-quality, lower-value land. If this is true, then we would expect our estimates to be biased downward. Our results fit this model. Nonetheless, it is heartening that the bias, particularly in Clinton County, does not appear to be especially severe.[31]

Table 10 provides the percentage price changes implied by the estimates from the Model 2 specification. The coefficients have been converted to percentage change following Halvorsen and Palmquist (1980). Although there is limited significance, as reported above, we do see significant declines in both Clinton and Franklin Counties of up to 26% in the repeat sales model, and positive impacts of up to 100% in Lewis County. The full sample results are less consistent. On the whole, the coefficients in the repeat sales model are smaller than those in the census block model, which is again suggestive of a selection effect being present in the full sample approaches.

It is also important to remember that our analysis includes year and month dummies to control for countywide, market-level, price fluctuations, so we are not likely to be attributing these sorts of trends erroneously to the existence of turbines. Furthermore, looking at monthly average prices by county, unlike much of the rest of the country, our sample area did not experience any major upward trends in prices during the sample period, nor a decline toward the end. Being very rural and somewhat isolated also makes these counties relatively immune to national real estate trends.

As we began this analysis, we expected that there might be informational effects at play regarding local or nonlocal buyers of property since, presumably, local residents will have more information about where and when turbines might be built. We do see that local buyers, on average, pay less for properties than nonlocal buyers, but there does not appear to be a differential effect for these two categories in the effect of wind turbines. To test this, we ran an alternative specification of the census block model with the local-buyer dummy variable interacted with the proximity variable, and this term was not significant.

Finally, Parsons (1990) argues that the implicit hedonic prices of locational attributes of homes will vary with the size of the lot on which each home sits. We test the effects of

[31] Although we do not report results here, estimates from the census block group model show a somewhat larger bias with larger negative effects from wind turbine proximity.

lot size on the marginal impact of wind turbines using a lot size/proximity interaction term. In that specification of the census block model, we find that the estimated coefficient on this interaction term is positive and significant in both Clinton and Franklin Counties. This indicates that parcels with larger lots are not as badly impacted by the proximity of turbines as homes with smaller lots.

VI. CONCLUSIONS

From a policy perspective, these results suggest that existing compensation schemes may not be fully compensating those landowners near wind developments, in some areas, for the externality costs that are being imposed. Existing PILOT programs and compensation to individual landowners are implicitly accounted for in this analysis, since we would expect these payments to be capitalized into sales prices, and still we find largely negative impacts in two of our three counties. This suggests that landowners, particularly those who do not have turbines on their properties and are thus not receiving direct payments from wind developers, are being harmed and have an economic case to make for more compensation. That is, while the markets for easements and PILOT programs may be properly accounting for harm to those who allow turbines on their property, they appear not to be accounting for harm to others nearby. This is a clear case of an uncorrected externality. If, in the future, developers are forced to account for this externality through increased payments, this would obviously increase the cost to developers and make it that much more difficult to economically justify wind projects. Importantly, in Lewis County, landowners do appear to be receiving sufficient compensation to prevent decay of property values.

This study does not say anything about the societal benefits from wind power and should not be interpreted as saying that wind development should be stopped, even when the property value effects are negative. If, in fact, wind power is being used to displace fossil-based electricity generation it may still be that the environmental benefits of such a trade exceed the costs.[32] However, in comparing those environmental benefits, we must include not only costs to developers (which include easement payments and PILOT programs), but also these external costs to property owners local to new wind facilities. Property values are an important component of any cost-benefit analysis and should be accounted for as new projects are proposed and go through the approval process.

Finally, this paper breaks with the prior literature in finding any statistically significant property-value impacts from wind facilities. We believe that this stems from our empirical approach that controls for omitted variables and endogeneity biases and employs a large sample size with reasonably complete data on home and property characteristics. Future studies that expand this sort of analysis to wind and other renewable power facilities in other regions are imperative to understanding the big picture of what will happen as these technologies grow in prominence.

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[32] This is the subject of a recent working paper by Kaffine, McBee, and Lieskovsky (2011). Their analysis suggests that, in New York, wind is unlikely to create substantial emissions reductions because of the small share of electricity provided by coal-fired generators.

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