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Spatial Hedonic Analysis of the Effects of US Wind Energy Facilities on Surrounding Property Values

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Abstract Rapid, large-scale U.S. deployment of wind turbines is expected to continue in the coming years. Because some of that deployment is expected to occur in relatively populous areas, concerns have arisen about the impact of turbines on nearby home values. Previous research on the effects of wind turbines on surrounding home values has been limited by small home-sale data samples and insufficient consideration of confounding home-value factors and spatial dependence. This study examines the largest set of turbine-proximal sales data to date: more than 50,000 home sales including 1,198 within 1 mile of a turbine (331 of which were within a half mile). The data span the periods well before announcement of the wind facilities to well after their construction. We use ordinary least squares and spatial-process difference-in-difference hedonic models to estimate the home-value impacts of the wind facilities, controlling for value factors existing prior to the wind facilities' announcements, the

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spatial dependence of home values, and value changes over time. A series of robustness models provide greater confidence in the results. We find no statistical evidence that home values near turbines were affected in the turbine post-construction or post-announcement/pre-construction periods.

Keywords Turbines · Wind · Property Value · Price · Hedonic · Spatial

Introduction

In 2012, approximately 13 gigawatts (GW) of wind turbines were installed in the United States, bringing total U.S. installed wind capacity to approximately 60 GW from more than 45,000 turbines (American Wind Energy Association AWEA 2013). Despite uncertainty about future extensions of the federal production tax credit, U.S. wind capacity is expected to continue growing by approximately 5–6 GW annually owing to state renewable energy standards and areas where wind can compete with natural gas on economics alone (Bloomberg New Energy Finance Bloomberg 2013); this translates into approximately 2,750 turbines per year.[1] Much of that development is expected to occur in relatively populated areas (e.g., New York, New England, the Mid-Atlantic and upper Midwest) (Bloomberg 2013).

In part because of the expected wind development in more-populous areas, empirical investigations into related community concerns are required. One concern is that the values of properties near wind developments may be reduced; after all, it has been demonstrated that in some situations market perceptions about an area's disamenities (and amenities)[2] are capitalized into home prices (e.g., Boyle and Kiel 2001; Jackson 2001; Simons and Saginor 2006). The published research about wind energy and property values has largely coalesced around a finding that homes sold after nearby wind turbines have been constructed do not experience statistically significant property value impacts. Additional research is required, however, especially for homes located within about a half mile of turbines, where impacts would be expected to be the largest. Data and studies are limited for these proximate homes in part because setback requirements generally result in wind facilities being sited in areas with relatively few houses, limiting available sales transactions that might be analyzed.

This study helps fill the research gap by collecting and analyzing data from 27 counties across nine U.S. states, related to 67 different wind facilities. Specifically, using the collected data, the study constructs a pooled model that investigates average effects near the turbines across the sample while controlling for the local effects of many potentially correlated independent variables. Property-value effect estimates are derived from two types of models: (1) an ordinary least squares (OLS) model, which is standard for this type of disamenity research (see, e.g., discussion in Jackson 2003; Sirmans et al. 2005), and (2) a spatial-process model, which accounts for spatial dependence. Each type of model is used to construct a difference-in-difference (DD) specification—which simultaneously controls for preexisting amenities or disamenities in areas where turbines were sited and changes in the community

[1] Assuming 2-MW turbines, the 2012 U.S. average (AWEA 2013), and 5.5 GW of annual capacity growth.

[2] Disamenities and amenities are defined respectively as disadvantages (e.g., a nearby noxious industrial site) and advantages (e.g., a nearby park) of a location.

after the wind facilities' construction was announced—to estimate effects near wind facilities after the turbines were announced and, later, after the turbines were constructed.[3]

The following four sections provide details on the Previous Literature, Methodology, Data, and Results, and which are followed by the concluding remarks.

Previous Literature

Although the topic is relatively new, the peer-reviewed literature investigating impacts to home values near wind facilities is growing. To date, results largely have coalesced around a common set of non-significant findings generated from home sales after the turbines became operational. Previous Lawrence Berkeley National Laboratory (LBNL) work in this area (Hoen et al. 2009 Hoen et al. 2011 found no statistical evidence of adverse property-value effects due to views of and proximity to wind turbines after the turbines were constructed (i.e., post-construction or PC). Other peer-reviewed and/or academic studies also found no evidence of PC effects despite using a variety of techniques and residential transaction datasets. These include homes surrounding wind facilities in Cornwall, United Kingdom (Sims and Dent 2007; Sims et al. 2008); a wind facility in Ontario (Vyn and McCullough 2014); multiple wind facilities in McLean County, Illinois (Hinman 2010); near the Maple Ridge Wind Facility in New York (Heintzelman and Tuttle 2012); and, near multiple facilities in Lee County, Illinois (Carter 2011). Analogously, a series of cases have found a lack of evidence supporting the claim that property values are impacted near existing wind facilities (Kenney v. The Municipal Property Assessment Corporation MPAC 2012; Anderson v. Board of Assessors of the Town of Falmouth 2013; Wisconsin Realtors et al. 2014). In contrast, one recent study did find impacts to land prices near a facility in North Rhine-Westphalia, Germany (Sunak and Madlener 2012). Taken together, these results imply that the PC effects of wind turbines on surrounding home values, if they exist, are often too small for detection or sporadic (i.e., a small percentage overall), or appearing in some communities for some types of properties but not others.

In the post-announcement, pre-construction period (i.e., PAPC), however, recent analysis has found more evidence of potential property value effects: by theorizing the possible existence of, but not finding, an effect (Laposa and Mueller 2010; Sunak and Madlener 2012); potentially finding an effect (Heintzelman and Tuttle 2012)[4]; and, consistently finding what the author terms an "anticipation stigma" effect (Hinman 2010). The studies that found PAPC property-value effects appear to align with earlier studies that suggested lower community support for proposed wind facilities before construction—potentially indicating a risk-averse (i.e., fear of the unknown) stance by community members—but increased support after facilities began operation (Gipe

[3] Throughout this report, the terms "announced/announcement" and "constructed/construction" represent the dates on which the proposed wind facility (or facilities) entered the public domain and the dates on which facility construction began, respectively. Home transactions can either be pre-announcement (PA), post-announcement/pre-construction (PAPC), or post-construction (PC).

[4] Heintzelman and Tuttle do not appear convinced that the effect they found is related to the PAPC period, yet the two counties in which they found an effect (Clinton and Franklin Counties, NY) had transaction data produced almost entirely in the PAPC period.

1995; Palmer 1997; Devine-Wright 2005; Wolsink 2007; Bond 2008; Bond 2010). Similarly, researchers have found that survey respondents who live closer to turbines support the turbines more than respondents who live farther away (Braunholtz and Scotland 2003; Baxter et al. 2013), which could also indicate more risk-adverse/fear of the unknown effects (these among those who live farther away). Analogously, a recent case in Canada, although dismissed, highlighted the fears that nearby residents have for a planned facility (Wiggins v. WPD Canada Corporation 2013).

Some studies have examined property-value conditions existing before wind facilities were announced (i.e., pre-announcement or PA). This is important for exploring correlations between wind facility siting and pre-existing home values from an environmental justice perspective and also for measuring PAPC and PC effects more accurately. Hoen et al. (2009, 2011) and Sims and Dent (2007) found evidence of depressed values for homes that sold before a wind facility's announcement and were located near the facility's eventual location, but they did not adjust their PC estimates for this finding. Hinman (2010) went further, finding value reductions of 12–20 % for homes near turbines in Illinois, which sold prior to the facilities' announcements; then using these findings to deflate their PC home-value-effect estimates.

Some research has linked wind-related property-value effects with the effects of better-studied disamenities (Hoen et al. 2009). The broader disamenity literature (e.g., Boyle and Kiel 2001; Jackson 2001; Simons and Saginor 2006) suggests that, although property-value effects might occur near wind facilities as they have near other disamenities, those effects (if they do exist) are likely to be relatively small, are unlikely to persist some distance from a facility, and might fade over time as home buyers who are more accepting of the condition move into the area (Tiebout 1956).

For example, a review of the literature investigating effects near high-voltage transmission lines (a largely visual disturbance, as turbines may be for many surrounding homes) found the following: property-value reductions of 0–15 %; effects that fade with distance, often only affecting properties crossed by or immediately adjacent to a line or tower; effects that can increase property values when the right-of-way is considered an amenity; and effects that fade with time as the condition becomes more accepted (Kroll and Priestley 1992). While potentially much more objectionable to residential communities than turbines, a review of the literature on landfills (which present odor, traffic, and groundwater-contamination issues) indicates effects that vary by landfill size (Ready 2010). Large-volume operations (accepting more than 500 t per day) reduce adjacent property values by 13.7 % on average, fading to 5.9 % one mile from the landfill. Lower-volume operations reduce adjacent property values by 2.7 % on average, fading to 1.3 % one mile away, with 20–26 % of lower-volume landfills not having any statistically significant impact. A study of 1,600 toxic industrial plant openings found adverse impacts of 1.5 % within a half mile, which disappeared if the plants closed (Currie et al. 2012). Finally, a review of the literature on road noise (which might be analogous to turbine noise) shows property-value reductions of 0–11 % (median 4 %) for houses adjacent to a busy road that experience a 10-dBA noise increase, compared with houses on a quiet street (Bateman et al. 2001).

It is not clear where wind turbines might fit into these ranges of impacts, but it seems unlikely that they would be considered as severe a disamenity as a large-volume landfill, which present odor, traffic, and groundwater-contamination issues. Low-volume landfills, with an effect near 3 %, might be a better comparison, because they have an industrial (i.e., non-natural) quality, similar to turbines, but are less likely to have clear health effects. If sound is the primary concern, a 4 % effect (corresponding to road noise) could be applied to turbines, which might correspond to a 10-dBA increase for houses within a half mile of a turbine (see e.g., Hubbard and Shepherd 1991). Finally, as with transmission lines, if houses are in sight but not within sound distance of turbines, there may be no property-value effects unless those homes are immediately adjacent to the turbines. In summary, assuming these potentially analogous disamenity effects can be transferred, turbine impacts might also be relatively small.

Of course, wind turbines have certain positive qualities that landfills, transmission lines, and roads do not always have, such as mitigating greenhouse gas emissions, no air or water pollution, no use of water during the generation of energy, and no generation of solid or hazardous waste that requires permanent storage/disposal (Intergovernmental Panel on Climate Change IPCC 2011). Moreover, wind facilities can, and often do, provide economic benefits to local communities (Lantz and Tegen 2009; Slattery et al. 2011; Brown et al. 2012; Loomis et al. 2012), which might not be the case for all other disamenities. Similarly, wind facilities can have direct positive effects on local government budgets through property tax or other similar payments (Loomis and Aldeman 2011), which might, for example, improve school quality and thus increase nearby home values (e.g., Haurin and Brasington 1996; Kane et al. 2006). These potential positive qualities might mitigate potential negative wind effects somewhat or even entirely.

The potentially small average property-value effect of wind turbines, possibly reduced further by wind's positive traits, might help explain why effects have not been discovered consistently in previous research. To discover potentially small effects relative to their margin of error, large amounts of data are needed. However, previous datasets of homes very near turbines have been small. Hoen et al. (2009, 2011) used 125 PC transactions within a mile of the turbines, while others used far fewer PC transactions within a mile: Heintzelman and Tuttle (2012) (n~35); Hinman (2010) (n~11), Carter (2011) (n~41), Sunak and Madlener (2012) (n~51), and Vyn and McCullough (2014) (n~23). Although these numbers of observations are adequate to examine large impacts (e.g., over 10 %), they are less likely to reveal small effects with any reasonable degree of statistical significance. Using results from Hoen et al. (2009) and the confidence intervals for the various fixed-effect variables in that study, estimates for the numbers of transactions needed to find effects of various sizes were obtained. Approximately 50 cases are needed to find an effect of 10 % and larger, 100 cases for 7.5 %, 200 cases for 5 %, 350 cases for 4 %, 700 cases for 3 %, and approximately 1,000 cases for a 2.5 % effect.[5] Therefore, in order to detect an effect in the range of 3 %–4 %, a dataset of approximately 350–700 cases within a mile of the turbines will be required to detect it statistically, a number that to-date has not been amassed by any of the previous studies. This research seeks to fill that gap.

As discussed above, in addition to being relatively small on average, impacts are likely to decay with distance. As such, an appropriate empirical approach must be able to reveal spatially diminishing effects. Some researchers have used continuous variables to capture these effects, such as linear distance (Hoen et al. 2009; Sims et al. 2008) and inverse distance (Heintzelman and Tuttle 2012; Sunak and Madlener 2012), but doing so forces the model to estimate effects at the mean distance. In some cases, those means can

[5] This analysis is available upon request from the authors.

be far from the area of expected impact. For example, Heintzelman and Tuttle (2012) estimated an inverse distance effect using a mean distance of more than 10 miles from the turbines, while Sunak and Madlener (2012) used a mean distance of approximately 1.9 miles. Using this approach weakens the ability of the model to quantify real effects near the turbines, where they are likely to be stronger. More importantly, this method encourages researchers to extrapolate their findings to the ends of the distance curve, near the turbines, despite having few observations at those distances to support these extrapolations. This was the case for Heintzelman and Tuttle (2012), who had fewer than 10 cases within a half mile in the two counties where effects were found and only a handful that sold in those counties after the turbines were built, yet they extrapolated their findings to a quarter mile and even a tenth of a mile, where they had very few (if any) cases. Similarly, Sunak and Madlener (2012) had only six PC sales within a half mile and 51 within 1 mile, yet they extrapolated their findings to these distance bands.

One way to avoid using a single continuous function to estimate effects at all distances is to use a spline model, which breaks the distances into continuous groups (Hoen et al. 2011), but this method still imposes structure on the data by forcing the ends of each spline to tie together. A second and more transparent method is to use fixed-effect variables for discrete distances, which imposes little structure on the data (Hoen et al. 2009; Hinman 2010; Carter 2011; Hoen et al. 2011). Although this latter method has been used in a number of studies, because of a paucity of data, the resulting models are often ineffective at detecting what might be relatively small effects very close to the turbines. As such, when using this method (or any other, in fact) it is important that the underlying dataset is large enough to estimate the anticipated magnitude of the effect sizes.

Finally, one rarely investigated aspect of potential wind-turbine effects is the possibly idiosyncratic nature of spatially averaged transaction data used in the hedonic analyses. Sunak and Madlener (2012) used a geographically weighted regression (GWR), which estimates different regressions for small clusters of data and then allows the investigation of the distribution of effects across all of the clusters. Although GWR can be effective for understanding the range of impacts across the study area, it is not as effective for determining an average effect or for testing the statistical significance of the range of estimates. Results from studies that use GWR methods are also sometimes counter-intuitive.[6] As is discussed in more detail in the methodology section, a potentially better approach is to estimate a spatial-process model that is flexible enough to simultaneously control for spatial heterogeneity and spatial dependence, while also estimating an average effect across fixed discrete effects.

In summary, building on the existing literature, further research is needed on property-value effects in particularly close proximity to wind turbines. Specifically, research is needed that uses a large set of data near the turbines, accounts for home values before the announcement of the facility (as well as after announcement but before construction), accounts for potential spatial dependence in unobserved factors effecting home values, and uses a fixed-effect distance model that is able to accurately estimate effects near turbines.

[6] For example, Sunak and Madlener (2012) find larger effects related to the turbines in a city that is farther from the turbines than they find in a town which is closer. Additionally, they find stronger effects in the center of a third town than they do on the outskirts of that town, which do not seem related to the location of the turbines.

Methodology

The present study seeks to respond to the identified research needs noted above, with this section describing our methodological framework for estimating the effects of wind turbines on the value of nearby homes in the United States.

Basic Approach and Models

Our methods are designed to help answer the following questions:

1 Did homes that sold prior to the wind facilities' announcement (PA)—and located within a short distance (e.g., within a half mile) from where the turbines were eventually located—sell at lower prices than homes located farther away?
2 Did homes that sold after the wind facilities' announcement but before construction (PAPC)—and located within a short distance (e.g., within a half mile)—sell at lower prices than homes located farther away?
3 Did homes that sold after the wind facilities' construction (PC)—and located within a short distance (e.g., within a half mile)—sell at lower prices than homes located farther away?
4 For question 3 above, if no statistically identifiable effects are found, what is the likely maximum effect possible given the margins of error around the estimates?

To answer these questions, the hedonic pricing model (Rosen 1974; Freeman 1979) is used in this paper, as it has been in other disamenity research (Boyle and Kiel 2001; Jackson 2001; Simons and Saginor 2006). The value of this approach is that is allows one to disentangle and control for the potentially competing influences of home, site, neighborhood, and market characteristics on property values, and to uniquely determine how home values near announced or operating facilities are affected.[7] To test for these effects, two pairs of "base" models are estimated, which are then coupled with a set of "robustness" models to test and bound the estimated effects. One pair is estimated using a standard OLS model, and the other is estimated using a spatial-process model. The models in each pair are different in that one focuses on all homes within 1 mile of an existing turbine (*one-mile* models), which allows the maximum number of data for the fixed effect to be used, while the other focuses on homes within a half mile (*half-mile* models), where effects are more likely to appear but fewer data are available.[8] We assume that, if effects exist near turbines, they are larger for the *half-mile* models than the *one-mile* models.

As is common in the literature (Malpezzi 2003; Sirmans et al. 2005), a semi-log functional form of the hedonic pricing model is used for all models, where the

[7] See Jackson (2003) for a further discussion of the Hedonic Pricing Model and other analysis methods.

[8] Because it is assumed that nuisance effects from turbines come in the form of, for example, views of, sounds from and/or shadow flicker from turbines, and that the models do not test for these effects directly, the *one-mile* and *half-mile* models, therefore, act as a proxy. Previous research has shown that distance is a good proxy for these effects, that these effects are likely to fade beyond one half mile, and that, therefore, the *half-mile* models are more likely to coincide with these effects than the *one-mile* models (e.g., Hoen et al. 2009; Hoen et al. 2011).

dependent variable is the natural log of sales price. The OLS *half-mile* model form is as follows:

$$\ln(SP_i) = \alpha + \sum_a \beta_1 (T_i \cdot S_i) + \beta_2 (W_i) + \sum_b \beta_3 (X_i \cdot C_i) + \beta_4 (D_i \cdot P_i) + \varepsilon_i \quad (1)$$

where

SP_i represents the sale price for transaction i,

α is the constant (intercept) across the full sample,

T_i is a vector of time-period dummy variables (e.g., sale year and if the sale occurred in winter) in which transaction i occurred,

S_i is the state in which transaction i occurred,

W_i is the census tract in which transaction i occurred,

X_i is a vector of home, site, and neighborhood characteristics for transaction i (e.g., square feet, age, acres, bathrooms, condition, percent of block group vacant and owned, median age of block group),[9]

C_i is the county in which transaction i occurred,

D_i is a vector of four fixed-effect variables indicating the distance (to the nearest turbine) bin (i.e., group) in which transaction i is located (e.g., within a half mile, between a half and 1 mile, between 1 and 3 miles, and between 3 and 10 miles),

P_i is a vector of three fixed-effect variables indicating the wind project development period in which transaction i occurred (e.g., PA, PAPC, PC),

$B_{1\text{-}3}$ is a vector of estimates for the controlling variables,

B_4 is a vector of 12 parameter estimates of the distance-development period interacted variables of interest,

ε_i is a random disturbance term for transaction i.

This pooled construction uses all property transactions in the entire dataset. In so doing, it takes advantage of the large dataset in order to estimate an average set of turbine-related effects across all study areas, while simultaneously allowing for the estimation of controlling characteristics at the local level, where they are likely to vary substantially across the study areas.[10] Specifically, the interaction of county-level fixed effects (C_i) with the vector of home, site, and neighborhood characteristics (X_i) allows different slopes for each of these independent variables to be estimated for each county. Similarly, interacting the state fixed-effect variables (S_i) with the sale year and sale winter fixed effects variables (T_i) (i.e., if the sale occurred in either Q1 or Q4) allows the estimation of the respective inflation/deflation and seasonal adjustments for each state in the dataset.[11] Finally, to control for the potentially unique collection of neighborhood characteristics that exist at the micro-level, census tract

[9] A "block group" is a US Census Bureau geographic delineation that contains a population between 600 to 3,000 persons.

[10] The dataset does not include "participating" landowners, those that have turbines situated on their land, but does include "neighboring" landowners, those adjacent to or nearby the turbines. One reviewer notes that the estimated average effects also include any effects from payments "neighboring" landowners might receive that might transfer with the home. Based on previous conversations with developers (see Hoen et al. 2009), we expect that the frequency of these arrangements is low, as is the right to transfer the payments to the new homeowner. Nonetheless, our results should be interpreted as "net" of any influence whatever "neighboring" landowner arrangements might have.

[11] Unlike the vector of home, site, and neighborhood characteristics, sale price inflation/deflation and seasonal changes were not expected to vary substantially across various counties in the same states in our sample and therefore the interaction was made at the state level. This assumption was tested as part of the robustness tests though, where they are interacted at the county level and found to not affect the results.

fixed effects are estimated.[12] Because a pooled model is used that relies upon the full dataset, smaller effect sizes for wind turbines will be detectable. At the same time, however, this approach does not allow one to distinguish possible wind turbine effects that may be larger in some communities than in others.

As discussed earlier, effects might predate the announcement of the wind facility and thus must be controlled for. Additionally, the area surrounding the wind facility might have changed over time simultaneously with the arrival of the turbines, which could affect home values. For example, if a nearby factory closed at the same time a wind facility was constructed, the influence of that factor on all homes in the general area would ideally be controlled for when estimating wind turbine effect sizes.

To control for both of these issues simultaneously, we use a difference-in-difference (*DD)* specification (see e.g., Hinman 2010; Zabel and Guignet 2012) derived from the interaction of the spatial (D_i) and temporal (P_i) terms. These terms produce a vector of 11 parameter estimates (β_4) as shown in Table 1 for the *half-mile* models and in Table 2 for the *one-mile* models. The omitted (or reference) group in both models is the set of homes that sold prior to the wind facilities' announcement and which were located more than 3 miles away from where the turbines were eventually located (A3). It is assumed that this reference category is likely not affected by the imminent arrival of the turbines, although this assumption is tested in the robustness tests.

Using the *half-mile* models, to test whether the homes located near the turbines that sold in the PA period were uniquely affected (*research question 1*), we examine A0, from which the null hypothesis is A0=0. To test if the homes located near the turbines that sold in the PAPC period were uniquely affected (*research question 2*), we first determine the difference in their values as compared to those farther away (B0-B3), while also accounting for any pre-announcement (i.e., pre-existing) difference (A0-A3) and any change in the local market over the development period (B3-A3). Because all covariates are determined in relation to the omitted category (A3), the null hypothesis collapses B0-A0-B3=0. Finally, in order to determine if homes near the turbines that sold in the PC period were uniquely affected (*research question 3*), we test if C0-A0-C3=0. Each of these *DD* tests are estimated using a linear combination of variables that produces the "net effect" and a measure of the standard error and corresponding confidence intervals of the effect, which enables the estimation of the maximum (and minimum) likely impacts for each research question. We use 90 % confidence intervals both to determine significance and to estimate maximum likely effects (*research question 4*).

Following the same logic as above, the corresponding hypothesis tests for the *one-mile* models are as follows: *PA*, A1=0; *PAPC*, B1-A1-B3=0; and, *PC,* C1-A1-C3=0.

[12] In part because of the rural nature of many of the study areas included in the research sample, these census tracts are large enough to contain sales that are located close to the turbines as well as those farther away, thereby ensuring that they do not unduly absorb effects that might be related to the turbines. Moreover each tract contains sales from throughout the study periods, both before and after the wind facilities' announcement and construction, further ensuring they are not biasing the variables of interest.

Table 1 Interactions between Wind Facility Development Periods and Distances – ½ Mile. Table presents a vector of 11 parameter estimates for the half-mile models based on three wind facility development periods (prior to announcement, after announcement but prior to construction, and post construction) and four distances to the nearest turbine (within ½ mile, between ½ and 1 mile, between 1 and 3 miles, and outside of 3 miles). The omitted (*or reference*) group (*A3*) is the set of homes that sold prior to the wind facilities' announcement and which were located more than 3 miles away from where the turbines were eventually located

Wind Facility Development Periods	Distances to Nearest Turbine			
	Within 1/2 Mile	Between 1/2 and 1 Mile	Between 1 and 3 Miles	Outside of 3 Miles
Prior to Announcement	A0	A1	A2	A3 (Omitted)
After Announcement but Prior to Construction	B0	B1	B2	B3
Post Construction	C0	C1	C2	C3

Spatial Dependence

As discussed briefly above, a common feature of the data used in hedonic models is the spatially dense nature of the real estate transactions. While this spatial density can provide unique insights into local real estate markets, one concern that is often raised is the impact of potentially omitted variables given that it is impossible to measure all of the local characteristics that affect housing prices. As a result, spatial dependence in a hedonic model is likely because houses located closer to each other typically have similar unobservable attributes. Any correlation between these unobserved factors and the explanatory variables used in the model (e.g., distance to turbines) is a source of omitted-variable bias in the OLS models. A common approach used in the hedonic literature to correct this potential bias is to include local fixed effects (Hoen et al. 2009; Hoen et al. 2011; Zabel and Guignet 2012), which is our approach as described in formula (1).

In addition to including local fixed effects, spatial econometric methods can be used to help further mitigate the potential impact of spatially omitted variables by modeling spatial dependence directly. When spatial dependence is present and appropriately

Table 2 Interactions between Wind Facility Development Periods and Distances - 1 Mile. Table presents a vector of 8 parameter estimates for the one-mile models based on three wind facility development periods (prior to announcement, after announcement but prior to construction, and post construction) and three distances to the nearest turbine (within 1 mile, between 1 and 3 miles, and outside of 3 miles). The omitted (or reference) group (*A3*) is the set of homes that sold prior to the wind facilities' announcement and which were located more than 3 miles away from where the turbines were eventually located

Wind Facility Development Periods	Distances to Nearest Turbine		
	Within 1 Mile	Between 1 and 3 Miles	Outside of 3 Miles
Prior to Announcement	A1	A2	A3 (Omitted)
After Announcement but Prior to Construction	B1	B2	B3
Post Construction	C1	C2	C3

modeled, more accurate (i.e., less biased) estimates of the factors influencing housing values can be obtained. These methods have been used in a number of previous hedonic price studies; examples include the price impacts of wildfire risk (Donovan et al. 2007), residential community associations (Rogers 2006), air quality (Anselin and Lozano-Gracia 2008), and spatial fragmentation of land use (Kuethe 2012). To this point, however, these methods have not been applied to studies of the impact of wind turbines on property values.

Moran's I is the standard statistic used to test for spatial dependence in OLS residuals of the hedonic equation. If the Moran's I is statistically significant (as it is in our models – see Variables of Interest Section), the assumption of spatial independence is rejected. To account for this, in spatial-process models, spatial dependence is routinely modeled as an additional covariate in the form of a spatially lagged dependent variable Wy, or in the error structure $\mu=\lambda W\mu+\varepsilon$, where ε is an identically and independently distributed disturbance term (Anselin 1988). Neighboring criterion determines the structure of the spatial weights matrix W, which is frequently based on contiguity, distance criterion, or k-nearest neighbors (Anselin 2002). The weights in the spatial-weights matrix are typically row standardized so that the elements of each row sum to one.

The spatial-process model, known as the SARAR model (Kelejian and Prucha 1998),[13] allows for both forms of spatial dependence, both as an autoregressive process in the lag-dependent and in the error structure, as shown by:

$$\begin{aligned} y &= \rho W y + X\beta + \mu, \\ \mu &= \lambda W \mu + \varepsilon. \end{aligned} \tag{2}$$

Equation (2) is often estimated by a multi-step procedure using generalized moments and instrumental variables (Arraiz et al. 2009), which is our approach. The model allows for the innovation term ε in the disturbance process to be heteroskedastic of an unknown form (Kelejian and Prucha 2010). If either λ or ρ are not significant, the model reduces to the respective spatial lag or spatial error model (SEM). In our case, as is discussed later, the spatial process model reduces to the SEM, therefore both *half-mile* and *one-mile* SEMs are estimated, and, as with the OLS models discussed above, a similar set of *DD* "net effects" are estimated for the PA, PAPC, and PC periods. One requirement of the spatial model is that the x/y coordinates be unique across the dataset. However, the full set of data (as described below) contains, in some cases, multiple sales for the same property, which consequently would have non-unique x/y coordinates.[14] Therefore, for the spatial models, only the most recent sale is used. An OLS model using this limited dataset is also estimated as a robustness test.

[13] SARAR refers to a "spatial-autoregressive model with spatial autoregressive residuals".

[14] The most recent sale weights the transactions to those occurring after announcement and construction that are more recent in time. One reviewer wondered if the frequency of sales was affected near the turbines, which is also outside the scope of the study, though this "sales volume" was investigated in Hoen et al. (2009), where no evidence of such an effect was discovered. Another correctly noted that the most recent assessment is less accurate for older sales, because it might overestimate some characteristics of the home (e.g., sfla, baths) that might have changed (i.e., increased) over time. This would tend to bias those characteristics' coefficients downward. Regardless, it is assumed that this occurrence is not correlated with proximity to turbines and therefore would not bias the variables of interest.

In total, four "base" models are estimated: an OLS *one-mile* model, a SEM *one-mile* model, an OLS *half-mile* model, and a SEM *half-mile* model. In addition, a series of robustness models are estimated as described next.

Robustness Tests

To test the stability of and potentially bound the results from the four base models, a series of robustness tests are conducted that explore: the effect that outliers and influential cases have on the results; a micro-inflation/deflation adjustment created by interacting the sale-year fixed effects with the county fixed effects rather than state fixed effects; the use of only the most recent sale of homes in the dataset to compare results to the SEM models that use the same dataset; the application of a more conservative reference category by using transactions between 5 and 10 miles (as opposed to between 3 and 10 miles) as the reference; and a more conservative reference category by using transactions more than 2 years PA (as opposed to simply PA) as the reference category. Each of these tests is discussed in detail below.

Outliers and Influential Cases

Most datasets contain a subset of observations with particularly high or low values for the dependent variables, which might bias estimates in unpredictable ways. In our robustness test, we assume that observations with sales prices above or below the 99 % and 1 % percentile are potentially problematic outliers. Similarly, individual sales transactions and the values of the corresponding independent variables might exhibit undue influence on the regression coefficients. In our analysis, we therefore estimate a set of Cook's Distance statistics (Cook 1977; Cook and Weisberg 1982) on the base OLS *half-mile* model and assume any cases with an absolute value of this statistic greater than one to be potentially problematic influential cases. To examine the influence of these cases on our results, we estimate a model with both the outlying sales prices and Cook's influential cases removed.

Interacting Sale Year at the County Level

It is conceivable that housing inflation and deflation varied dramatically in different parts of the same state. In the base models, we interact sale year with the state to account for inflation and deflation of sales prices, but a potentially more-accurate adjustment might be warranted. To explore this, a model with the interaction of sale year and county, instead of state, is estimated.

Using Only the Most Recent Sales

The dataset for the base OLS models includes not only the most recent sale of particular homes, but also, if available, the sale prior to that. Some of these earlier sales occurred many years prior to the most recent sale. The home and site characteristics (square feet, acres, condition, etc.) used in the models are populated via assessment data for the home.

For some of these data, only the most recent assessment information is available (rather than the assessment from the time of sale), and therefore older sales might be more prone to error as their characteristics might have changed since the sale.[15] Additionally, the SEMs require that all x/y coordinates entered into the model are unique; therefore, for those models only the most recent sale is used. Excluding older sales therefore potentially reduces measurement error, and also enables a more-direct comparison of effects between the base OLS model and SEM results.

Using Homes between 5 and 10 Miles as Reference Category

The base models use the collection of homes between 3 and 10 miles from the wind facility (that sold before the announcement of the facility) as the reference category in which wind facility effects are not expected. However, it is conceivable that wind turbine effects extend farther than 3 miles. If homes outside of 3 miles are affected by the presence of the turbines, then effects estimated for the target group (e.g., those inside of 1 mile) will be biased downward (i.e., smaller) in the base models. To test this possibility and ensure that the results are not biased, the group of homes located between 5 and 10 miles is used as a reference category as a robustness test.

Using Transactions Occurring More than 2 Years before Announcement as Reference Category

The base models use the collection of homes that sold before the wind facilities were announced (and were between 3 and 10 miles from the facilities) as the reference category, but, as discussed in Hoen et al. (2009, 2011), the announcement date of a facility, when news about a facility enters the public domain, might be after that project was known in private. For example, wind facility developers may begin talking to landowners some time before a facility is announced, and these landowners could share that news with neighbors. In addition, the developer might erect an anemometer to collect wind-speed data well before the facility is formally "announced," which might provide concrete evidence that a facility may soon to be announced. In either case, this news might enter the local real estate market and affect home prices before the formal facility announcement date. To explore this possibility, and to ensure that the reference category is unbiased, a model is estimated that uses transactions occurring more than 2 years before the wind facilities were announced (and between 3 and 10 miles) as the reference category.

Combined, this diverse set of robustness tests allows many assumptions used for the base models to be tested, potentially allowing greater confidence in the final results.

Data

The data used for the analysis are comprised of four types: wind turbine location data, real estate transaction data, home and site characteristic data, and census data. From

[15] As discussed in more detail in the Data Section, approximately 60 % of all the data obtained for this study (that obtained from CoreLogic) used the most recent assessment to populate the home and site characteristics for all transactions of a given property.

those, two additional sets of data are calculated: distance to turbine and wind facility development period. Each data type is discussed below. Where appropriate, variable names are shown in *italics*.

Wind Turbine Locations

Location data (i.e., x/y coordinates) for installed wind turbines were obtained via an iterative process starting with Federal Aviation Administration obstacle data, which were then linked to specific wind facilities by Ventyx[16] and matched with facility-level data maintained by LBNL. Ultimately, data were collected on the location of almost all wind turbines installed in the U.S. through 2011 (n~40,000), with information about each facility's announcement, construction, and operation dates as well as turbine nameplate capacity, hub height, rotor diameter, and facility size.

Real Estate Transactions

Real estate transaction data were collected through two sources, each of which supplied the home's sale price (*sp*), sale date (*sd*), x/y coordinates, and address including zip code. From those, the following variables were calculated: natural log of sale price (*lsp*), sale year (*sy*), if the sale occurred in winter (*swinter*) (i.e., in Q1 or Q4).

The first source of real estate transaction data was CoreLogic's extensive dataset of U.S. residential real estate information.[17] Using the x/y coordinates of wind turbines, CoreLogic selected all arms-length single-family residential transactions between 1996 and 2011 within 10 miles of a turbine in any U.S. counties where they maintained data (not including New York – see below) on parcels smaller than 15 acres.[18] The full set of counties for which data were collected were then winnowed to 26 by requiring at least 250 transactions in each county, to ensure a reasonably robust estimation of the controlling characteristics (which, as discussed above, are interacted with county-level fixed effects), and by requiring at least one PC transaction within a half mile of a turbine in each county (because this study's focus is on homes that are located in close proximity to turbines).

The second source of data was the New York Office of Real Property Tax Service (NYORPTS),[19] which supplied a set of arms-length single-family residential transactions between 2001 and 2012 within 10 miles of existing turbines in any New York county in which wind development had occurred prior to 2012. As before, only parcels smaller than 15 acres were included, and only those counties in which a minimum of 250 transactions and at least one PC transaction were within a half mile of a turbine. Both CoreLogic and NYORPTS provided the most recent home sale and, if available, the prior sale.

[16] See the EV Energy Map, which is part of the Velocity Suite of products at www.ventyx.com.

[17] See www.corelogic.com.

[18] The 15 acre screen was used because of a desire to exclude from the sample any transaction of property that might be hosting a wind turbine, and therefore directly benefitting from the turbine's presence (which might then increase property values). To help ensure that the screen was effective, all parcels within a mile of a turbine were also visually inspected using satellite and ortho imagery via a geographic information system.

[19] See www.orps.state.ny.us

Home and Site Characteristics

A set of home and site characteristic data was also collected from both data suppliers: 1000s of square feet of living area (*sfla1000*), number of acres of the parcel (*acres*), year the home was built (or last renovated, whichever is more recent) (*yrbuilt*), and the number of full and half bathrooms (*baths*).[20] Additional variables were calculated from the other variables as well: log of 1,000s of square feet (*lsfla1000*),[21] the number of acres less than 1 (*lt1acre)*,[22] age at the time of sale (*age*), and age squared (*agesqr*).[23]

Regardless of when the sale occurred, CoreLogic supplied the related home and site characteristics as of the most recent assessment, while NYORPTS supplied the assessment data as of the year of sale.[24]

Census Information

Each of the homes in the data was matched (based on the x/y coordinates) to the underlying census block group and tract via ArcGIS. Using the year 2000 block group census data, each transaction was appended with neighborhood characteristics including the median age of the residents (*medage*), the total number of housing units (*units*), the number vacant (*vacant*) homes, and the number of owned (*owned*) homes. From these, the percentages of the total number of housing units in the block group that were vacant and owned were calculated, i.e., *pctvacant* and *pctowned*.

Distances to Turbine

Using the x/y coordinates of both the homes and the turbines, a Euclidian distance (in miles) was calculated for each home to the nearest wind turbine (*tdis*), regardless of when the sale occurred (e.g., even if a transaction occurred prior to the wind facility's installation).[25] These were then broken into four mutually exclusive distance bins (i.e., groups) for the base *half-mile* models: inside a half mile, between a half and 1 mile, between 1 and 3 miles, and between 3 and 10 miles. They were broken into three mutually exclusive bins for the base *one-mile* models: inside 1 mile, between 1 and 3 miles, and between 3 and 10 miles.

Wind Facility Development Periods

After identifying the nearest wind turbine for each home, a match could be made to Ventyx' dataset of facility-development announcement and construction dates. These

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[20] *Baths* was calculated in the following manner: full bathrooms+(half bathrooms x 0.5). Some counties did not have *baths* data available, so for them *baths* was not used as an independent variable.

[21] The distribution of *sfla1000* is skewed, which could bias OLS estimates, thus *lsfla1000* is used instead, which is more normally distributed. Regression results, though, were robust when *sfla1000* was used instead.

[22] This variable allows the separate estimations of the 1st acre and any additional acres over the 1st.

[23] *Age* and *agesqr* together account for the fact that, as homes age, their values usually decrease, but further increases in age might bestow countervailing positive "antique" effects.

[24] See footnote 14.

[25] Before the distances were calculated, each home inside of 1 mile was visually inspected using satellite and ortho imagery, with x/y coordinates corrected, if necessary, so that those coordinates were on the roof of the home.

facility-development dates in combination with the dates of each sale of the homes determined in which of the three facility-development periods (*fdp*) the transaction occurred: *pre-announcement* (PA), *post-announcement-pre-construction* (PAPC), or *post-construction* (PC).

Data Summary

After cleaning to remove missing or erroneous data, a final dataset of 51,276 transactions was prepared for analysis.[26] Table 3 contains a summary of those data. The average unadjusted sales price for the sample is $122,475. Other average house characteristics include the following: 1,600 square feet of living space; house age of 48 years[27]; land parcel size of 0.90 acres; 1.6 bathrooms; in a block group in which 74 % of housing units are owned, 9 % are vacant, and the median resident age is 38 years; located 4.96 miles from the nearest turbine; and sold at the tail end of the PA period. As shown in the map of the study area (Fig. 1), the data are arrayed across nine states and 27 counties (see Table 4), and surround 67 different wind facilities.

The data are arrayed across the temporal and distance bins as would be expected, with smaller numbers of sales nearer the turbines, as shown in Table 5. Of the full set of sales, 1,198 occurred within 1 mile of a then-current or future turbine location, and 376 of these occurred post construction; 331 sales occurred within a half mile, 104 of which were post construction. Given these totals, the models should be able to discern a post construction effect larger than ~3.5 % within a mile and larger than ~7.5 % within a half mile (see discussion in Section 2). These effects are at the top end of the expected range of effects based on other disamenities (high-voltage power lines, roads, landfills, etc.).

As shown in Table 6, the home sales occurred around wind facilities that range from a single-turbine project to projects of 150 turbines, with turbines of 290–476 f. (averaging almost 400 ft) in total height from base to tip of blade and with an average nameplate capacity of 1,637 kW. The average facility was announced in 2004 and constructed in 2007, but some were announced as early as 1998 and others were constructed as late as 2011.

Results

This section contains analysis results and discussion for the four base models, as well as the results from the robustness models.

[26] Cleaning involved the removal of all data that did not have certain core characteristics (sale date, sale price, *sfla, yrbuilt, acres, median age*, etc.) fully populated as well as the removal of any sales that had seemingly miscoded data (e.g., having a *sfla* that was greater than *acres,* having a *yrbuilt* more than 1 year after the sale, having less than one *bath*) or that did not conform to the rest of the data (e.g., had *acres* or *sfla* that were either larger or smaller, respectively, than 99 % or 1 % of the data). OLS models were rerun with those "nonconforming" data included with no substantive change in the results in comparison to the screened data presented in the report.

[27] Age could be as low as−1 (for a new home) for homes that were sold before construction was completed.

Table 3 Summary Transaction Statistics. Table summarizes the transaction data, showing a description, mean, standard deviation, minimum, and maximum for each variable

Variable	Description	Mean	Std. Dev.	Min	Max
sp	sale price in dollars	$ 122,475	$ 80,367	$ 9,750	$ 690,000
lsp	natural log of sale price	11.52	0.65	9.19	13.44
sd	sale date	1/18/2005	1,403 days	1/1/1996	9/30/2011
sy	sale year	2005	3.84	1996	2011
sfla1000	living area in 1000s of square feet	1.60	0.57	0.60	4.50
lsfla1000	natural log of sfla1000	0.41	0.34	−0.50	1.50
acres	number of acres in parcel	0.90	1.79	0.03	14.95
acreslt1*	acres less than 1	−0.58	0.34	−0.97	0.00
age	age of home at time of sale	48	37	−1	297
agesq	age squared	3,689	4,925	0	88,209
baths**	number of bathrooms	1.60	0.64	1.00	5.50
pctowner	fraction of house units in block group that are owned (as of 2000)	0.74	0.17	0.63	0.98
pctvacant	fraction of house units in block group that are vacant (as of 2000)	0.09	0.10	0.00	0.38
med_age	median age of residents in block group (as of 2000)	38	6	20	63
tdis	distance to nearest turbine (as of December 2011) in miles	4.96	2.19	0.09	10.00
fdp***	facility development period of nearest turbine at time of sale	1.94	0.87	1.00	3.00

Note: The number of cases for the full dataset is 51,276

* acreslt1 is calculated as follows: acres (if less than 1) * - 1

** Some counties did not have bathrooms populated; for those, these variables are entered into the regression as 0

*** fdp periods are: 1, pre-announcement; 2, post-announcement-pre-construction; and, 3, post-construction

Estimation Results for Base Models

Estimation results for the "base" models are shown in Table 7 and Table 8.[28] In general, given the diverse nature of the data, the models perform adequately, with adjusted R^2 values ranging from 0.63 to 0.67 (bottom of Table 8).

Control Variables

The controlling home, site, and block group variables, which are interacted at the county level, are summarized in Table 7. Table 7 focuses on only one of the base

[28] The OLS models are estimated using the areg procedure in Stata with robust (White's corrected) standard errors (White 1980). The spatial error models are estimated using the *gstslshet* routine in the sphet package in R, which also allows for robust standard errors to be estimated. See: http://cran.r-project.org/web/packages/sphet/sphet.pdf

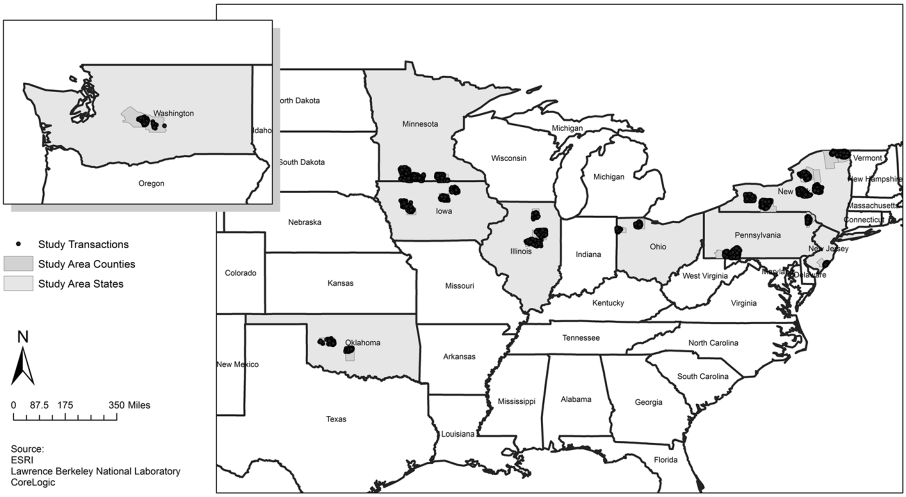

Fig. 1 Transactions, States, and Counties. Figure shows a map of the U.S. states and counties in which study transactions took place, with dots denoting specific transaction locations. The states include Washington, Minnesota, Iowa, Illinois, Oklahoma, Ohio, Pennsylvania, New York, and New Jersey. Each state has one or more concentrated clusters of study transactions indicating transactions within 10 miles of an existing wind turbine

models, the *one-mile* OLS model; The full set of results are available upon request from the authors. [29] To concisely summarize results for all of the 27 counties, the table contains the percentage of all 27 counties for which each controlling variable has statistically significant (at or below the 10 % level) coefficients for the *one-mile* OLS model. For those controlling variables that are found to be statistically significant, the table further contains mean values, standard deviations, and minimum and maximum levels.

Many of the county-interacted controlling variables (e.g., *lsfla1000, lt1acre, age, agesqr, baths,* and *swinter*) are consistently (in more than two thirds of the counties) statistically significant (with a p-value<0.10) and have appropriately sized mean values. The seemingly spurious minimum and maximum values among some of the county-level controlling variables (e.g., *lt1acre* minimum of−0.069) likely arise when these variables in particular counties are highly correlated with other variables, such as square feet (*lsfla1000*), and also when sample size is limited.[30] The other variables (*acres* and the three block group level census variables: *pctvacant, pctowner,* and *med_age*) are statistically significant in 33–59 % of the counties. Only one variable's mean value—the percent of housing units vacant in the block group as of the 2000 census (*pctvacant*)—was counterintuitive. In that instance, a positive coefficient was estimated, when in fact, one would expect that increasing the percent of vacant housing

[29] The controlling variables' coefficients were similar across the base models, so only the *one-mile* results are summarized here.

[30] The possible adverse effects of these collinearities were fully explored both via the removal of the variables and by examining VIF statistics. The VOI results are robust to controlling variable removal and have relatively low (<5) VIF statistics.

Table 4 Summary of Transactions by County. Table lists the frequency distribution of transactions by county, state, and distance from the nearest wind turbine

County	State	<1/2 mile	1/2–1 mile	1–3 miles	3–10 miles	Total
Carroll	IA	12	56	331	666	1,065
Floyd	IA	3	2	402	119	526
Franklin	IA	8	1	9	322	340
Sac	IA	6	77	78	485	646
DeKalb	IL	4	8	44	605	661
Livingston	IL	16	6	237	1,883	2,142
McLean	IL	18	88	380	4,359	4,845
Cottonwood	MN	3	10	126	1,012	1,151
Freeborn	MN	17	16	117	2,521	2,671
Jackson	MN	19	28	36	149	232
Martin	MN	7	25	332	2,480	2,844
Atlantic	NJ	34	96	1,532	6,211	7,873
Paulding	OH	15	58	115	309	497
Wood	OH	5	31	563	4,844	5,443
Custer	OK	45	24	1,834	349	2,252
Grady	OK	1	6	97	874	978
Fayette	PA	1	2	10	284	297
Somerset	PA	23	100	1,037	2,144	3,304
Wayne	PA	4	29	378	739	1,150
Kittitas	WA	2	6	61	349	418
Clinton	NY	4	6	49	1,419	1,478
Franklin	NY	16	41	75	149	281
Herkimer	NY	3	17	354	1,874	2,248
Lewis	NY	5	6	93	732	836
Madison	NY	5	26	239	3,053	3,323
Steuben	NY	5	52	140	1,932	2,129
Wyoming	NY	50	50	250	1,296	1,646
Total		331	867	8,919	41,159	51,276

would lower prices; this counter-intuitive effect may be due to collinearity with one or more of the other variables, or possible measurement errors.[31]

The sale year variables, which are interacted with the state, are also summarized in Table 7, with the percentages indicating the number of states in which the coefficients are statistically significant. The inclusion of these sale year variables in the regressions control for inflation and deflation across the various states over the study period. The coefficients represent a comparison to the omitted year, which is 2011. All sale year state-level coefficients are statistically significant in at least 50 % of the states in all years except 2010,

[31] The removal of this, as well as the other block group census variables, however, did not substantively influence the results of the VOI.

Table 5 Frequency Crosstab of Wind Turbine Distance and Development Period Bins. Table shows the frequency distribution of transaction data by development period (PA, PAPC, and PC) and distance from the nearest wind turbine (< ½ mile, ½–1 mile, 1–3 miles, and 3–10 miles)

	<1/2 mile	1/2–1 mile	1–3 miles	3–10 miles	total
PA	143	383	3,892	16,615	21,033
PAPC	84	212	1,845	9,995	12,136
PC	104	272	3,182	14,549	18,107
total	331	867	8,919	41,159	51,276

and they are significant in two thirds of the states in all except 3 years. The mean values of all years are appropriately signed, showing a monotonically ordered peak in values in 2007, with lower values in the prior and following years. The minimum and maximum values are similarly signed (negative) through 2003 and from 2007 through 2010 (positive), and are both positive and negative in years 2003 through 2006, indicating the differences in inflation/deflation in those years across the various states. This reinforces the appropriateness of interacting the sale years at the state level. Finally, although not shown, the model also contains 250 fixed effects for the census tract delineations, of which approximately 50 % were statistically significant.

Variables of Interest

The variables of interest, the interactions between the *fdp* and *tdis* bins, are shown in Table 8 for the four base models. The reference (i.e., omitted) case for these variables are homes that sold prior to the wind facilities' announcement (PA) and are located between 3 and 10 miles from the wind turbines' eventual locations. In relation to that group of transactions, three of the eight interactions in the *one-mile* models and four of the 11 interactions in the *half-mile* models produce coefficients that are statistically significant (at the 10 % level).

Across all four base models none of the PA coefficients show statistically significant differences between the reference category (outside of 3 miles) and the group of transactions within a mile for the *one-mile* models (OLS:−1.7 %, *p*-value 0.48; SEM:−0.02 %, *p*-value 0.94)[32] or within a half- or between one-half and one-mile for the *half-mile* models (OLS inside a half mile: 0.01 %, *p*-value 0.97; between a half and 1 mile:−2.3 %, *p*-value 0.38; SEM inside a half mile: 5.3 %, *p*-value 0.24; between a half and 1 mile:−1.8 %, *p*-value 0.60). Further, none of the coefficients are significant, and all are relatively small (which partially explains their non-significance). Given these results, we find an absence of evidence of a PA effect for homes close to the turbines (*research question 1*).

[32] p-values are not shown in the table can but can be derived from the standard errors, which are shown.

Table 6 Wind Facility Summary. Table presents the mean, minimum, 25th percentile, median, 75th percentile, and maximum values for eight characteristics describing the 67 wind facilities located in the study areas

	mean	min	25th pct.	median	75th pct.	max
turbine rotor diameter (feet)	262	154	253	253	269	328
turbine hub height (feet)	256	197	256	262	262	328
turbine total height (feet)	388	290	387	389	397	476
turbine capacity (kW)	1,637	660	1,500	1,500	1,800	2,500
facility announcement year	2004	1998	2002	2003	2005	2010
facility construction year	2007	2000	2004	2006	2010	2011
number of turbines in facility	48	1	5	35	84	150
nameplate capacity of facility (MW)	79	1.5	7.5	53	137	300

Note: The data correspond to 67 wind facilities located in the study areas. Mean values are rounded to integers

Turning to the PAPC and PC periods, the results also indicate statistically insignificant differences in average home values, all else being equal, between the reference group of transactions (sold in the PA period) and those similarly located more than 3 miles from the turbines but sold in the PAPC or PC periods. Those differences are estimated to be between−0.8 % and−0.5 %.

The results presented above include both OLS and spatial models. Prior to estimating the spatial models, the Moran's I was calculated using the residuals of an OLS model that uses the same explanatory variables as the spatial models and the same dataset (only the most recent transactions). The Moran's I statistic (0.133) was highly significant (p-value 0.00), which allows us to reject the hypothesis that the residuals are spatially independent. Therefore, there was justification in estimating the spatial models. However, after estimation, we determined that only the spatial error process was significant. As a result, we estimated spatial error models (SEMs) for the final specification. The spatial autoregressive coefficient, lambda (bottom of Table 8), which is an indication of spatial autocorrelation in the residuals, is sizable and statistically significant in both SEMs (0.26, p-value 0.00). The SEM models' variable-of-interest coefficients are quite similar to those of the OLS models. In most cases, the coefficients are the same sign, approximately the same level, and often similarly insignificant, indicating that although spatial dependence is present it does not substantively bias the variables of interest. The one material difference is the coefficient size and significance for homes outside of 3 miles in the PAPC and PC periods, 3.3 % (p-value 0.000) and 3.1 % (p-value 0.008), indicating there are important changes to home values over the periods that must be accounted for in the later DD models in order to isolate the potential impacts that occur due to the presence of wind turbines.

Impact of Wind Turbines

As discussed above, there are important differences in property values between development periods for the reference group of homes (those located outside of 3 miles) that must be

Table 7 Levels and Significance for County- and State-Interacted Controlling Variable Coefficients. Table summarizes the controlling home, site, and block group variables—which are interacted at the county level—for the one-mile OLS model. The table contains the percentage of all 27 counties for which each controlling variable has statistically significant (at or below the 10 % level) coefficients. For those controlling variables found to be statistically significant, the table contains mean values, standard deviations, and minimum and maximum levels of the coefficients. The table also summarizes the sale year variables, which are interacted at the state level; the percentages indicate the number of states in which the coefficients are statistically significant. The coefficients represent a comparison to the omitted year, 2011

Variable	% of Counties/States Having Significant (p-value<0.10) Coefficients	Statistics for Significant Variables			
		Mean	St Dev	Min	Max
lsfla1000	100 %	0.604	0.153	0.332	0.979
acres	48 %	0.025	0.035	−0.032	0.091
lt1acre	85 %	0.280	0.170	−0.069	0.667
age	81 %	−0.006	0.008	−0.021	0.010
agesqr	74 %	−0.006	0.063	−0.113	0.108
baths*	85 %	0.156	0.088	0.083	0.366
pctvacant	48 %	1.295	3.120	−2.485	9.018
pctowner	33 %	0.605	0.811	−0.091	2.676
med_age	59 %	−0.016	0.132	−0.508	0.066
swinter	78 %	−0.034	0.012	−0.053	−0.020
sy1996	100 %	−0.481	0.187	−0.820	−0.267
sy1997	100 %	−0.448	0.213	−0.791	−0.242
sy1998	100 %	−0.404	0.172	−0.723	−0.156
sy1999	100 %	−0.359	0.169	−0.679	−0.156
sy2000	88 %	−0.298	0.189	−0.565	−0.088
sy2001	88 %	−0.286	0.141	−0.438	−0.080
sy2002	67 %	−0.261	0.074	−0.330	−0.128
sy2003	67 %	−0.218	0.069	−0.326	−0.119
sy2004	75 %	−0.084	0.133	−0.208	0.087
sy2005	67 %	0.082	0.148	−0.111	0.278
sy2006	67 %	0.128	0.158	−0.066	0.340
sy2007	67 %	0.196	0.057	0.143	0.297
sy2008	56 %	0.160	0.051	0.084	0.218
sy2009	50 %	0.138	0.065	0.071	0.219
sy2010	33 %	0.172	0.063	0.105	0.231

* % of counties significant is reported only for counties that had the baths variable populated (17 out of 27 counties)

Although not summarized, the model also contains 250 census tract fixed effects

Controlling variable statistics are provided for only the one-mile OLS model but did not differ substantially for other models. All variables are interacted with counties, except for sale year (sy), which is interacted with the state

accounted for. Further, although they are not significant, differences between the reference category and those transactions inside of 1 mile in the PA period still must be accounted for if

Table 8 Results of Interacted Variables of Interest: *fdp* and *tdis*. Table shows the interactions between the *fdp* and *tdis* bins for the four base models comprising OLS and SEM estimates for the one-mile and half-mile models. The reference (omitted) case for these variables comprises homes that sold prior to the wind facilities' announcement (*PA*) and are located between 3 and 10 miles from the wind turbines' eventual locations

		one-mile OLS	*one-mile* SEM	*half-mile* OLS	*half-mile* SEM
fdp	tdis	β (se)	β (se)	β (se)	β (se)
PA	< 1 mile	−0.017	0.002		
		(0.024)	(0.031)		
PA	1–2 miles	−0.015	0.008		
		(0.011)	(0.016)		
PA	> 3 miles	Omitted	Omitted		
		n/a	n/a		
PAPC	< 1 mile	−0.035	−0.038		
		(0.029)	(0.033)		
PAPC	1–2 miles	−0.001	−0.033.		
		(0.014)	(0.018)		
PAPC	> 3 miles	−0.006	−0.033***		
		(0.008)	(0.01)		
PC	< 1 mile	0.019	−0.022		
		(0.026)	(0.032)		
PC	1–2 miles	0.044***	−0.001		
		(0.014)	(0.019)		
PC	> 3 miles	−0.005	−0.031**		
		(0.010)	(0.012)		
PA	< 1/2 mile			0.001	0.053
				(0.039)	(0.045)
PA	1/2 - 1 mile			−0.023	−0.018
				(0.027)	(0.035)
PA	1-2 miles			−0.015	0.008
				(0.011)	(0.016)
PA	> 3 miles			Omitted	Omitted
				n/a	*n/a*
PAPC	< 1/2 mile			−0.028	−0.065
				(0.049)	(0.056)
PAPC	1/2 - 1 mile			−0.038	−0.027
				(0.033)	(0.036)
PAPC	1–2 miles			−0.001	−0.034
				(0.014)	(0.017)
PAPC	> 3 miles			−0.006	−0.033***
				(0.008)	(0.009)
PC	< 1/2 mile			−0.016	−0.036
				(0.041)	(0.046)
PC	1/2 - 1 mile			0.032	−0.016
				(0.031)	(0.035)
PC	1–2 miles			0.044***	−0.001

Table 8 (continued)

		one-mile OLS	*one-mile* SEM	*half-mile* OLS	*half-mile* SEM
fdp	tdis	β (se)	β (se)	β (se)	β (se)
				(0.014)	(0.018)
PC	> 3 miles			−0.005	−0.031**
				(0.010)	(0.012)
lambda		0.247 ***		0.247 ***	
		(0.008)		(0.008)	
n		51,276	38,407	51,276	38,407
adj R-sqr		0.67	0.64	0.67	0.64

Note: p-values: < 0.1 *, < 0.05 **, <0.01 ***; items with no asterisk have p-values≥0.1 and are not significant

accurate measurements of PAPC or PC wind turbine effects are to be estimated. The DD specification accounts for both of these critical effects.

Table 9 shows the results of the DD tests across the four models, based on the results for the variables of interest presented in Table 8.[33] For example, to determine the net difference for homes that sold inside of a half mile (drawing from the *half-mile* OLS model) in the PAPC period, we use the following formula: PAPC half-mile coefficient (−0.028) less the PAPC 3-mile coefficient (−0.006) less the PA half-mile coefficient (0.001), which equals −0.024 (without rounding), which equates to 2.3 % difference,[34] and is not statistically significant.

None of the DD effects in either the OLS or SEM specifications are statistically significant in the PAPC or PC periods, indicating that we do not observe a statistically significant impact of wind turbines on property values. Some small differences are apparent in the calculated coefficients, with those for PAPC being generally more negative/less positive than their PC counterparts, perhaps suggestive of a small announcement effect that declines once a facility is constructed. Further, the inside-a-half-mile coefficients are more negative/less positive than their between-a-half-and-1-mile counterparts, perhaps suggestive of a small property value impact very close to turbines.[35] However, in all cases, the sizes of these differences are smaller than the margins of error in the model (i.e., 90 % confidence interval) and thus are not statistically significant. Therefore, based on these results, we do not find evidence supporting either of our two core hypotheses (*research questions 2 and 3*). In other words, there is no statistical evidence that homes in either the PAPC or PC periods that

[33] All DD estimates for the OLS models were calculated using the post-estimation "lincom" test in Stata, which uses the stored results' variance/covariance matrix to test if a linear combination of coefficients is different from 0. For the SEM models, a similar test was performed in R.

[34] All differences in coefficients are converted to percentages in the table as follows: exp(coef)-1.

[35] Although not discussed in the text, this trend continues with homes between 1 and 2 miles being less negative/more positive than homes closer to the turbines (e.g., those within 1 mile).

Table 9 "Net" Difference-in-Difference Impacts of Turbines. Table shows the results of the DD tests across the four models, based on the results for the variables of interest presented in Table 8. For example, to determine the net difference for homes that sold inside of a half mile (drawing from the half-mile OLS model) in the PAPC period, we use the following formula: PAPC half-mile coefficient (−0.028) less the PAPC 3-mile coefficient *(−0.006*) less the PA half-mile coefficient (*0.001*), which equals −0.023 (*with rounding*), which equates to a 2.3 % difference and is not statistically significant

		< 1 Mile	< 1 Mile	< 1/2 Mile	< 1/2 Mile
		OLS	SEM	OLS	SEM
fdp	tdis	b/se	b/se	b/se	b/se
PAPC < 1 mile		−1.2 %	−0.7 %		
		(0.033)	*(0.037)*		
PC < 1 mile		4.2 %	0.7 %		
		(0.030)	(0.035)		
PAPC < 1/2 mile				−2.3 %	−8.1 %
				(0.060)	(0.065)
PAPC 1/2 - 1 mile				−0.8 %	2.5 %
				(0.039)	(0.043)
PC < 1/2 mile				−1.2 %	−5.6 %
				(0.054)	(0.057)
PC 1/2 - 1 mile				6.3 %	3.4 %
				(0.036)	(0.042)

Note: p-values: < 0.1 *, < 0.05 **, <0.01 ***; items with no asterisk have p-values ≥0.1 and are not significant. None of the values in this table are statistically significant

sold near turbines (i.e., within a mile or even a half mile) did so for less than similar homes that sold between 3 and 10 away miles in the same period.

Robustness Tests

Table 10 summarizes the results from the robustness tests. For simplicity, only the DD coefficients are shown and only for the *half-mile* OLS models.[36] The first two columns show the base OLS and SEM *half-mile* DD results (also presented earlier, in Table 9), and the remaining columns show the results from the robustness models as follows: exclusion of outliers and influential cases from the dataset (*outlier*); using sale year/county interactions instead of sale year/state (*sycounty*); using only the most recent sales instead of the most recent and prior sales (*recent*); using homes between 5 and 10 miles as the reference category, instead of homes between 3 and 10 miles (*outside5*); and using transactions occurring more than 2 years before announcement as the

[36] Results were also estimated for the *one-mile* OLS models for each of the robustness tests and are available upon request: the results do not substantively differ from what is presented here for the *half-mile* models. Because of the similarities in the results between the OLS and SEM "base" models, robustness tests on the SEM models were not prepared as we assumed that differences between the two models for the robustness tests would be minimal as well.

Table 10 Robustness Half-Mile Model Results. Table summarizes robustness tests results. Only the DD coefficients are shown and only for the half-mile OLS models. The first two columns show the base OLS and SEM half-mile DD results. The remaining columns show the results from the following robustness models: exclusion of outliers and influential cases from the dataset (*outlier*); using sale year/county interactions instead of sale year/state (*sycounty*); using only the most recent sales instead of the most recent and prior sales (*recent*); using homes between 5 and 10 miles as the reference category, instead of homes between 3 and 10 miles (*outside5*); and using transactions occurring more than 2 years before announcement as the reference category instead of using transactions simply before announcement (*prior*)

				Robustness OLS Models				
		Base OLS	Base SEM	outlier	sycounty	recent	outside5	prior
fdp	tdis	β (se)	β (se)	β (se)	β (se)	β (se)	β (se)	β (se)
PAPC	< 1/2 mile	−2.3 %	−8.1 %	−4.7 %	−4.2 %	−5.6 %	−1.7 %	0.1 %
		(0.060)	(0.065)	(0.056)	(0.060)	(0.066)	(0.060)	(0.062)
PAPC	1/2 - 1 mile	−0.8 %	2.5 %	−1.7 %	−2.5 %	2.3 %	−0.2 %	0.4 %
		(0.039)	(0.043)	(0.036)	(0.039)	(0.043)	(0.039)	(0.044)
PC	< 1/2 mile	−1.2 %	−5.6 %	−0.5 %	−1.8 %	−4.3 %	−0.3 %	1.3 %
		(0.054)	(0.057)	(0.047)	(0.054)	(0.056)	(0.054)	(0.056)
PC	1/2 - 1 mile	6.3 %	3.4 %	6.2 %	3.8 %	4.1 %	7.1 %	7.5 %
		(0.036)	(0.041)	(0.033)	(0.036)	(0.042)	(0.036)	(0.041)

Note: p-values: < 0.1 *, < 0.05 **, <0.01 ***; items with no asterisk have p-values ≥0.1 and are not significant. None of the values in this table are statistically significant

reference category instead of using transactions simply *before* announcement (*prior*).

The robustness results have patterns similar to the base model results: none of the coefficients are statistically different from zero; all coefficients (albeit non-significant) are lower in the PAPC period than the PC period; and, all coefficients (albeit non-significant) are lower (i.e., less negative/more positive) within a half mile than outside a half mile.[37] In sum, regardless of dataset or specification, there is no change in the basic conclusions drawn from the base model results: there is no evidence that homes near operating or announced wind turbines are impacted in a statistically significant fashion. Therefore, if effects do exist, either the average impacts are relatively small (within the margin of error in the models) and/or sporadic (impacting only a small subset of homes). Moreover, these results seem to corroborate what might be predicted given the other, potentially analogous disamenity literature that was reviewed earlier, which might be read to suggest that any property value effect of wind turbines might coalesce at a maximum of 3–4 %, on average. Of course, we cannot offer that corroboration directly because, although the size of the coefficients in the models presented here are reasonably consistent with effects

[37] This trend also continues outside of 1 mile, with those coefficients being less negative/more positive than those within 1 mile.

of that magnitude, none of our models offer results that are statistically different from zero.

Conclusion

Wind energy facilities are expected to continue to be developed in the United States. Some of this growth is expected to occur in more-populated regions, raising concerns about the effects of wind development on home values in surrounding communities.

Previous published and academic research on this topic has tended to indicate that wind facilities, after they have been constructed, produce little or no effect on home values. At the same time, some evidence has emerged indicating potential home-value effects occurring after a wind facility has been announced but before construction. These previous studies, however, have been limited by their relatively small sample sizes, particularly in relation to the important population of homes located very close to wind turbines, and have sometimes treated the variable for distance to wind turbines in a problematic fashion. Analogous studies of other disamenities—including high-voltage transmission lines, landfills, and noisy roads—suggest that if reductions in property values near turbines were to occur, they would likely be relatively small, on average, but to discover such small effects near turbines, much larger amounts of data are needed than have been used in previous studies. Moreover, previous studies have not accounted adequately for potentially confounding home-value factors, such as those affecting home values before wind facilities were announced, nor have they adequately controlled for spatial dependence in the data, i.e., how the values and characteristics of homes located near one another influence the value of those homes (independent of the presence of wind turbines).

This study helps fill those gaps by collecting a very large data sample and analyzing it with methods that account for confounding factors and spatial dependence. We collected data from more than 50,000 home sales among 27 counties in nine states. These homes were within 10 miles of 67 different then-current or existing wind facilities, with 1,198 sales that were within 1 mile of a turbine (331 of which were within a half mile)—many more than were collected by previous research efforts. The data span the periods well before announcement of the wind facilities to well after their construction. We use OLS and spatial-process difference-in-difference hedonic models to estimate the home-value impacts of the wind facilities; these models control for value factors existing prior to the wind facilities' announcements, the spatial dependence of home values, and value changes over time. We also employ a series of robustness models, which provide greater confidence in our results by testing the effects of data outliers and influential cases, heterogeneous inflation/deflation across regions, older sales data for multi-sale homes, the distance from turbines for homes in our reference case, and the amount of time before wind-facility announcement for homes in our reference case.

Across all model specifications, we find no statistical evidence that home prices near wind turbines were affected in either the post-construction or post-announcement/pre-construction periods. Therefore, if effects do exist, either the average impacts are relatively small (within the margin of error in the models) and/or sporadic (impacting only a small subset of homes). If small effects are to be discovered in future research, even larger samples of data may be required. For those interested in estimating such effects on a more micro (or local) scale, such as appraisers, these possible data requirements may be especially daunting, though it is also true that the inclusion of additional market, neighborhood, and individual property characteristics in these more-local assessments may sometimes improve model fidelity.

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