Do wind turbines affect the sale price of single-family homes?
Evidence from McLean County, Illinois

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Abstract. Despite the contentiousness of the recent expansion of wind turbines across the American landscape, little rigorous empirical work estimates its effects. This thesis examines the effect of wind turbines in McLean County, Illinois, on property sale prices, a major concern for many host communities. I use data on the locations and dates of construction of wind turbines from two wind farms and detailed information on over 7,000 property transactions over a 21 year period. A repeat-sales fixed effects estimator is used to control for potential unobserved property characteristics that could influence sale prices. Results show that properties within 1.5 miles of wind turbines have lower values than those further away. However, tests for validity that arbitrarily place turbines where they are not achieve similar results, casting serious doubt on analysis that does not control for the temporal and spatial determinants of sale price.

1. Introduction

For the past decade, wind energy has been the fastest growing source of energy in the United States, increasing by nearly 2,000% from 2000 to 2012 (Wind Powering America 2013). This rapid growth has significantly altered the landscape around the US. Many communities have vehemently opposed the development of wind energy projects to the point that projects have been delayed, downsized, and canceled.[1] Despite wind energy's promise as an economic boon to rural communities around the world, those opposed to wind farms often point to the potential negative effect of wind turbines on nearby property values. Empirical estimates of these effects enable governments to assess the true costs and benefits of wind energy for their constituents and project developers and communities to make informed decisions.

Unlike forms of energy infrastructure that impact the landscape, such as high voltage transmission line or fossil fuel plants, wind turbines are widely supported by Americans. According to a poll conducted by Gallup (2009), wind energy development is supported by a large majority of the public in the United States. Further, wind energy is promoted by climate change activists, federal and state government agencies, and energy companies. However, many residents are concerned about noise and sleep disturbances as well as impact of wind turbines on an area's viewshed,[2] but others do not report these complaints (Cummings 2009). Furthermore, wind energy is a highly visible and highly salient environmental factor, partly because wind turbines are typically built on landscapes with a wide view and at high elevations and partly because of their inherent large size and unique shape (Pasqualetti, Gipe, and Righter 2002).

Despite these concerns, little empirical work investigates the relationship between wind turbines and property values. Conclusions from existing work vary greatly. Hoen, Wiser, Cappers,

[1] For example the Gail Wind Farm project in western Michigan was discontinued after active and organized opposition from community groups made negotiating lease agreements too costly (Charlotte Business Journal 2012). The high-profile offshore Cape Wind project in Massachusetts' Nantucket Sound was delayed for almost a decade due to opposition from nearby residents (New York Times 2010).

[2] Phadke (2010) defines a viewshed as "everything, including land, water, biotic and cultural elements, that is visible to a person standing at a particular location."

Thayer, and Sethi (2011) found no significant effects of wind turbines proximity and property values over time. However, Heintzelman and Tuttle (2012) find that proximity to wind turbines results in a 7.73% to 14.87% decline in property values. The current paper aims to reconcile these disparate conclusions by applying repeat sales fixed effects estimation approach to a study area in McLean County, Illinois, where two wind farms have been constructed over the past decade.

This paper estimates two types of hedonic[3] models using home sale data from McLean County, Illinois: first, an ordinary least squares specification with census block group level fixed effects using all residential sales; second, an ordinary least squares specification using only properties that were sold at least once before and after the announcement of the first wind farm. These specifications both aim to control for omitted variables that could result in biased coefficients if another unobservable characteristic of properties is changing home values. The results suggest that within 1 and 1.5 miles away from properties, wind turbines could be decreasing property sale prices. However, residual analysis and a comparison with results from “quixotic”, or, completely fake, wind farms artificially added to the data casts doubt on the reliability of these findings.[4]

Early studies on wind turbines and property values suffer from a small number of observations. Hoen (2006) performs a log-linear regression on 280 sales that occurred within 5 miles of a wind farm and uses field visits and a Geographic Information System (GIS) simulation to rate the extremity of visual impacts on view from homes. However, very few of the sales occurred before the construction of the wind farm and even fewer occurred before the announcement of the wind farm. Sims and Dent (2007) have a larger number of sales (1,052) but have no sales that occur after the construction of the wind farm and omit many home characteristics, such as home quality. Sims, Dent and Oskrochi (2008) include more home characteristics but only have prices of 201 sales from within

[3] Hedonic regression analysis decomposes the price of a good, in this case homes, into the prices of its characteristics.

[4] I use the word quixotic throughout this paper to refer to a robustness check on my baseline results. The choice of this descriptor, while admittedly cliché, nicely reflects the imaginary or unreal property of the wind turbines in my robustness check and references Miguel de Cervantes’ “Don Quixote,” in which the titular character jousts with windmills that he believes to be monstrous giants.

a half-mile of a wind farm, and do not compare them with the prices of homes further away from the wind farm. These early studies all find no impact of wind turbines on property values, exclude observations from varying distances from wind turbines before and after their construction, and most likely omit unobserved property characteristics.

Later studies have data on more properties and include sales that occurred before the announcement of a wind farm, but use relatively blunt measures for the "treatment" of wind turbines. Laposa and Mueller (2010) find significantly negative effects of wind turbines on property values, but only use a dummy variable to distinguish homes that were "near to" or "far from" a proposed wind farm. Their specification excludes neighborhood characteristics and does not address the potential effect of omitted property characteristics, such as building quality. The authors attribute their results to the national housing crisis that occurred during the construction of the wind farm and do not conclude that wind turbines decrease property values. Hinman (2010) uses a difference-in-difference estimator and controls for spatial autocorrelation and spatial heterogeneity using expanded geographic coordinates.[5] She also includes an extended sensitivity analysis that allows the announcement of the wind turbine to have a different effect than operational wind turbines by included multiple stages. Hinman finds that homes sold within 1 mile of an announced wind turbine experience a decrease in sale price but homes sold during the operational phase of the wind farm do not, lending evidence to wind turbine anticipation stigma.[6] However, her analysis includes very few sales that occur within 3 miles of an operational wind turbine and does not address potential omitted variable bias. Carter (2011) also finds no impact of wind turbines and uses a dummy variable to signify the presence of wind turbines within 3 miles. Carter improves upon past analyses by including homes' distances to the sites of wind turbines before they were constructed in order to address possible endogeneity, which would produce false negative results if homes near wind turbines already have lower property

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[5] Expanded geographic coordinates refers to the XY coordinates in the following forms: X ; Y ; X*Y ; X^2*Y^2 ; X^2 ; Y^2. Expanded geographic coordinates better accounts for spatial heterogeneity within fixed effect groups by controlling for linear and non-linear relationships in the variation associated with property location.

[6] Wind turbine anticipation stigma is discussed further in Section 3.

values, and finds no effect on property values.

More recent studies use sophisticated data and estimation techniques to address potential omitted variable bias. Hoen et al. (2009) estimate ten sets of models, using both repeat-sales and fixed effects methods, property characteristics, and view ratings of 7,459 sales from ten study areas across the United States. They conclude that wind turbines do not affect property values. Hoen et al. (2011), using the same data, present a neighborhood-level fixed effects estimator and control for the sale prices of neighboring houses. However, they only include home sales prior to 2005, when the U.S. installed wind capacity was 85% lower than in 2012 and therefore include fewer homes within 3 miles of wind turbines. Again, this radius excludes any effects within 3 miles of wind turbines. Heintzelman and Tuttle (2011) also use repeat-sales and fixed effects estimators to obtain significant and very negative coefficients for the presence wind turbines. Heintzelman and Tuttle estimate separate effects three study areas in New York and include homes with multiple turbines within one-half a mile. Heintzelman and Tuttle also test the effects of continuous, ordered, and density measures of wind turbines. Both studies test multiple functional forms and various measures of the presence of wind turbines to control for spatial autocorrelation, omitted variable bias, and endogeneity to produce compelling analyses.

The two most thorough studies, Heintzelman and Tuttle (2012) and Hoen et al. (2011; 2009), reach different conclusions with similar fixed effect, repeat-sales estimation techniques. The defining differences between these studies, including the scale and geographic distribution of study areas, the level of detail in wind turbine proximity measurements, the use of site visits to measure the scenic impacts of wind turbines on individual properties, and the decision to pool or keep separate study areas, do not point to a clear explanation for the difference in results. For example, Heintzelman and Tuttle's unpooled data and inclusion of properties very near wind turbines could show that the state of New York is more susceptible to a decrease in property values due to the presence of wind turbines, or their exclusion of view information could falsely attribute lower property values to a non-existent view of wind turbines. The multiple estimators, view data, and nation-wide survey employed by Hoen et al. could more comprehensively capture the influence of wind turbines, but their pooling of data, limited distance measurements, and pre-2005 sample could mask subtle differences of effects of wind turbines across study areas and time periods.

To establish the political context of this research, I should also mention the proliferation of property value studies commissioned by local governments. Government and industry proponents of wind energy development frequently cite the findings of Hoen et al. (2009; 2011) to substantiate claims that proximity to wind turbines either do not affect property values or increase them.[7] Community groups question the methods used by the authors themselves as well as the interpretations of government and industry agents on the grounds that turbines were too far away (more than 3 miles) from homes to measure any effects, among other concerns.[8] This dispute illustrates a distrust that pervades many interactions of potential host communities with government agencies and wind energy companies; communities perceive that their concerns are avoided in academic, inaccessible research. Government and industry often do little do assuage these sentiments by following a "decide, announce, and defend" land use planning approach.[9] In response, communities attempt to fill an information gap by funding their own studies. For example, a Wisconsin community group commissioned the condemnation appraisal consulting firm Appraisal Group One (2009) to conduct an opinion survey of realtors in Dodge and Fond Du Lac counties in Wisconsin. Realtors estimated a 43% decrease in value for properties adjacent to wind farms. While the methods of this and other commissioned studies do not meet the standards of peer review, their findings show that local

[7] Good illustrations include a frequently asked questions page for the Department of Energy (US DOE, 2010) and the weblog of the wind industry association (AWEA, 2012).

[8] McCann (2012), published on the main online forum for opposed community groups, provides a detailed description of common concerns with the Hoen et al (2009; 2011) study.

[9] As the phrasing implies, a "decide, announce, and defend" approach means that land use planners, whether government or industry, form a plan without public input and then defend the original plan against the public's criticisms after announcement.

knowledge and experience may be at odds with econometric evidence from the studies cited above.[10] Land use planners have an opportunity to work with host communities to commission studies that acknowledge communities' concerns while also using econometrically rigorous techniques.

In this paper, I use a repeat-sales fixed effect estimation technique that includes continuous distance, ordered distance level, and density measures of the presence of wind turbines within a radius of 3 miles in the study area of McLean County, Illinois. McLean County, specifically the Twin Groves wind farm, was also the subject of Hinman (2010). My approach allows me to compare my findings with both Hinman and Heintzelman and Tuttle (2012). I seek to identify whether it was Heintzelman and Tuttle's methodology or their choice of study area that led to their anomalous results. My baseline results indicate that wind turbines decrease property sale prices but my sensitivity analysis suggests that researchers need reevaluate the effectiveness of a repeat sale fixed effects estimator in measuring the effect of environmental disamenities on home prices.

Section 2 describes the study area in McLean County, Illinois. Section 3 outlines the hedonic price theory in the context of wind turbines as an environmental disamenity. Section 4 presents empirical techniques and discusses estimation issues. I present summary statistics and data limitations in Section 5. Section 6 describes the results of baseline models. Section 7 discusses residuals of the baseline models and presents the results of a set of "quixotic" models that cast doubt on the baseline results. Section 8 discusses the implications of these results and concludes.

2. Study Area Background

Illinois currently ranks fourth among U.S. States in installed wind energy capacity, with 3,055 megawatts (MW) as of the third quarter of 2012, according to the US Department of Energy.[11] Illinois' status is partially due to high wind resources; the state ranks 15th nationwide in terms of land area suitable for wind development. The Illinois state government also contributes to the high level of

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[10] A thorough literature review of all wind turbine property value impact studies prior to 2010 is available in Hinman (2010).

[11] See http://www.windpoweringamerica.gov/wind_installed_capacity.asp .

wind energy generation capacity, pursuing a renewable energy portfolio standard of 18.75% of electricity generated from wind by 2026. Further, the availability of power lines to the urban population of Chicago eases transmission issues that inhibit wind energy development in other states.

Illinois has also borne the environmental effects of traditional sources of energy. While pollution levels from coal have decreased over the past two decades, coal-power electricity is still the primary source of sulfur dioxide, nitrous oxides, and carbon dioxide emissions in the state (US Energy Information Agency, 2010). Illinois has also seen severe and increasing non-point groundwater pollution due to the expansion of large-scale agriculture (Illinois EPA, 2012). These environmental effects, combined with the flight of many manufacturing companies impose a double environmental-economic burden on Central Illinois. Wind energy expansion is appealing as a boon to local economies, and at a lower environmental cost.

Table 1 profiles current demographic and economic statistics of interest for McLean County and the state of Illinois. While it is the largest county in Illinois by area, McLean County is home to only about 1.3% of the Illinois population. The county has higher levels of education, income, and white residents than the rest of the state but the level of poverty is about the same. The median value of homes and the population density is lower in McLean County than in Illinois overall, reflecting the generally lower value of rural homes. It is important to note that only about two out of three residents own homes in McLean County, and the results of this study only reflect the behavior of this group.

McLean County is a state and national leader in wind energy development. The Twin Groves wind farm, one of the two wind farms analyzed in this paper, is the largest operational wind farm east of the Mississippi River. The County's second operational wind farm, White Oak, was approved in late 2007. The Black Prairie and Bright Stalk projects were approved in 2010, but construction has not yet begun.[12]

[12] The Pantagraph Online (2005- 2012), the local paper for the Bloomington-Normal area, last reported that the Bright Stalk and Black Prairie projects had been approved. No stories have been run since 2010 reporting progress on either project, and in 2012 the Pantagraph reported the Bright Stalk project as "on hold" by EDP Renewables (Gonzalez 2012).

Table 2 shows the four wind projects that have been approved in McLean County. I combine the Twin Groves phases I and II start dates because I was unable to obtain a start date for the second phase.[13] The dates shown were used to estimate the date that a wind turbine enters a homeowner's utility function, that is, when a turbine could be said to "exist" in the context of a property sale. Only the Twin Groves and White Oak wind farms are included in the current analysis due to the delay in the construction of the other two wind farms.[14]

McLean County's prolific wind farm development has not been free from the community conflict that affects the wind farm siting process throughout the United States. The White Oak project was delayed due to ongoing negotiations between a concerned citizens group and project developers. Residents, concerned about the potential noise and health effects, have urged county leaders to impose stricter standards on wind farm developers; a total of 17 research and reporting requirements administered by the county board to the Bright Stalk project.[15] Other residents voiced support for these local wind energy projects because of the perceived benefits of carbon emissions reduction and location economic development in the form of wind turbine manufacturing and construction jobs, tax revenue to avoid spending cuts for education and road maintenance, and supplemental income for landowners who lease land for wind turbines and facilities.

Figures 1 and 2 are photographs of the White Oak and Twin Groves wind farms. These figures illustrate the low, rolling hills formed by glacial moraines and intense agricultural land use

[13] Hinman (2010) uses the same study area of McLean County and also pools the start dates of Twin Groves phases I and II. Her paper also provides a thorough review of the wind farm permitting process in McLean County.

[14] Wind farms projects across the country were delayed pending the renewal of wind energy production tax credits (The Huffington Post 2012). The tax credits were quietly extended for a year following the "Fiscal Cliff" negotiations at the end of 2012.

[15] Wind farm ordinances vary tremendously across the country. In Illinois, the creation of wind farm ordinances occurs at the county level. Some counties have no control over the wind farm permitting process because it occurs at the state level, as is the case in Oregon (National Wind Coordinating Committee 2012). The majority of requirements applied to the Bright Stalk project had not been formulated at the time of earlier projects in McLean County. For example, the Twin Groves project only required a special use permit from the county board (Hinman 2010).

that dominate the landscapes. The lack of large vegetation that might interfere with view is also clear, although this impression is exaggerated by the winter season in which these photos were taken. These images also give an idea of the severity with which the viewshed of many homes could be affected: most properties sold nearby will have a clear view of the nearest wind turbine along with several other turbines.

3. Theoretical Model

This section establishes how economists might expect the presence of wind turbines to affect property values by integrating wind turbine effects into consumer real estate choice. Hedonic price theory forms the foundation for this current paper.[16] Rosen (1974) defines hedonic prices as the implicit prices of the attributes of a good, as revealed by comparing goods with differentiated characteristics. In the context of the housing market, differentiated goods are assumed to be negotiated by the consumer and the producer. Both the consumer and the producer are assumed to be small enough to have no market power. Given these assumptions, the amount a consumer is willing to pay for good z is a function of z_n characteristics. Formally:

$$[3.1] \quad P_z = P(z_1, z_2, \dots, z_n)$$

The indivisibility of the attributes of good z implies that the consumer maximizes utility subject to a multidimensional, non-linear budget constraint. The price of attribute z_i may be increasing or decreasing with the quantity of attribute z_i. This decision can be expressed as:

$$[3.2] \quad \begin{array}{ll} \text{Maximize} & U(x, z_1, z_2, \dots, z_n; \alpha) \\ \text{Subject to} & y = x + P(z_1, z_2, \dots, z_n) \end{array}$$

where α is a vector of socioeconomic characteristics, y is total income, and x is a matrix of other goods with a price of 1. A consumer maximizes utility by choosing goods so that the marginal rate of substitution of characteristic z_i for composite good x equals the marginal price of z_i:

$$[3.3] \quad \frac{\frac{\partial U}{\partial (z_i)}}{\frac{\partial U}{\partial x}} = \frac{\partial p(z)}{\partial (z_i)} = p(z_i)$$

[16] This summary relies heavily on the explanation presented in Anderson (2001).

Given this the implicit price for characteristic z_i , the consumer's bid function is:

[3.4] $\theta(z_n, u, y; \alpha)$

where θ is the maximum price a consumer will pay for particular house with z_n characteristics at a fixed utility level u . The consumer maximization problem can incorporate this bid function by modifying the utility function:

[3.5] $U(y - \theta, z_1, z_2, \dots, z_n; \alpha) = u$

Equation [3.5] represents a surface that relates changes in the amount of characteristic z_i to changes in the total willingness to pay at the same utility level. The consumer will maximize utility by choosing the quantity of attribute z_i where the marginal bid for the attribute equals the marginal implicit price of the attribute:

[3.6] $\frac{\partial\theta(z;u;y)}{\partial(z_i)} = \frac{\partial p(z)}{\partial(z_i)}$

Producers maximize profit by choosing to supply a product with a specific set and amount of attributes. The producer's maximization problem is:

[3.7] Maximize $\pi = m * p(z) - c(m, z; \beta)$

where profit π are revenues minus costs for m units of good z given a set of factor prices β . To solve this maximization problem, the producer will produce the quantity of good z such that the marginal price of attribute z_i is equal to the marginal cost of an additional unit of that attribute:

[3.8] $\frac{\partial p(z)}{\partial(z_i)} = p(z_i) = \frac{\frac{\partial c(m,z;\beta)}{\partial(z_i)}}{m}$

From this solution, the producer has an offer function that parallels the consumer's bid function:

[3.9] $\phi(z, \pi; \beta)$

where φ is the minimum price a producer will accept for good z to still make profit π . Given this offer function, the producer will produce m units of good z such that the marginal offer of attribute z_i is equal to the marginal price of that attribute:

[3.10] $\frac{\partial\phi(z;\pi)}{\partial(z_i)} = \frac{\partial p(z)}{\partial(z_i)}$

The interaction of the bid and offer functions of all consumers and producers in a market will determine the price schedule *p(z)* , which individual consumers and producers take for granted. Graphically, the hedonic equilibrium will be determined by the matching of the tangencies of consumer bid functions and producer offer functions across quantities of attribute z_i as shown in Figure 3.1.

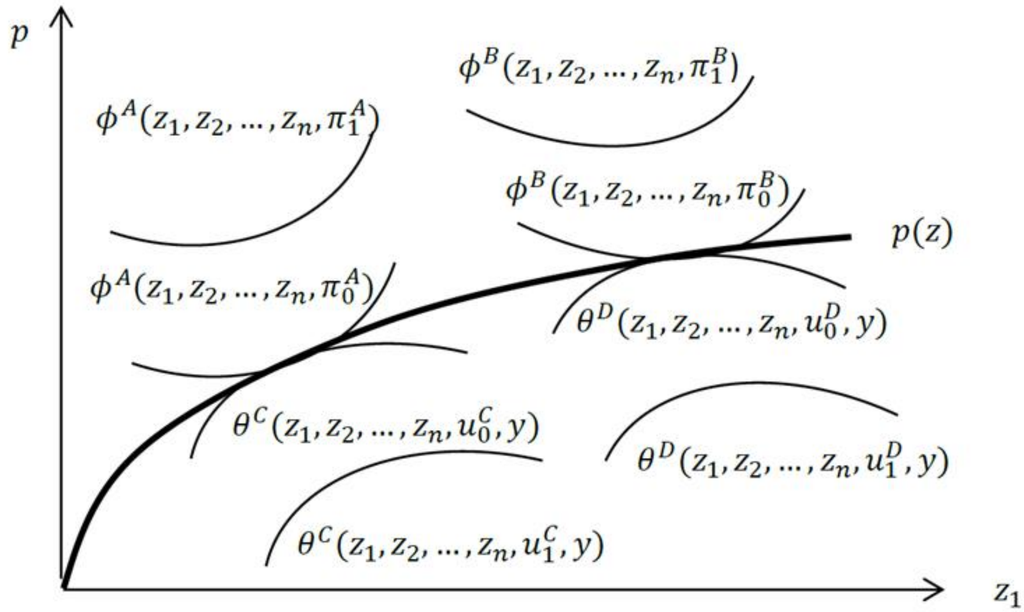

Figure 3.1. The family of bid and offer functions that establish the hedonic equilibrium price function.

Therefore, the marginal implicit price of characteristic z_i can be obtained by regressing home value on home characteristics.

Freeman (1979) applies hedonic price theory to the influence of environmental amenities on property values. Under this model, the selling price of a house P_h is a function of structural characteristics S_n, neighborhood characteristics N_k, and environmental quality Q_m:

[3.11] $P_h = P_h(S_1 \ldots S_n, N_1 \ldots N_k, Q_1 \ldots Q_m)$

Freeman posits that the price of environmental quality increases in quality at a diminishing in rate:

[3.12] $\partial P_h / \partial Q_m > 0$
[3.13] $\partial\partial P_h / \partial\partial Q_m < 0$

Hoen et al. (2009) apply the work of Rosen and Freeman to the case of wind turbines. Hoen et al. posit that wind turbines could affect the selling price of a home in one of three ways: through the down-grading of the scenic vista of a house (*scenic vista stigma*); by changing the character of the area around the home (*area stigma*); or by directly creating disruptive noise or shadows near the dwelling (*nuisance stigma*). These three stigmas may affect properties differently at various distances. For example, only properties very near turbines could be affected by nuisance stigma,

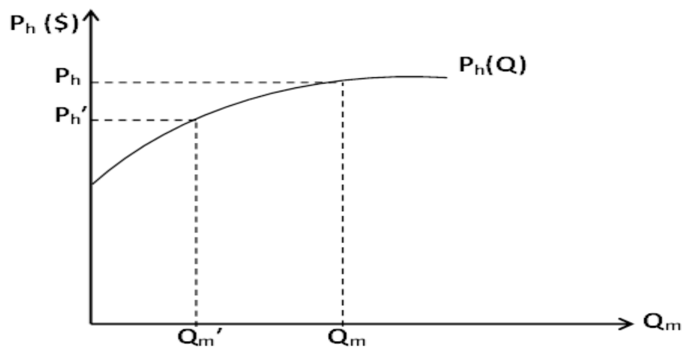

Figure 3.2. Willingness to pay for decreased environmental quality after the addition of an environmental disamenity.

whereas turbines within a medium range could be construed has having a potential impact on a house's scenic vista. Turbines further away could create area stigma. These stigmas may to decrease the environmental quality of a home from Q_m to $Q_m{}'$, thereby reducing willingness to pay for a home experiencing these stigmas as shown in Figure 3.2. The feasible ranges of these stigmas depends respectively on the range of the noise and shadows created by turbines, the original viewshed of the property, and the extent that wind turbines affect the overall character of an area.[17]

Many organizations and researchers suggest the possibility that wind turbines increase home values.[18] Indeed, many onlookers describe wind turbines and farms as "beautiful" and "sculptural" and others prefer them for their symbolism of clean energy and local economic development (National Research Council, 2007). More concretely, landowners receive income from turbines on

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[17] While flickering shadows caused by wind turbines only affect homes within 1000 feet (about a fifth mile) of a wind turbine, the distance at which wind turbines are considered to be an acoustic nuisance is disputed. Audible sound can only be heard with about a half mile of a wind turbine, but infrasound (low frequency inaudible sound) has been reported more than two miles from wind turbines. Topology, ground cover, and other factors can also alter these thresholds. See Cummings (2011) for a review on wind turbine sound.

[18] Again, see the frequently asked questions page for the Department of Energy (US DOE, 2010) and the weblog of the wind industry association (AWEA 2012).

their property, so if a nearby turbine is located on a sold property there could be positive effects of proximity to wind turbines within a close radius. While these are both theoretical possibilities, past studies, community groups, and concerned local governments have focused on the potential negative stigmas of wind energy projects. Hoen et al. (2009) encourages future studies to examine these possibilities.

Hoen et al. (2011) also suggests that the anticipation of these stigmas before the construction of wind turbines could create a fourth stigma that affects property values: *wind turbine anticipation stigma*. Wind turbine anticipation stigma is posited to be the result of risk-averse behavior in reaction to the unknown potential influence of wind turbines on a property. These theoretical considerations can be expressed in the following guiding equation:

[3.14] $$P_{ijt} = (\beta_0 Structure_{ijt},\ \beta_1 Neighborhood_{jt}\ ,\ \beta_2 Environmental_{ijt}\ ,\ \beta_4 Scenic_{ijt}\ ,\ \beta_5 Area_{ijt}\ ,\ \beta_6 Nuisance_{ijt})$$

where the selling price P of house i in neighborhood j at some time t before or after the construction of wind turbines is a function of structural characteristics, neighborhood characteristics, environmental quality, the effect of wind turbines on the scenic vista of a house, the effect of wind turbines on the character of the surrounding area, and the creation of any nuisance by the wind turbines.

The second stage of hedonic regression analysis proposed in Rosen (1974) would allow the derivation of the demand curve for homes with and without the treatment of wind turbines. The first stage, outlined above, only allows the estimation of the equilibrium price schedule shown in Figure 1, whereas the second stage would allow the estimation of the underlying bid and offer functions of consumers and producers. Second stage hedonic regression analysis is plagued by econometric difficulties. Because the characteristic of the presence of a wind turbine cannot be “unbundled” from homes near wind turbines, the pure relationship between the price and quantity demanded of wind turbines is cannot be estimated without additional information. Otherwise the second stage, using the price of the wind turbine presence estimated in the first stage as an explanatory variable, must simply reuse information. However, Eckland, Heckman, and Nesheim (2004) suggest that nonparametric modeling techniques can help identify the unknown structure of consumer demand. Netusil, Chattopadhyay, and Kovacs (2010) find that a two-stage least squares estimation would allow the identification of the demand function if instruments could be identified that are correlated with the presence of an amenity but uncorrelated with consumer tastes. However, Palmquist (1992) shows that first-stage regression analysis adequately measures total costs in cases with a small number of observations and a small geographic area. The case of wind turbines exhibits relatively localized potential externalities. Further, the current paper does not seek to measure consumer demand for residential proximity to wind turbines, but rather to identify whether wind turbines have had any significant measurable effects on home values. If these effects are shown to exist, the next step is to calculate the disutility or utility to for homebuyers using second stage hedonic regression analysis.

4. Econometric Technique

This paper measures the effect of wind turbines on home prices by estimating several models.[19] I seek to isolate the effect of the presence of a wind turbine near a property on the value of a home from other characteristics of the structure and neighborhood of a property as well as the timing of the sale. These other characteristics may be correlated with the proximity of wind turbines if, for example, smaller homes are closer to wind turbines. The natural log of the dependent variable, the

[19] The econometric approach used in this paper draws from Carter (2011), which found no effect of wind turbines on property values, and Heintzelman and Tuttle (2012), which found large and significant negative effects of proximity to wind turbines on property values. Carter (2011) includes a variable for distance to the nearest wind turbine in 2011, regardless of the time of sale, in addition to interaction terms between this distance and a dummy variable that equals 1 if the sale occurred when the turbine was constructed. The inclusion a variable for distance to the nearest wind turbine in 2011controls for the unobserved effects of proximity to the site of a future turbine which might make it appear that turbines decrease home values when really turbines are built near lower value homes. Therefore, the interaction term is the coefficient of interest. Heintzelman and Tuttle (2012) take a different approach. They update the distance to the nearest turbine over time, so before any wind turbines are built they are effectively infinitely far away. They also use a repeat-sales sample to control for unobserved time-invariant home characteristics, which fulfills the same role as the distance to the nearest future turbine in Carter. The Heintzelman and Tuttle approach has the benefit of being able to update the distance to the nearest wind turbine when there are multiple wind turbines nearby, but has the disadvantage of this is that I must make an arbitrary choice for the distance value before a nearby wind farm in built. My paper primarily uses the approach in Carter (2011), but compares those results to results obtained using the method of Heintzelman and Tuttle (2012).

price of homes, is used to account for diminishing returns to home characteristics for home buyers. The three types of fixed effects models can be expressed by:

$$[4.1] \quad \ln(Price_{ijt}) = \beta_0 + \beta_1 X_{ij} + \beta_2 \lambda_t + \beta_3 m_t + \beta_4 \alpha_j + \beta_5 ln(Distance_{ij}) + \beta_6 ln(Distance_{ij}) * Announced_t + \beta_7 ln(Distance)_{ij} * Operational_t + \varepsilon_{ijt}$$

$$[4.2] \quad \ln(Price_{ijt}) = \beta_0 + \beta_1 X_{ij} + \beta_2 \lambda_t + \beta_3 m_t + \beta_4 \alpha_j + \beta_5 Dummy_{ij} + \beta_6 Dummy_{ij} * Announced_t + \beta_7 Dummy_{ij} * Operational_t + \varepsilon_{ijt}$$

$$[4.3] \quad \ln(Price_{ijt}) = \beta_0 + \beta_1 X_{ij} + \beta_2 \lambda_t + \beta_3 m_t + \beta_4 \alpha_j + \beta_5 Count_{ij} + \beta_6 Count_{ij} * Announced_t + \beta_7 Count_{ij} * Operational_t + \varepsilon_{ijt}$$

where $Price_{ijt}$ is the real sale price of home i in neighborhood j at a given time t, X_{ij} is a vector of time-invariant property characteristics, λ_t represents year dummy variables, m_t represents month dummy variables, and α_j is a vector of neighborhood fixed effects. The variable $\ln(Distance_{ij})$ is the natural log of the distance between a property and the nearest wind turbine in 2012, which allows for a curved relationship between sale price and proximity to a wind turbine. The dummy variable $Dummy_{ij}$ represents the presence of a wind turbine within any of several distance levels away from a property in 2012. The third wind variable is $Count_{ij}$, which measures the number of turbines within concentric circles that use the same intervals as the distance levels. All three wind variables are interacted with the dummy variables $Announce_t$ and $Operational_t$ that equal one if the sale occurred during the announcement or operational period of the nearest turbine and zero otherwise. These interaction terms are my variables of interest.

Economists have an intuitive reason to use fixed effects because theory tells us that the neighborhood in which a property is located in is a characteristic considered by buyers. Census block group level fixed effects are used for the α_j neighborhood fixed effects. I test several other levels of fixed effects including municipality, zip code, census tract and census block. The census block group allows the smallest geographic level of fixed effects that contained sufficient variation in distances from turbines.[20] The census block group fixed effects control for unobserved factors that affect a

[20] The smallest fixed effects level, the census block, would have been ideal. However, this would have led to fewer than 4 sales per census block, which would remove too much variation, including distance to wind

property's sale price that can be explained by that property's location within a particular census block group.

The second set of models uses an even finer level of fixed effects—at the property-level—by only including sales that were sold at least once before and at least once after the construction of the Twin Groves wind farm. This specification includes the same three types of turbine proximity measures as the previous models in equations [4.1] – [4.3] :

[4.4] $$\ln(Price_{ijt}) = \beta_0 + \beta_1\lambda_t + \beta_2 m_t + \beta_3\eta_j + \beta_4 ln(Distance)_{ij} * Announced_t + \beta_5 ln(Distance)_{ij} * Operational_t + \varepsilon_{ijt}$$

[4.5] $$\ln(Price_{ijt}) = \beta_0 + \beta_1\lambda_t + \beta_2 m_t + \beta_3\eta_j + \beta_4 Turbine_{Dummy_{ij}} * Announced_t + \beta_5 Turbine_{Dummy_{ij}} * Operational_t + \varepsilon_{ijt}$$

[4.6] $$\ln(Price_{ijt}) = \beta_0 + \beta_1\lambda_t + \beta_2 m_t + \beta_3\eta_j + \beta_4 Turbine_{Count_{ij}} * Announced_t + \beta_5 Turbine_{Count_{ij}} * Operational_t + \varepsilon_{ijt}$$

Equations 4.4, 4.5, and 4.6 include η_i , a dummy variable for each property. Property-level fixed effects scoop out all the variation that can be explained by an individual property's observed or unobserved property characteristics that do not change over time. For this set of models, the variation on which the wind variable estimates will be based is a change in price that is not explained by time-invariant property characteristics, seasonal time trends, and year to year time trends. The tradeoff for the mitigation of omitted variable bias is that a dummy variable for each property greatly decreases the degrees of freedom for each model, which inflates standard errors and could decrease coefficient significance levels. Further, this specification leaves the risk that if the property values near wind turbines are declining at a faster rate than other homes due to some other omitted time-variant factor a false negative effect could be found.

The measurement of any effect of wind turbines on property values is obstructed by three

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turbines. The zip code and municipality have a similar geographic scale to census block group, but irregularities in the boundaries (ragged edges) of these groups do not cluster nearby observations as neatly as census block groups. Census tracts are too large and contained up to 457 sales. Heintzelman and Tuttle (2012) also employ census block group-level fixed effects. The census block groups have heterogeneous geographic areas because they are based on population levels, but given that areas of high population density might be more heterogeneous than an equivalent area with low population density, this may actually be a better measure of neighborhood effects that group divisions that use equivalent areas.

main estimation issues. First, there may be unobserved variables omitted from the analysis that co-determine sale prices, such as structure or neighborhood quality.[21] If one or more of these omitted variables is correlated with the residuals, then other coefficients of included variables are biased. The related problem of endogeneity also could bias results if some unobserved third variable affects both likelihood of wind turbine placement and the home prices, or if home prices affect the likelihood of wind turbine placement. Only the problem of time-invariant omitted variable bias can be addressed through a property-level fixed effects estimator using repeat-sales, which holds all characteristics of a property, including unobserved characteristics, constant across time. An instrumental variable approach is required to determine if wind turbines truly cause a decrease in property values, or if instead locations where property values are declining or where homeowners are willing to accept lower sale prices attract wind project developers. Particularly at a county level (as opposed to a state or national level where policies could create natural experiments) such an instrument is not obvious.[22]

The spatial component of this analysis also introduces the problem of spatial autocorrelation, where home prices are likely correlated with those of their neighbors. This is addressed by census block group- and property-level fixed effects which scoop out any variation that can be attributed simply to the location of a property within a geographic area, in addition to error clustering, which allow the errors of individual properties to correlate at the fixed effect level of either census block group or individual property.

[21] Hedonic regression analysis is notorious for a high likelihood of omitted variable bias given the huge range of characteristics that affect prices, particularly in the real estate market. Any structural characteristic, such as home style, building quality, or landscaping, or neighborhood characteristics, such as location in a cul-de-sac, presence of sidewalk, or neighboring home quality, that was not available is an omitted variable that will bias results.

[22] Geographic and topographical characteristics of a location are often correlated with the presence of wind turbines. However, many of these characteristics, such as elevation or distance to transmission lines, could also affect property values. Shown in Table 3, distance to nearest major road, distance to nearest highway, the presence of an airport within 5 kilometers (3.1 miles), wind power class at 50 meters, and elevation in meters were all tested as instruments for this analysis. Table 4 reveals that wind power class and elevation show promise as instruments, with correlation coefficients of -0.19 and -0.57 respectively with distance in meters to the nearest turbine. However, a Hausman test between an IV regression and an OLS regression yielded a chi-squared coefficient of 18, which does not reject the null hypothesis that an IV regression is superior. However, future research could test finer measures of these potential instruments.

Finally, longitudinal analyses are at risk of temporal autocorrelation as prices in the previous period may co-determine prices in the current period. I address temporal autocorrelation by including month dummy variables, which control for seasonal peaks and valleys in sale prices, and year dummy variables, which control for larger trends over time.

5. Data Description and Summary Statistics

Data come from multiple sources in varying formats. I obtain sales transaction and property characteristic data from the McLean County Assessor Office. As shown in Tables 3 and 4, property characteristic data includes information on the size of the dwelling and the property, on the existence of structures on the property other than the primary dwelling, and on structural features such as bathrooms and fireplaces. Properties were sold over the time period starting in January 1991 to July 2012. I adjust sale price for inflation using the US Bureau of Labor Statistics consumer price index for all urban consumers and code the addresses of properties in ESRI ArcMap using an address locator constructed from the US Census Bureau TIGER File database.[23] Point files of the locations on the wind turbines were obtained through the Freedom of Information Act from the Federal Aviation Administration and compiled by KidWind, Inc.[24] Distance in meters to the nearest turbine was measured in ESRI ArcMap.

Table 5 provides the summary statistics used in the analysis for the all-sales and repeat-sales subsamples. During the study period there were a total of 7,185 sales of 4,134 properties, of these 716 properties were sold at least once before and once after the announcement of the first wind farm for a total of 1,903 repeat-sales transactions. In general, the all-sales and repeat-sales subsamples are very similar. The sale price ranges from $10,135 to $776,273 with a mean of $97,806 in year 2000

[23] TIGER stands for “Topologically Integrated Geographic Encoding and Referencing.” This data is available for download at http://www.census.gov/geo/maps-data/data/tiger-line.html .

[24] This data set is available for download at: http://learn.kidwind.org/teach/gis .

dollars.[25] The nearest operational turbine at the time of sale is about 200 meters (0.12 miles) away from the property, but the mean is about 12,400 meters (7.7 miles) away for the all-sales sample. However, in both samples less than 11% percent of sales, only 813 transactions, were fewer than 4,828 meters (3 miles) from the nearest future wind turbine, as shown in Table 6. Table 7 further shows that 13% of all sales occurred after the nearest turbine becomes operational. This implies that very few homes in this subsample would theoretically be affected by nuisance or visual stigma.

Other observable home characteristics are almost identical between the all-sales and repeat-sales samples, as shown in Tables 5 and 7. The homes in this sample have large variation in age and size. Most have garages and central air conditioning. Very few homes, only 0.79%, are attached to farm properties. Note that a greater percentage of sales occur in later years as well as during summer months, revealing the importance of including year and month dummies in the model.

The geographic distribution of property sales is shown in Figure 3. Many sales from the largest city in the study area, Bloomington-Normal, were omitted from the analysis due to higher levels of error in these properties' addresses. Further, a preponderance of urban transactions in the sample could bias coefficient estimates if homes prices in urban and rural areas are differentially affected by home characteristics. Overall, properties are evenly distributed across the county at varying distances from wind farms. The change in sale frequency and sale price over time is shown in Figure 4. There appears to be a large drop in sale frequency right after the announcement of the Twin Groves wind farm, but it is not clear if this is simply an exogenous shock or a causal result of the wind farm announcement. Sale prices and frequencies do not appear to be affected by the 2008 housing crisis. This is further illustrated in Figure 5. Rural counties and my sample were clearly insulated from the housing bubble and crash that affected the rest of Illinois.

These data carry a risk of measurement error both in the measurement of proximity to wind turbine and in the start date of the existence of wind turbines. First, because addresses were coded

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[25] Transactions below $10,000 in real price were excluded from the data as these properties are unlikely to be arms-length transactions. This cut off is standard and employed by Heintzelman and Tuttle (2012).

using an address locator the location of property sales were considered to be along a road—not the precise location of the dwelling. Further, given that addresses were matched by hand and drew from a data set with multiple spelling errors, it is possible a few addresses did not correspond with the actual location of properties.[26] Given the small number of observations less than 3 miles from a wind turbine, the coefficients of the dummy variables are likely sensitive to even a handful of incorrect measures of proximity to wind turbines. Finally, the address locator created from US Census Bureau information only had data on addresses up to 2010. This means that homes built since then were excluded from analysis.

Second, the timing of the existence of wind turbines for homebuyers may not be accurately reflected in the date that turbines are announced or become operational. Developers release maps of proposed turbine sites prior to permit approval and construction and testing of turbines begins years before the wind farms become operational. This information leakage was partially corrected for by including separate periods for the announcement and operation of the wind farms, but information about the location of wind turbines that was available before the approval of the projects could have affected home prices. Further, the possible effect of the two approved but not yet constructed wind farms, Bright Stalk and Black Prairie, is not included in analysis and could bias results if their approval in 2010 affected home values.

6. Results

Table 8 shows results from the six models across the all-sales and repeat-sales samples. Model 1 uses a census block fixed effect level with a continuous measure of distance to the nearest wind turbine. The coefficient on the natural log of distance to the nearest turbine in 2012 is negative but insignificant. Neither interaction term of continuous distance with the announcement or operational period is statistically different from zero. This makes sense, as the majority of homes are so far from a wind turbine that they are likely not affected by it. In Model 2, the dummy variables indicating levels of distance from the nearest turbine in 2012 are not statistically different from zero.

[26] The ArcMap geocoding match score was set to 85, generally accepted as a “good” match for urban and suburban areas. Addresses which were tied were coded as matched.

The interaction terms between the announcement dummy and distance 0.5-, 1-, and 1.5- mile levels are very large, negative, and significant, suggesting that the announcement of the wind farms decreases property sale prices. The interaction terms for these distance levels, as well as for the 2-mile distance level, with the operational period are also large and negative, although only significant for the 1-, 1.5-, and 2-mile levels. This suggests that the decrease in property values persists into the operational phase of wind turbines and rejects the hypothesis that wind turbine stigma subsides after operation. Model 3 includes counts of turbines within the same distance levels from 0.5 to 3 miles away from homes. These results tell a less clear story; the coefficient of the counts of turbines in 2012 with 1.5 miles is significant, large and negative, but the coefficients on the levels nearer and farther away are significant large and positive, indicating that there is not a clear relationship between sale prices and the likelihood of having one additional future turbine near a property. Interacted with the announcement period, however, and additional turbine within 0.5 miles has a large and significant negative effect on prices. The coefficients on turbine counts interacted with the operational period are not significantly different from zero. All three models have an R-squared of about 0.54, shown in Table 9. Taken together, the results of Models 1 through 3 suggest that the presence of wind turbines is decreasing property values within a radius of 1 to 1.5 miles away during both the announcement at operational phases.

Across Models 1 through 3, there is virtually no change in the sign, magnitude, or significance level of the structural and neighborhood controls, as shown in Table 9. This means that the addition of wind variables is not picking up the effects of changes in observable variables. As the size of the single family home or other structures on the property increase, so does the sale price. Most of these controls are significant and have the expected sign, and those with unexpected signs are not statistically different from zero. The negative and significant sign on the dummy variable for homes with a porch could be attributed to an unobserved quality characteristic; perhaps lower quality homes or homes with less landscaping tend to have porches. Proximity to rivers increases sale prices which makes sense given that water features tend to be desirable in a neighborhood. Proximity to railroads is significant and negative, perhaps because these areas tend to be more industrial and less desirable residential areas.

Models 4 through 6 regress the natural log of the real price on continuous, dummy, and count measures of proximity to wind turbines using the repeat-sales subsample. In these models, measures of distance to the nearest wind turbine in 2012 are not needed because property-level fixed effects hold all time-invariant property characteristics constant. The R-squared for these three models is consistently about 0.76, indicating that the property-level fixed effects sweep out much of the variation in sale prices compared to the all-sales models. As with Model 1, the measures of continuous distance in Model 4 are not statistically different from zero. In Model 5, levels of distance are not significant during the announcement period, although the coefficient on the 1-mile distance level is large and negative. During the operational period, both the 0.5-mile and 1.5-mile distance levels are large and negative, but only the 1-mile distance level is statistically significant (at the 1% level). In Model 6, none of the interaction terms between turbine dummy or count variables are statistically different from zero. Taken collectively, the results from these repeat-sales models tell a less clear story than Models 1 through 3. There is still some evidence that wind turbines decreased sale prices within a radius of 1 mile, but these results are not reflected in Models 4 or 6. However, it is important to remember that the repeat-sales sample is much smaller than the all-sales sample and many transactions very near wind turbines were not repeat-sales and were thus excluded. Further, the inclusion of a dummy variable for each of the 717 repeat sale properties likely inflated standard error.

Across Models 1 through 3, tests for multicollinearity using pairwise correlation and variance inflation factors reveal very little collinearity between structural and spatial controls.[27] The Breusch-Pagan test for heteroskedacity significantly rejected the null hypothesis that the residuals are homoskedastic, but a plot of the residuals reveals errors centered around zero, as shown in Figure 6. Clustered standard errors at the fixed effect level were therefore used for all six models. The linear

[27] The highest variance inflation factor was 10 on ln(distance to nearest highway). All others, besides the time and census block group dummies, age, and age squared, were below 5.

cutoff in the lower left-hand corner of Figure 6 occurs because the homes included were bounded at the real price of $10,000. The residual versus actual plot in Figure 7 shows this linear cut-off again and also reveals that the model is systematically overestimating the prices of more expensive homes and underestimating the prices of low homes. The correlation coefficient between the residuals and the natural log of the real price is 0.67 for the all-sales model and 0.48 for the repeat-sales model. This strongly suggests that there are time-variant omitted variables that were not scooped out by the property-level fixed effects and are affecting sale prices.

Figures 8 and 9 reveal a pattern in the spatial distribution of residuals for both the all-sales and repeat-sales models. In general, the residuals appear to be distributed in a spatially random way. For Models 1 and 4, the correlation coefficient between the residuals and the natural log of distance to the nearest turbine interacted with the announcement period and operational period dummies are both less than 0.000.

7. Sensitivity and Residual Analysis

While the results presented in Section 6 seem to clearly suggest that proximity to an operational turbine, and perhaps an announced turbine, decreases home sale price, careful analysis of the residuals of these models casts some doubt on this conclusion. Three techniques were used to test the robustness of the initial results. First, the residuals of Models 2 and 4, which provided the most evidence of a negative effect of wind turbines on sale prices, are regressed on the levels of announced and operational wind turbines. Table 10 shows the results of Models 2.R and 4.R . A comparison to the correlation coefficients in Table 8 shows that many of the announcement and operational period distance levels significantly predict the residuals in a similar pattern as the distance levels predict sale price. These results suggest that at least some of the large magnitude of the negative coefficients in Models 2 and 4 could be due to time-variant omitted variables that are contaminating the effect of wind turbines on sale prices.

Second, I conduct estimation separately for the Twin Groves and White Oak wind farms. I exploit the difference in the timing of the announcement and operational periods of the two wind farms to examine whether time trends are the source of the baseline results.[28] Using the same functional forms and Models 1 through 6, I include separate distance measures for the White Oak and Twin Groves wind farms. The difference in the timing of announcement and operation between these two wind farms shows that the negative effect of wind turbines on home values persists from 2005, when the Twin Grove wind farm was announced, to 2012, when the White Oak wind farm became operational. Shown as Models 2.A and 4.A in Table 11, the distance levels continue to show that, even when national housing prices were trending upwards, the announcement of the Twin Groves wind farm significantly decreases home values within a radius of 1.5 miles. However, the operational period of the Twin Groves wind farm and the announcement period of the White Oak wind farm have the most consistently large, negative and significant distance level coefficients, so it is possible that the period of 2008 to 2010 pushed down housing prices. However, the fact that negative, large and significant coefficients also occur for periods before 2008 and after 2010 decreases the likelihood of an interaction effect between the housing crisis and these homes. This supports the initial results suggesting that proximity to announced and operational wind turbines is decreasing property values rather than the effect of unobserved heterogeneous time trends.

Finally, I test the possibility that time-variant spatial heterogeneity was the cause of the large negative coefficients by creating two “quixotic” wind farms that were the same number of turbines in the same orientation as the real wind farms and performing the same six regressions as in Models 1 through 6 on these new distances. In ArcMap, I move the Twin Grove and White Oak wind farms to different locations in McLean County that are similar distances from the Bloomington-Normal metro and major highways as the real wind farms. The quixotic wind farms are shown in comparison to the actual wind farms in Figure 10. I measure the distance to these ghost wind farms in the same way and using the same dates for announcement and operation as I do for the actual wind farms. These new measurements essentially assign dummy variables for distance levels within 3 miles to a new and completely different set of homes in order to “shake up” the matrix in a quasi-random way. The

[28] See Table 2 for dates of wind farm announcement and approval.

correlation between distance to the real wind farms and distance to the quixotic wind farms is relatively high given that the quixotic wind farms were purposefully moved to a similar part of the county as the real farms. However, the correlation between the distance levels for the real and quixotic turbines is virtually zero since there are no transactions that occur within 3 miles of both the real and quixotic turbines.[29] If the coefficients on the measures of distance to the ghost wind farms are similar to the coefficients on the measures of distance from the real wind farms, this will cast doubt on the validity on the reliability of the original results.

Table 12 compares the estimated percentage changes from the dummy variable distances from announced and operational turbines across the original Models 2 and 4. I also test the specification used by Heintzelman and Tuttle (2012), which found large and significant decreases in sales prices due after the announcement of wind farms, using the McLean County data and present the estimated percentage changes as Models 2.B and 4.B.[30] The estimated percentage changes from the quixotic wind farm models using dummy variable distance levels are presented as Models 2.C and 4.C. These results are presented alongside the actual results from Heintzelman and Tuttle (2012).

Table 12 reveals several interesting relationships. Overall, the results from Models 2, 2.B, 4, and 4.B resemble the results of found it Heintzelman and Tuttle (2012). The largest percentage changes are around 1 mile for both an announced or operational turbine and predict a decrease in the range of 20 to 40%. The repeat sales models predict significant negative effects of wind turbines within a smaller radius than do models using a full sample. Models 2 and 2.B predict very similar percentage changes; the significant and negative effect of wind turbines extends to 1.5 miles during the announcement period and about 2 miles during the operational period. Between repeat-sales Models 4 and 4.B the magnitudes are very similar but the significance levels of coefficients in Model 4.B are much higher. This is likely due to a handful of properties that had an updated distance level

[29] The highest correlation coefficient is between

[30] Heintzelman and Tuttle (2012) use a measure of distance where a non-existent turbine is almost infinitely far away. Distance is transformed to the natural log of the inverse distance. As wind farms are announced or become operational during the time of the sale transaction, distance is updated.

within 3 miles between the announcement and operational periods for in Model 4.B but not in Model 4.

The most interesting result in Table 12 is that the magnitude and significance of many of the coefficients on the distance levels in Models 2.C and Models 4.C are very similar to the other Models. Model 4.C, which uses a repeat-sales sample, predicts a 23% decrease in sale prices with the addition of a quixotic turbine within 1 and 1.5 miles away from a property and is significant at the 1% level. Model 4.B predicts a 40% decrease significant at the 1% level in sale price due to an additional turbine within 0.5 and 1 mile away, a while Heintzelman and Tuttle (2012) estimated a 26% decrease for a turbine within 1.5 and 2 miles which is significant at the 5% level. These results suggest that a repeat-sale, property-level fixed effects specification may not adequately isolate the effect of wind turbines on sale prices.

After these additional analyses, there remains the possibility that proximity to wind turbines does indeed decrease sale prices but the extreme effects seen in the original analysis are weakened. Rather than isolating and interpreting one coefficient of one distance level, examining the continuum of magnitudes and significance within 0.5 to 3 miles is necessary. While the ghost wind farm models 2.C and 4.C predict coefficients that mimic the magnitude, sign, and significance level of the same distance level as Models 2 and 2.B, the presence of large, positive and significant coefficients differentiates it from the findings of models 2, 2.B, 4 and 4.B and makes it more likely that these four models are reflecting some decrease in home values associated with wind turbine announcement and operation. The addition of the quixotic models neither confirms nor refutes the findings of this paper, but it does cast doubt on the reliability of the repeat sale hedonic model. Further research could investigate the robustness of findings from this and other papers that rely on the repeat sales specification to isolate the effects of environmental disamenities.

8. Discussion and Conclusion

The results of this paper must be interpreted with caution given limitations of the methodology of both the original analysis and the residual analysis. A lack of data impedes the investigation of several important aspects of the relationship between wind turbines on property values. Property characteristics were only available for the year 2011, so if homes were remodeled or deteriorated in quality in a systematically different way for homes near and far away from wind turbines, these effects were attributed to the arrival of wind turbines. Characteristics of the sale transaction itself, such as where the buyer was moving from or the days on market of the home were not included.[31] Similarly, if neighborhood characteristics changed over time in a systematic way, the static spatial controls will not have captured this effect and the coefficients of interest will be biased. Further, the measurement of any change in home prices also excludes other concerns that community members have voiced, such as residents simply abandoning their dwellings and an overall decrease sale volume. Future studies could investigate the inclusion of time-variant characteristics on the results of hedonic regression analysis as well as include analyses on any changes in home abandonment or days-on-market metrics.

The additional regressions using the quixotic turbines conducted in Section 8 are compelling, but they too face the limitation of omitted time variant variable bias. There are likely other unobserved time-variant characteristics affect these regressions. Future studies could refine a method using technique similar to the quixotic turbines to evaluate how well a hedonic regression analysis can isolate the effects of environmental disamenties. Regardless of these limitations, this paper demonstrates how a thorough residual analysis is necessary to understand the robustness of results.

Given that this paper uses similar methodology as previous papers, (see Heintzelman and Tuttle, 2012; Carter, 2011; and Hoen et al., 2011) and the study area of Hinman (2010), some useful comparisons can be made. This paper does not show that there is a negative and consistently significant effect of the continuous distance measure, nor as large negative and significant effects very near turbines as did Heintzelman and Tuttle. The main difference between that repeat-sales specification and that of the current paper is that a variable for whether the homebuyer was from the same area was included, and that they assumed wind turbines began existing at the date of the

[31] The zip code of the buyer was included in Heintzelman and Tuttle (2012).

publication of the final Environmental Impact Statement (which would have been sometime between the announcement and operation of the turbines). Their specification could have captured more of a negative effect if in McLean County homebuyers had less information about the impact of wind turbines because they were not from the area or because the information about the locations of the turbines was less publicized. The alternative explanation is that homebuyers in upstate New York having different preferences than homebuyers in McLean County, which is plausible if more people might have vacation homes in those areas than in McLean County or if wind energy has a different public image between the two places. Further, academics and wind developers acknowledge that New England, including Heintzelman and Tuttle's study areas in upstate New York, is the seat of more vocal and active community groups and formal lawsuits challenging wind energy development.[32] It is likely that a greater number of residents are more involved in the public discourse about wind energy development in the study area of Heintzelman and Tuttle relative to other regions in the US, where the wind energy discourse is either less heated or has had a shorter time frame to emerge.

Hinman (2010) found evidence to support wind turbine anticipation stigma theory but found no evidence of wind turbine area, scenic, or nuisance stigma. My results imply decreases in during both the announcement and operational periods at distances that imply the existence of scenic and nuisance stigma. There are three possible reasons for this: first, Hinman's results do not reflect decreases in property values within 3 miles of wind turbines, and this paper and Heintzelman and Tuttle (2012) only found results within 2 miles of wind turbines; second, Hinman's paper only includes a year's worth of sales after the Twin Groves wind farm became operational, whereas this paper includes three and a half years' worth of sales after operation, allowing more observations near wind turbines; third, unlike Hinman, this paper also includes sales near the more recently constructed White Oak wind farm, which besides providing more observations near wind turbines was also more

[32] In Vermont, protests and acts of civil disobedience have occurred (Carpenter 2011). In Western Massachusetts lawsuits and appeals have delayed what will be the largest wind farm in Massachusetts for almost a decade.

controversial than the Twin Groves wind farm.

This paper presents weak evidence that wind turbines decrease home values within of two miles, but the sensitivity analyses suggest that future research is necessary to prove that the presence of wind turbines is indeed the cause of these large, negative and significant decreases in home values. In the face of these uncertain conclusions, what action should developers, governments and communities take? The answer to this question lies in the larger literature advising local government responses to wind energy expansion. Community groups often call for property value guarantees but given the frequent fluctuations of home values regardless of proximity to wind turbines this does not seem ideal. Another option is to use setbacks, a minimum distance between turbines and dwellings, to protect nearby homeowners' sale prices.[33]

Perhaps more fundamentally, land use planners must gauge if homeowners and potential homebuyers are concerned about the property value impacts of wind turbines, or if concerns about procedural fairness, wildlife impacts, or nuisance concerns are more pressing. Communities are the best to ask about what the local costs and benefits of wind energy projects are and local knowledge can have a large impact on the planning and net benefit of these projects and are even more important in the face of empirical uncertainty.

[33] In most areas, setbacks are already used to reduce numerous other potential impacts of wind turbines, ranging from simply one and a half times the turbine height to protect dwellings from the turbine falling over, out to a mile from dwellings or neighboring property lines to avoid nuisance and visual impacts. Other community groups have called for much greater setbacks. Current debate usually revolves around set back distances around

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Figures and Tables

Figure 1. Photograph of White Oak wind farm. Taken January 15, 2013.

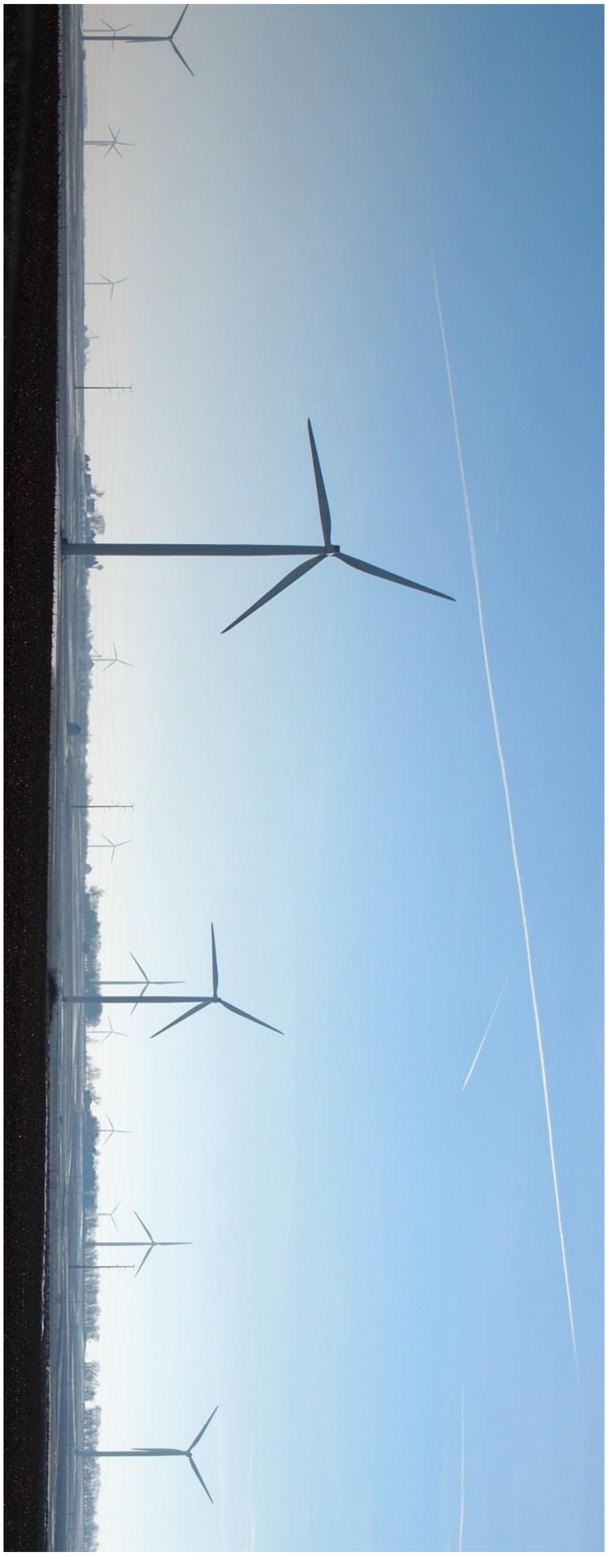


Figure 2. Photograph of Twin Groves Wind Farm with Substation and Transmission Lines. Taken January 15, 2013.

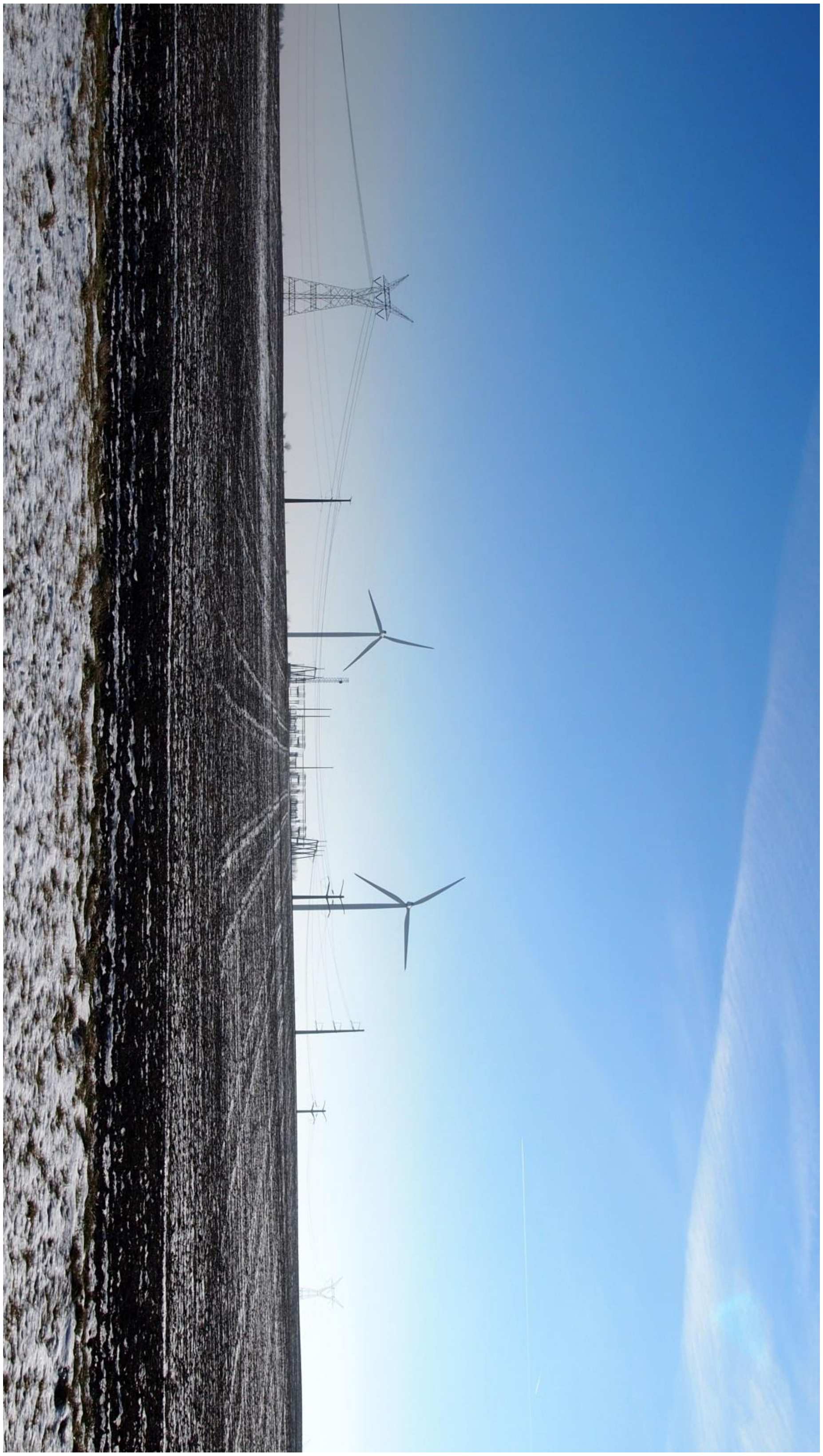
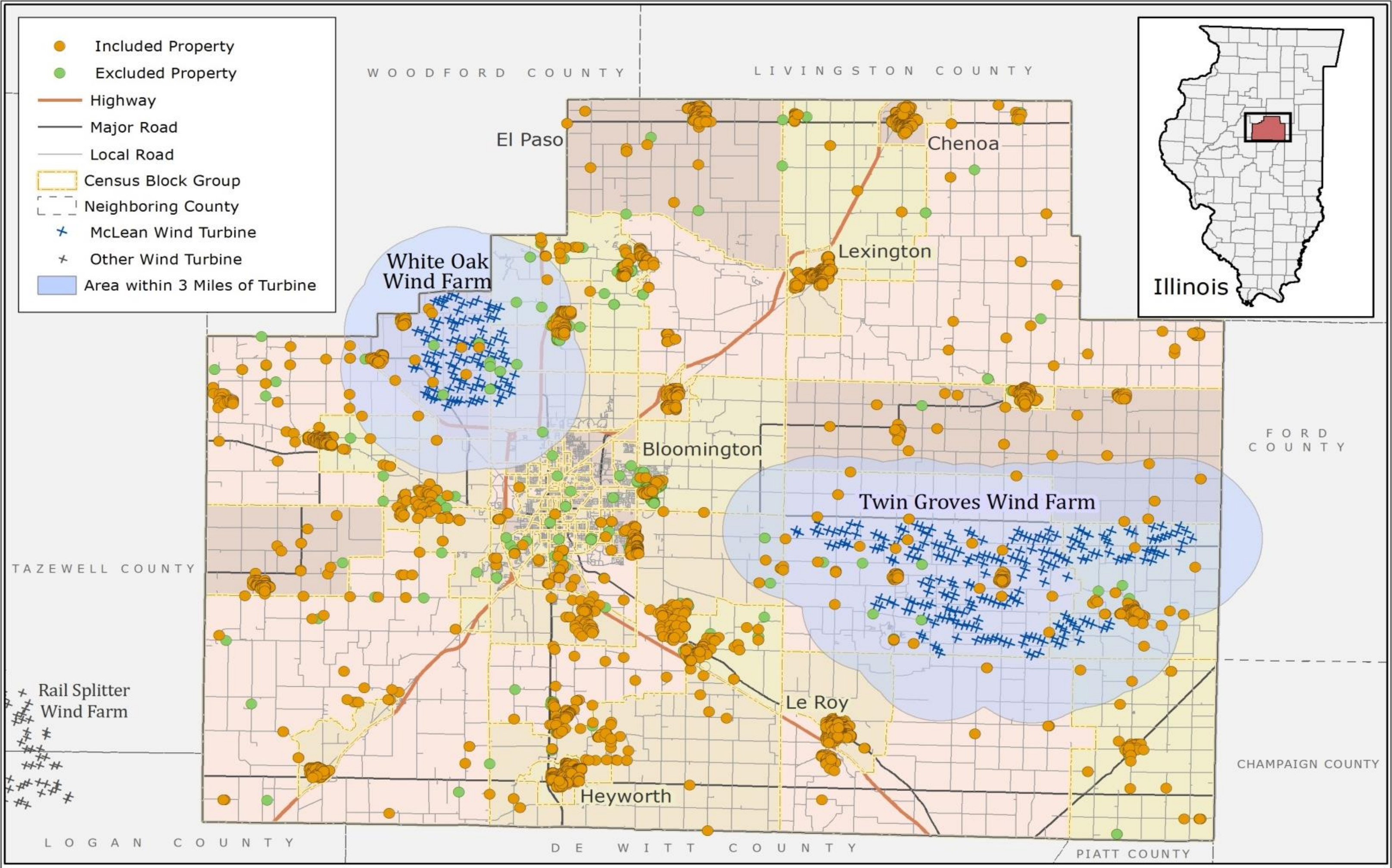


Figure 3. Map of McLean County and Properties Included in Analysis



Notes: This map shows the locations of properties and wind farms included in analyses. Orange dots show properties included in analysis and green dots show properties that were excluded either because they lacked needed data or contained an obvious error. Wind turbines within the county and a 3 mile buffer zone are shown in blue. Twin Groves I and II were announced in 2005, operational in 2008. White Oak was announced in 2008, operational in 2012 Rail Splitter was announced in 2007, operational in 2009.

Figure 4. Frequency of Sale Prices over Time and Dates of Wind Farm Timeline

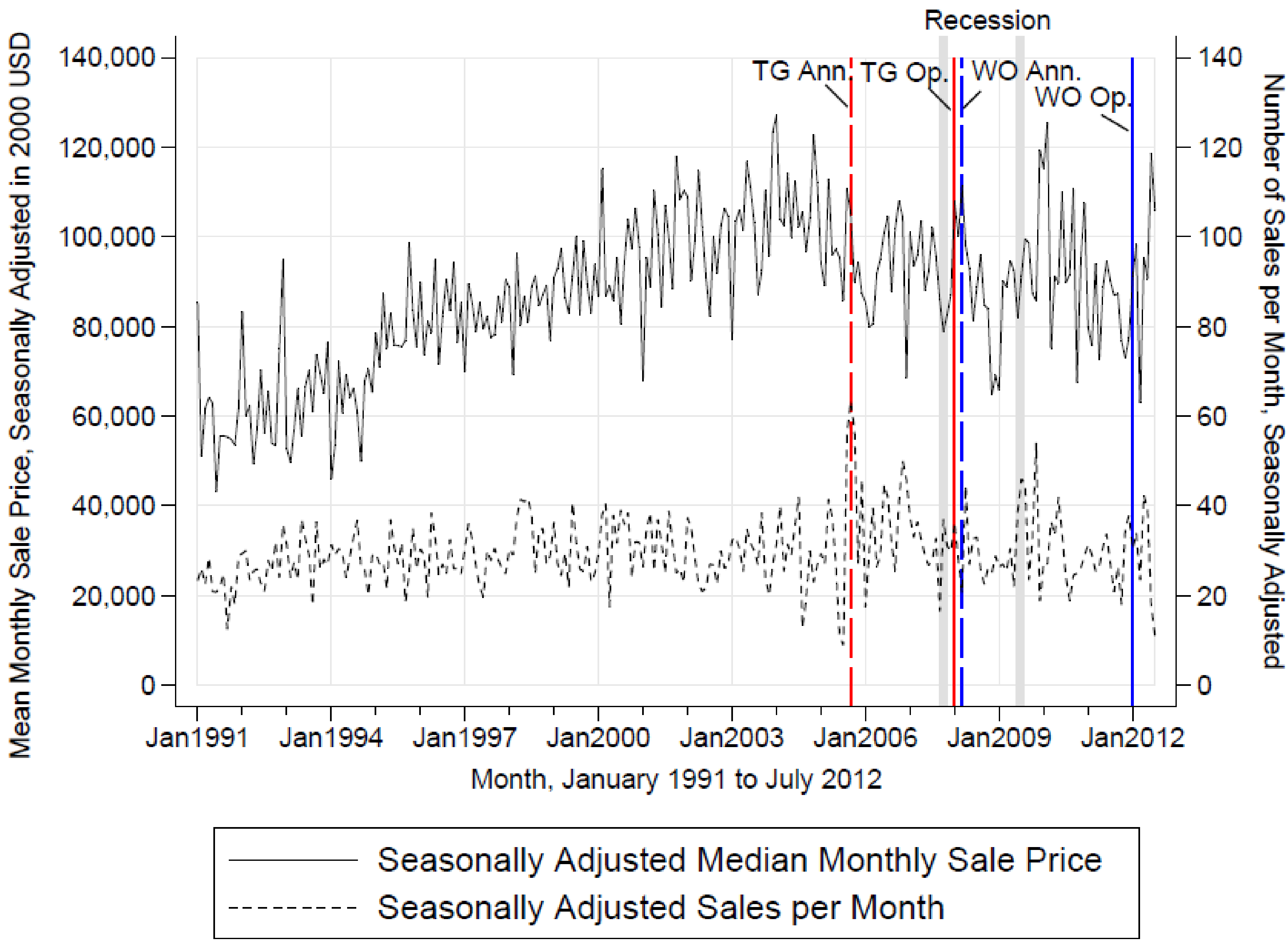


Figure 5. Comparison of Median Housing Values Over Time, Illinois and Rural Counties, 1991 to 2012

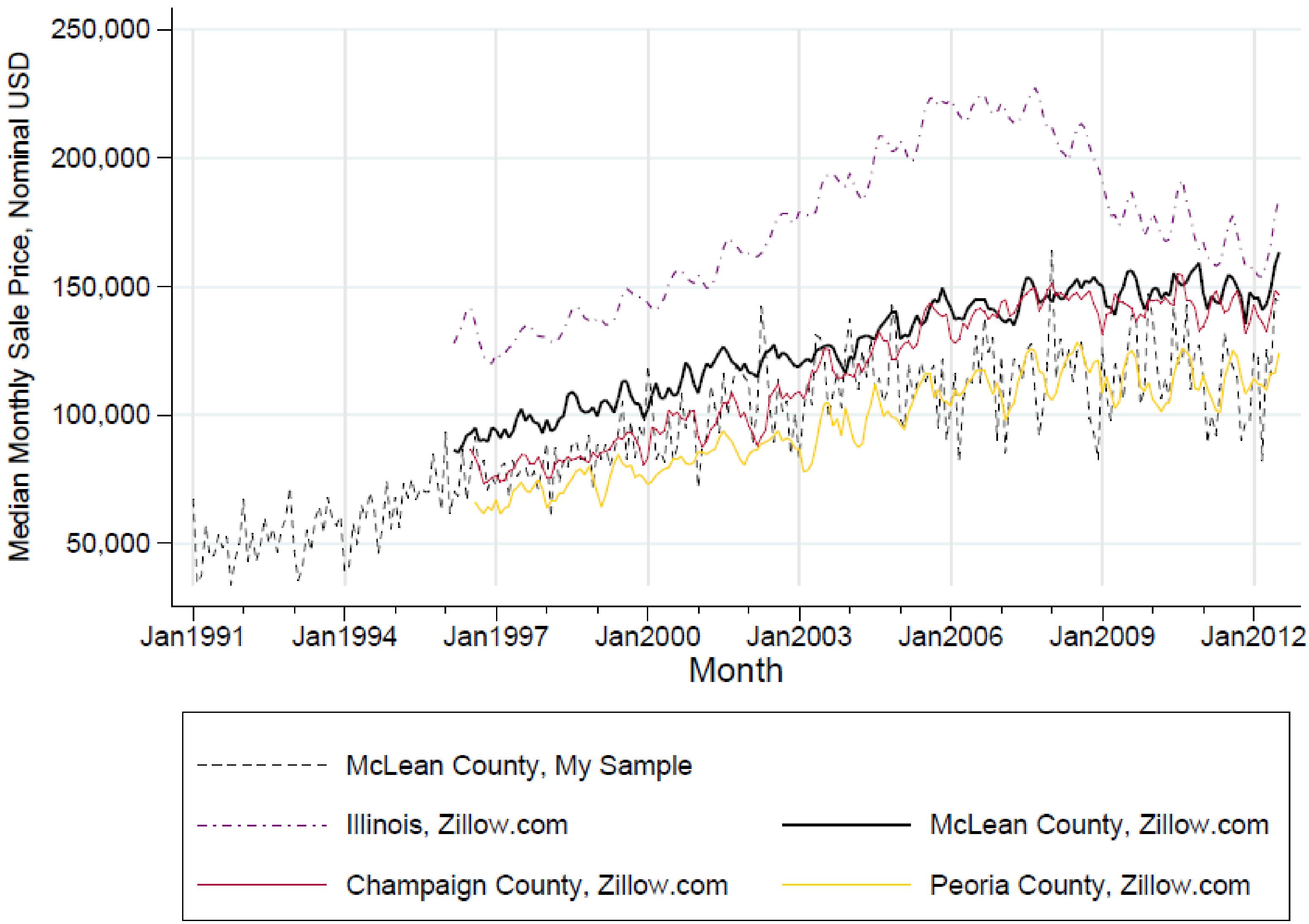


Figure 6. Residuals versus Fitted Home Prices Plot for All-Sales Sample using only ln(Distance) Measure

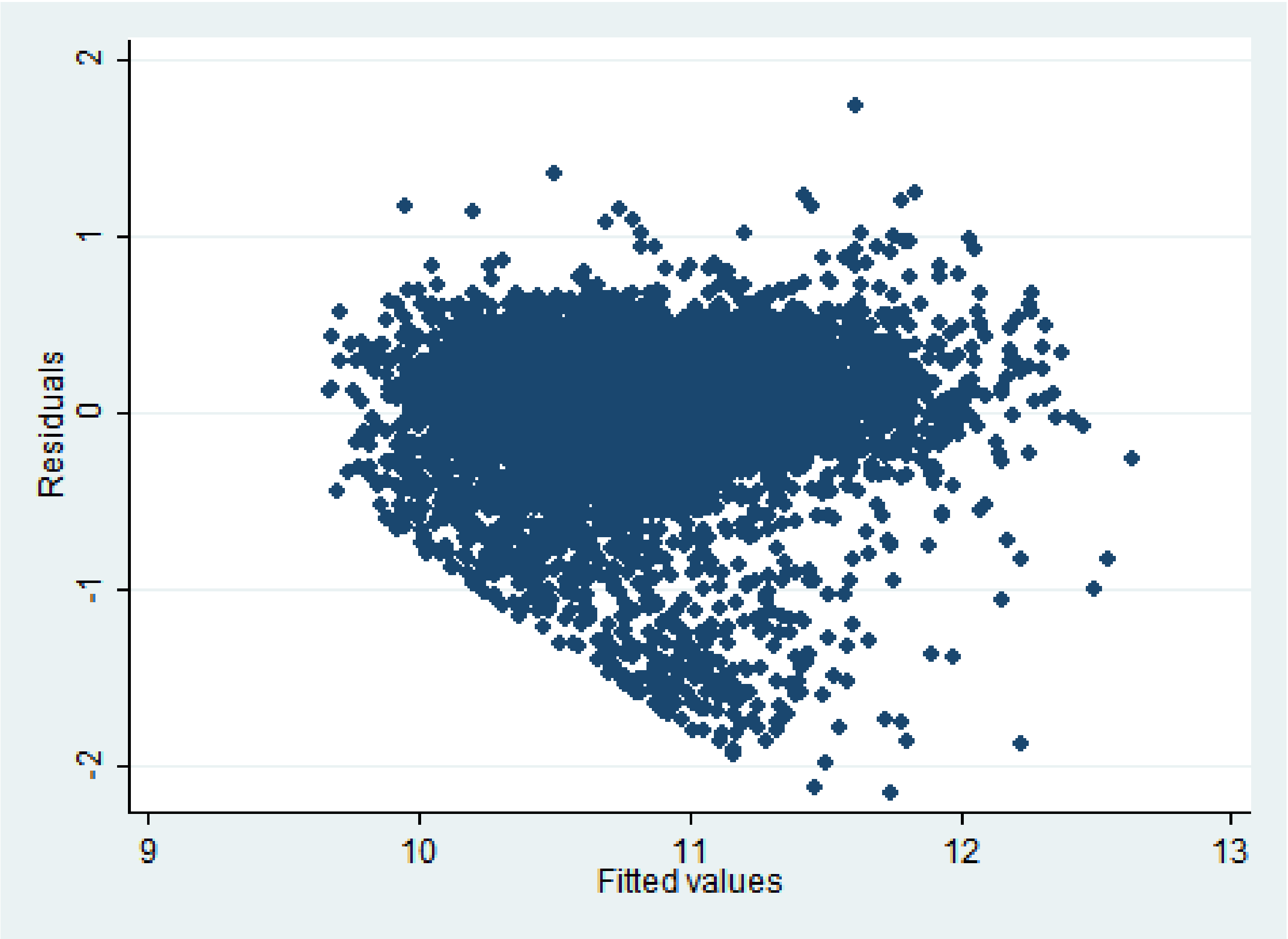


Figure 7. Residual versus Actual Home Prices Plot for All-Sales Sample using only ln(Distance) Measure

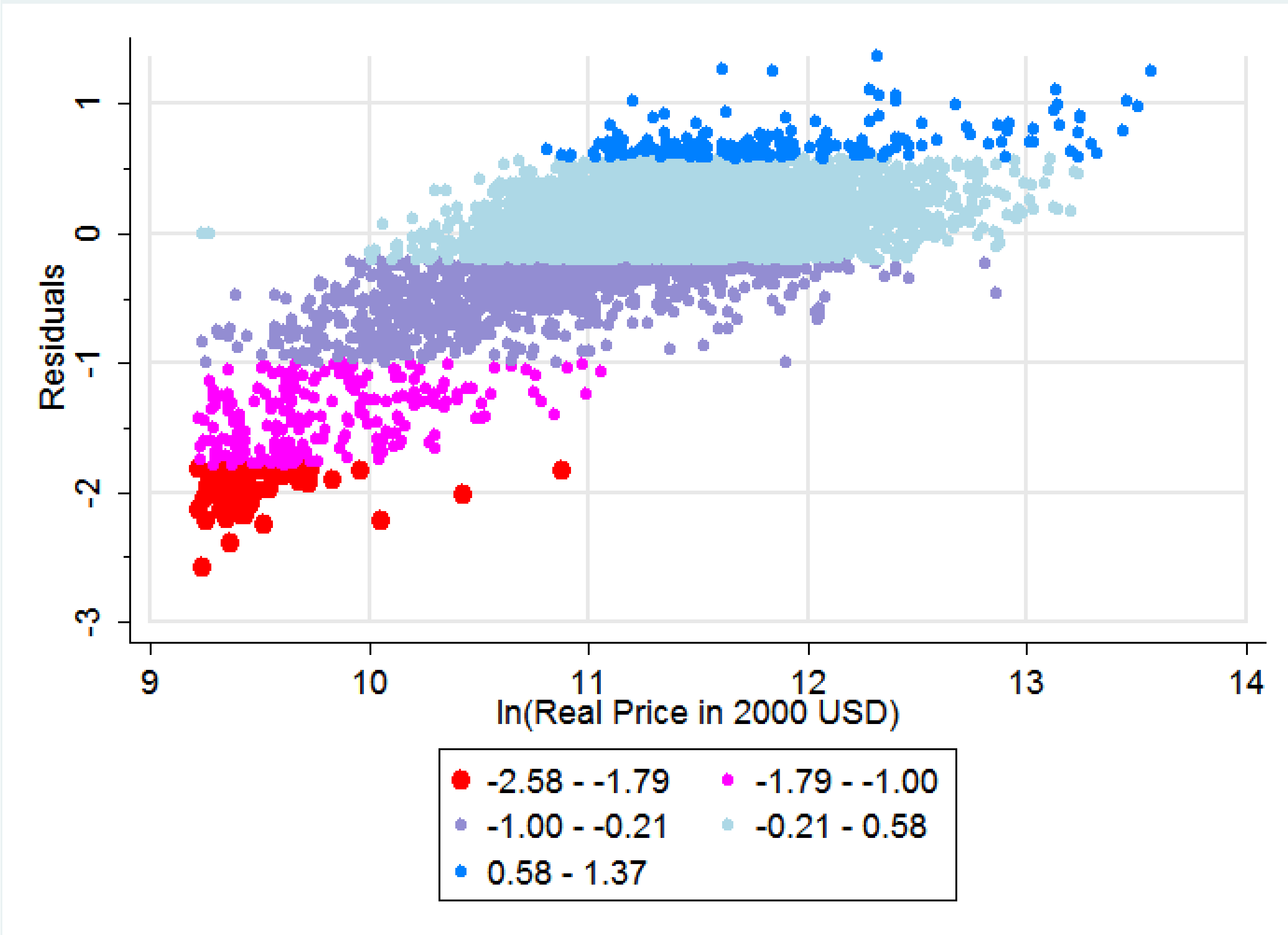
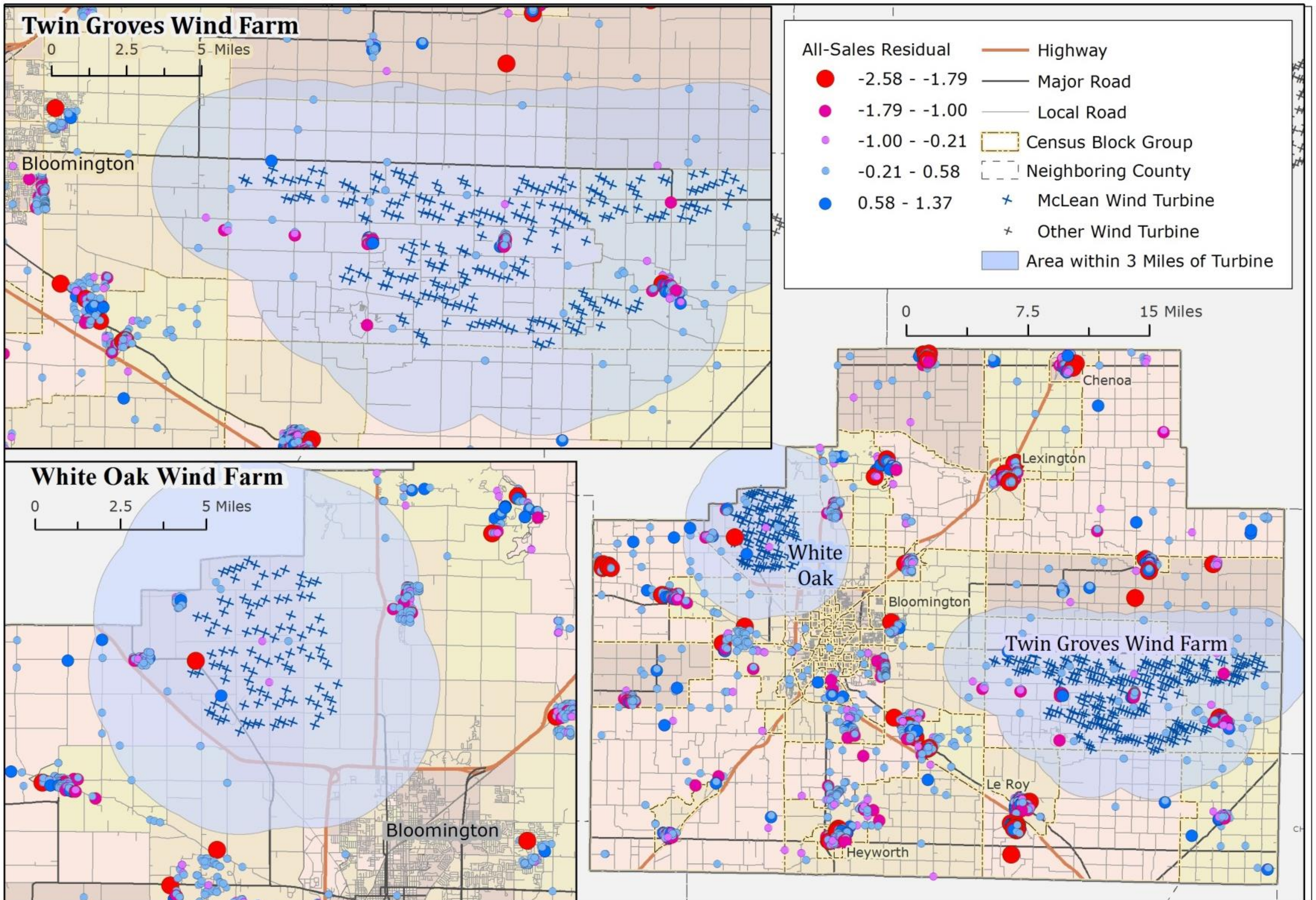


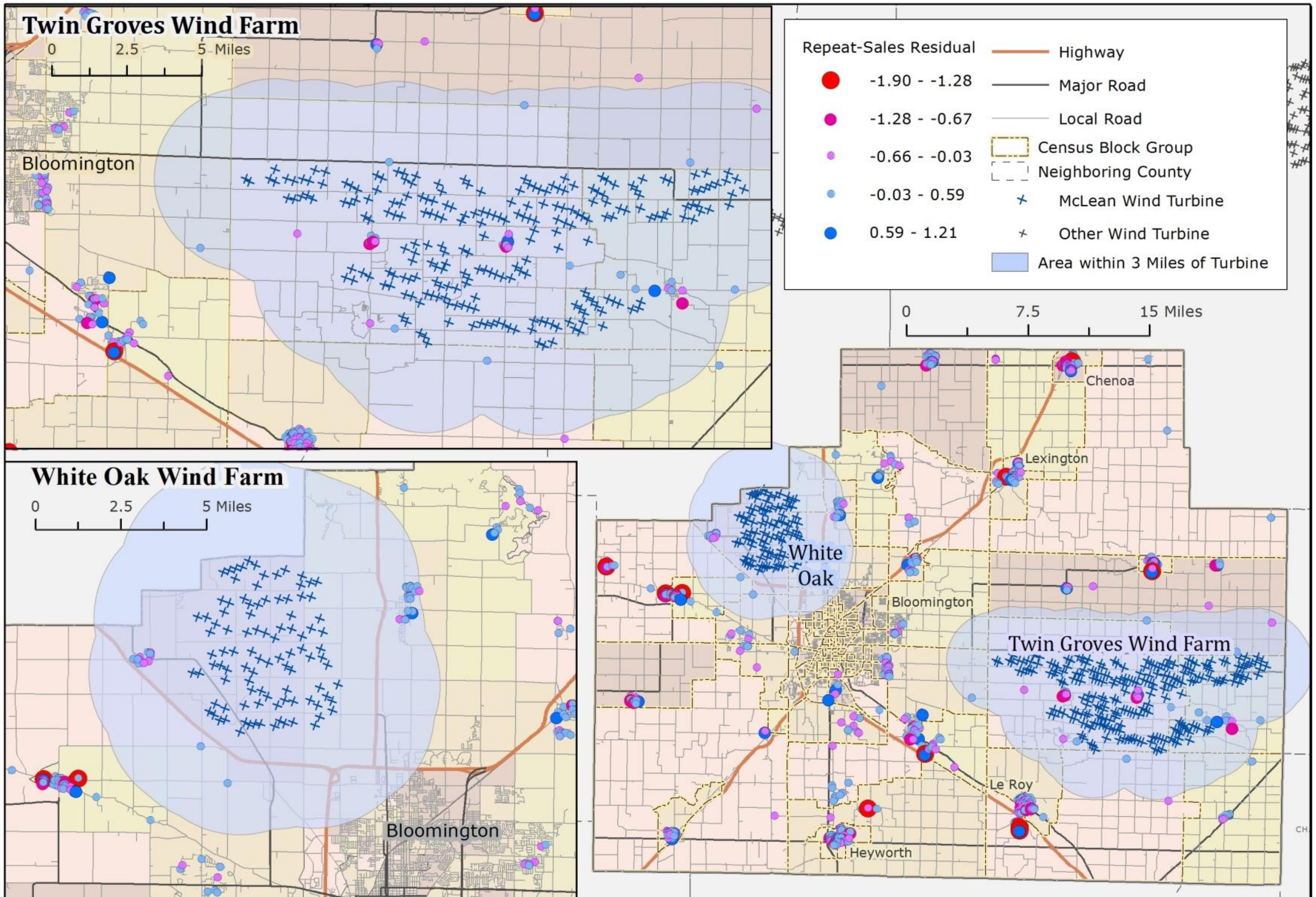
Figure 8. Map of Property Location and Residuals for All-Sales Model



Notes: This map shows the locations of sales transactions and the values of their residuals for a census block group level fixed effects model with no variable for proximity to wind turbines. Residuals are classified using equal interval divisions.

Natalie Camplair
April 17, 2013
Source: US Census Tiger Line Files; Kind Wind Inc.; Author's Calculations
Projection: NAD 1984 UTM Zone 16N

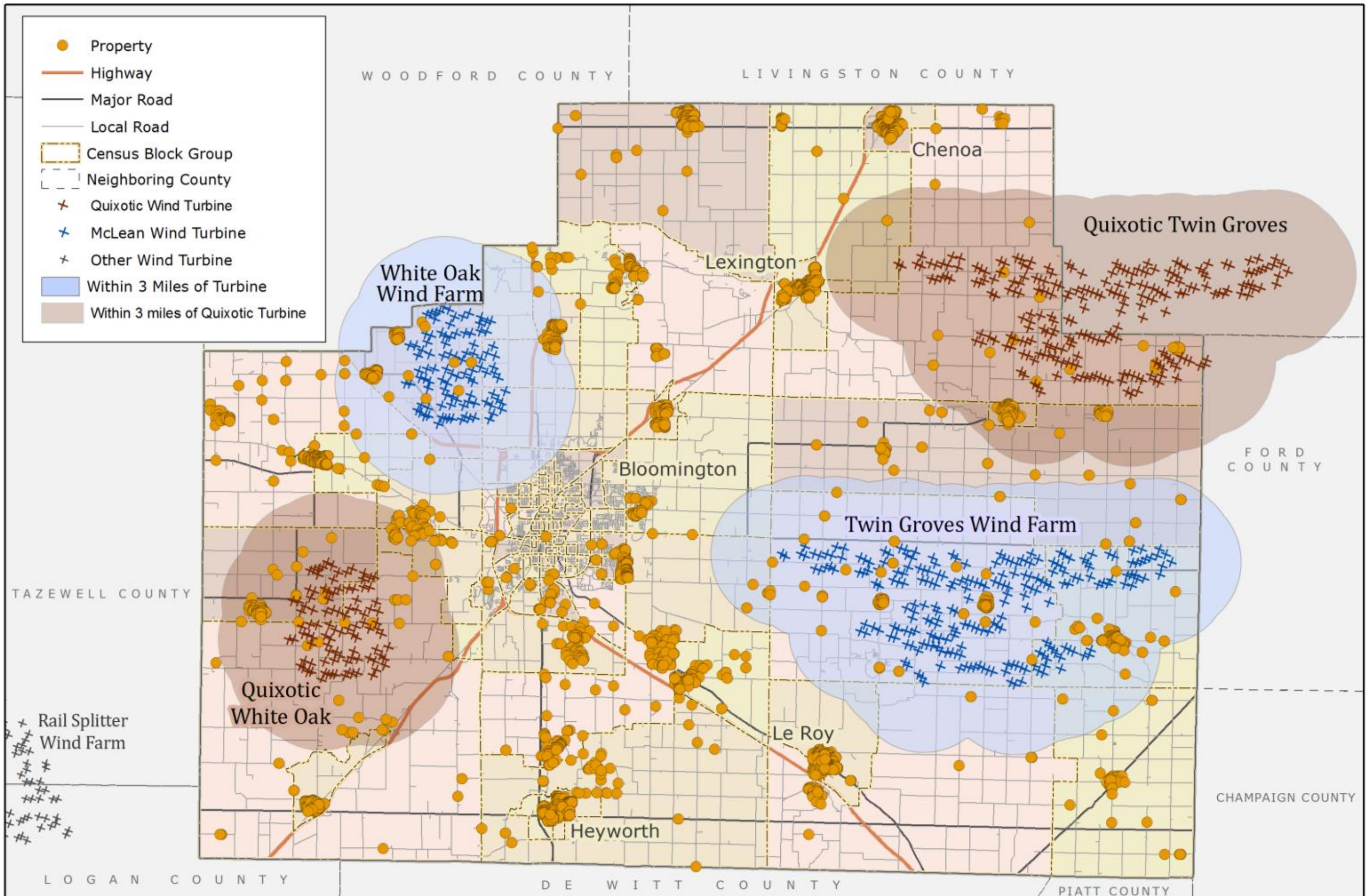
Figure 9. Map of Property Location and Residuals for Repeat-Sales Model



Notes: This map shows the locations of sales transactions and the values of their residuals for a parcel-level level fixed effects model and a repeat-sales sample with no variable for proximity to wind turbines. Residuals are classified using equal interval divisions.

Natalie Camplair
April 17, 2013
Source: US Census Tiger Line Files; Kind Wind Inc.; Author's Calculations
Projection: NAD 1984 UTM Zone 16N

Figure 10. Map of Properties and Real and Quixotic Wind Farms.



Notes: This map shows the locations of two completely fake wind farms and their buffer zones. The distance between these unreal turbines was measured in the same way that distance to the real wind farms is. Results are presented in Models 2.C and 4.C.

0 5 10 Miles

Natalie Camplair
April 17, 2013
Source: US Census Tiger Line Files;
Kind Wind Inc.; Author's Calculations
Projection: NAD 1984 UTM Zone 16N

Table 1. Demographic and Socioeconomic Characteristics of McLean County and Illinois.

	McLean County	Illinois
Population, 2011 estimate	170,556	12,869,257
High school degree or higher, percent of persons age 25+, 2007-2011	93.4%	86.6%
Bachelor's degree or higher, percent of persons age 25+, 2007-2011	41.1%	30.7%
Median household income, 2007-2011	$59,410	$56,576
Persons below poverty level, percent, 2007-2011	13.4%	13.1%
Percent of population that is White (Non-Hispanic), 2010	81.9%	63.7%
Housing units, 2011	70,183	5,297,318
Homeownership rate, 2007-2011	67.8%	68.7%
Median value of owner-occupied housing units, 2007-2011	$154,600	$198,500
Land area in square miles, 2010	1,183.38	55,518.93
Persons per square mile, 2010	143.3	231.1
Source: US Census Bureau State & County QuickFacts		

Table 2. Wind Farm Projects in Mclean County, Illinois.

	Twin Groves I and II	White Oak	Black Prairie	Bright Stalk
Status as of 6/2012	Operational	Operational	Approved	Approved
Approval Date	9/2005	3/2008[34]	1/2010	10/2010
Construction Start Date	7/2006	9/2010	-	-
Operation Date	1/2008	1/2012	-	-
Turbine Number	240	110	Approx. 333	Approx. 223
Turbine Rating	1.5 MW	1.5 MW	-	-
Developer	EDP Renewables[35]	InVenergy	EDP Renewables	EDP Renewables
Source: The Pantagraph Online, 2005-2012, verified in Hinman (2010)				

Table 3. Instrumental Variable Tests, sources and summary statistics of key variables. N = 7,185

Possible Instruments	Source	Resolution	Mean	St.Dev.	Min.	Max.
Wind speed class at 50 meters	US Department of Energy	1 km	2.93	0.28	2	4
Elevation (m)	USGS	0.1 km	236.27	12.86	195	278
Airport within 5 km	USGS	-	41.09%	-	0	1
ln(Distance to Nearest Highway in Meters)	US Census TIGER Line File	-	-8.07	1.24	-10.31	-2.87
ln(Distance to Nearest Main Road in Meters)	US Census TIGER Line File	-	-9.74	1.57	-9.29	2.18
ln(Distance to Nearest Transmission Line in Meters)	US Census TIGER Line File	-	-8.44	1.08	-10.41	-3.05
	FEMA (Vintage 1993), via US Department of Energy	-	-7.86	1.28	-9.82	-0.18

Table 4. Instrumental Variables Tests, key correlation coefficients. N = 7,185

[34] The White Oak project was permitted by the county in 2007, but appeals by a concerned community group delayed construction and final siting decisions until an agreement was reached in 2008.

[35] EDP Renewables has also been incorporated under the names Horizon Wind Energy and Zilkha Renewable Energy.

Possible Endogenous Wind Variables	ln(Adjusted Price of Property)	ln(Distance to Nearest Wind Turbine)	=1 if at least one turbine between 0.5 within 1 mile	=1 if at least one turbine within 3 miles	Number of turbines within 3 miles
Possible Instruments					
Wind Speed Class at 50 meters	-0.11	-0.19	0.14	0.20	0.15
Elevation (meters)	0.14	-0.57	0.34	0.26	0.40
Airport within 5 Kilometers	0.07	-0.01	-0.13	0.07	-0.17
ln(Distance to Nearest Highway in Meters)	-0.07	-0.11	0.16	0.05	0.16
ln(Distance to Nearest Main Road in Meters)	-0.14	-0.13	0.15	0.23	0.17
ln(Distance to Nearest Transmission Line in Meters) [FEMA]	-0.03	-0.28	-0.09	0.06	-0.07
ln(Distance to Nearest Transmission Line in Meters) [Census]	-0.00	-0.08	-0.17	0.11	-0.14

Table 5. Mclean County Summary Statistics

	All-sales N = 7,185				Repeat-sales N = 1,903			
	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max
Adjusted Price (2000 USD)	97,806.20	62,431.90	10,135.90	776,273	97,158.60	56,469.90	10,135.90	513,939
Distance to Nearest Operational Turbine in 2012, meters	12,140.4	6,532.37	203	29,149	12,071.50	6,353.56	610.83	29,125
Distance to Nearest Announced, Non-Operational Turbine at Time of Sale, meters	12,326.7	7,016.4	203.00	29,149	12,264.40	7,018.90	831.00	29,125
Distance to Nearest Operational Turbine at Time of Sale, meters	12,404.4	6,764.5	203.00	29,149	12,377.70	6,920.50	610.83	29,125
Age of House (Years)	50.70	41.81	1	177	52.01	42.01	1	175
Size of House (Square Feet)	1,266.36	538.01	164	15,060	1,220.34	639.14	164	14,387
Lot Size (Acres)	0.60	1.98	0.02	111.42	0.50	1.06	0.06	25.43
Number of Stories	1.38	0.42	1	3	1.38	0.43	1	2
Number of Fireplaces	0.32	0.47	0	2	0.32	0.47	0	2
Number of Bathrooms	1.32	0.56	1	5	1.31	0.53	1	3

Table 6. Means and Frequencies for Categorical Measures of Proximity to Nearest Wind Turbine

Wind Turbine Variable	All-sales, N=7,185		Repeat-sales, N=1,903	
Nearest Operational Turbine in 2012 is within 0.5 mile (Frequency)	42		11	
Nearest Operational Turbine in 2012 is between 0.5 and 1 mile	184		50	
Nearest Operational Turbine in 2012 is between 1 and 1.5 miles	247		49	
Nearest Operational Turbine in 2012 is between 1.5 and 2 miles	78		22	
Nearest Operational Turbine in 2012 is between 2 and 3 miles	262		73	
Nearest Operational Turbine in 2012 within 3 miles	813		205	
Nearest Announced, Non-Operational Turbine at Time of Sale is within 0.5 mile (Frequency)	7		0	
Nearest Announced, Non-Operational Turbine at Time of Sale is between 0.5 and 1 mile	18		6	
Nearest Announced, Non-Operational Turbine at Time of Sale is between 1 and 1.5 miles	41		11	
Nearest Announced, Non-Operational Turbine at Time of Sale is between 1.5 and 2 miles	14		8	
Nearest Announced, Non-Operational Turbine at Time of Sale is between 2 and 3 miles	34		22	
Nearest Announced, Non-Operational Turbine at Time of Sale is within 3 miles	114		47	
Nearest Operational Turbine at Time of Sale is within 0.5 mile (Frequency)	10		5	
Nearest Operational Turbine at Time of Sale is between 0.5 and 1 mile	27		19	
Nearest Operational Turbine at Time of Sale is between 1 and 1.5 miles	32		9	
Nearest Operational Turbine at Time of Sale is between 1.5 and 2 miles	3		0	
Nearest Operational Turbine at Time of Sale is between 2 and 3 miles	15		8	
Nearest Operational Turbine at Time of Sale is within 3 miles	87		41	
Number of Operational Turbines in 2012 is within 0.5 mile (Mean| Max)	0.01	6	0.01	2
Number of Operational Turbines in 2012 is within 1 mile	0.20	16	0.20	11
Number of Operational Turbines in 2012 is within 1.5 miles	0.68	37	0.68	27
Number of Operational Turbines in 2012 is within 2 miles	1.24	64	1.29	46
Number of Operational Turbines in 2012 is within 3 miles	3.68	103	3.60	102
Number of Announced, Non-Operational Turbines at Time of Sale is within 0.5 mile (Mean| Max)	0.00	6	0.00	0
Number of Announced, Non-Operational Turbines at Time of Sale is within 1 mile	0.02	16	0.01	11
Number of Announced, Non-Operational Turbines at Time of Sale is within 1.5 miles	0.08	37	0.06	27
Number of Announced, Non-Operational Turbines at Time of Sale is within 2 miles	0.16	62	0.15	45
Number of Announced, Non-Operational Turbine at Time of Sale is within 3 miles	0.48	103	0.53	92
Number of Operational Turbines at Time of Sale is within 0.5 mile (Mean| Max)	0.00	3	0.00	2
Number of Operational Turbines at Time of Sale is within 1 mile	0.03	14	0.08	11
Number of Operational Turbines at Time of Sale is within 1.5 miles	0.11	27	0.26	27
Number of Operational Turbines at Time of Sale is within 2 miles	0.19	45	0.46	45
Number of Operational Turbines at Time of Sale is within 3 miles	0.50	102	1.12	102

Table 7. Frequencies for All-sales and Repeat-sales Samples

	All-sales N = 7,185	Repeat-sales N = 1,903
Sales During Nearest Turbine Announcement	12.93%	15.71%
Sales After Nearest Turbine is Operational	13.01	24.49
Garage	88.02%	88.28%
Porch	30.31	30.48
Shed	0.49	0.53
Carport	0.28	0.00
Brick Exterior	30.73	30.85
Pool	0.45	0.16
Finished Basement	9.20	9.93
Attic	0.24	0.42
Patio	11.37	10.83
Central Air Conditioning	70.13	73.41
Farm Property	0.79	0.58
Log Exterior	0.17	0.26
Mobile Home	0.01	0.00
Month		
Jan	4.24%	3.73%
Feb	5.08	4.68
March	7.78	7.46
April	9.05	9.88
May	10.54	11.19
June	10.72	11.77
July	9.85	9.83
Aug	10.65	11.04
Sept	9.6	8.57
Oct	8.94	8.46
Nov	7.5	7.36
Dec	6.05	6.04
Year		
1991	3.45%	2.10%
1992	4.19	3.10
1993	4.43	3.42
1994	4.48	3.00
1995	4.37	2.84
1996	4.37	2.73
1997	4.34	3.15
1998	5.39	4.57
1999	4.45	3.57
2000	5.21	4.31
2001	4.75	4.36
2002	4.22	3.31
2003	4.62	3.68
2004	4.52	4.15
2005	5.69	5.41
2006	5.58	3.57
2007	4.84	2.36
2008	4.57	7.99
2009	5.12	10.88
2010	4.52	8.46
2011	4.45	7.67
2012	2.44	5.36
Number of Sales per Property		
1	30.76%	-
2	31.83	29.8%
3	20.82	33.16
4	11.09	23.91
5	5.50	13.14

Table 8. Results of All-sales and Repeat-sales Models, Variables of Interest.
Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

	All-sales			Repeat-Sales		
	[1]	[2]	[3]	[4]	[5]	[6]
Dependent Variable	Natural Log of Adjusted Sale Price					
ln(dist_2012)	-0.036					
	(0.081)					
ln(dist_2012)*Announce	-0.001			0.001		
	(0.003)			(0.005)		
ln(dist_2012)*PostOp	0.003			0.006		
	(0.005)			(0.007)		
Turbine0.5mi		0.121				
		(0.196)				
Turbine0.5mi_1mi		0.066				
		(0.177)				
Turbine1mi_1.5mi		-0.018				
		(0.167)				
Turbine1.5mi_2mi		-0.040				
		(0.178)				
Turbine2mi_3mi		0.049				
		(0.059)				
Turbine0.5mi*Announce		-0.409***				
		(0.137)				
Turbine0.5mi_1mi*Announce		-0.140***			-0.475	
		(0.037)			(0.401)	
Turbine1mi_1.5mi*Announce		-0.072***			0.007	
		(0.026)			(0.099)	
Turbine1.5mi_2mi*Announce		0.095			0.068	
		(0.083)			(0.129)	
Turbine2mi_3mi*Announce		0.041			0.092	
		(0.026)			(0.066)	
Turbine0.5mi*PostOp		-0.274			-0.150	
		(0.176)			(0.112)	
Turbine0.5mi_1mi* PostOp		-0.374***			-0.518***	
		(0.029)			(0.174)	
Turbine1mi_1.5mi* PostOp		-0.214***			-0.079	
		(0.047)			(0.256)	
Turbine1.5mi_2mi* PostOp		-0.377**				
		(0.145)				
Turbine2mi_3mi* PostOp		0.125			0.068	
		(0.094)			(0.215)	
Count0.5mi			0.044**			
			(0.017)			
Count 0.5mi_1mi			-0.036***			
			(0.009)			
Count 1mi_1.5mi			0.034***			
			(0.012)			
Count1.5mi_2mi			0.000			
			(0.008)			
Count2mi_3mi			-0.006**			
			(0.003)			
Count0.5mi*Announce			-0.125***			0.061
			(0.031)			(0.122)
Count0.5mi_1mi*Announce			0.016			-0.053
			(0.024)			(0.079)

Table 8, Continued	All-sales			Repeat-Sales		
	[1]	[2]	[3]	[4]	[5]	[6]
Count1mi_1.5mi*Announce			-0.004			0.007
			(0.019)			(0.056)
Count1.5mi_2mi*Announce			-0.000			0.002
			(0.008)			(0.009)
Count2mi_3mi*Announce			-0.001			0.061
			(0.002)			(0.122)
Count0.5mi*PostOp			-0.073			0.027
			(0.081)			(0.233)
Count0.5mi_1mi* PostOp			0.001			-0.033
			(0.015)			(0.077)
Count1mi_1.5mi* PostOp			-0.018			-0.063
			(0.013)			(0.079)
Count1.5mi_2mi* PostOp			0.018			0.053
			(0.017)			(0.044)
Count2mi_3mi* PostOp			-0.008*			-0.009
			(0.004)			(0.015)

Table 9. Results of All-sales and Repeat-sales Models, Controls and Estimation Details
Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

	All-sales			Repeat-Sales		
	[1]	[2]	[3]	[4]	[5]	[6]
Age of Structure	0.004***	0.004***	0.004***			
	(0.001)	(0.001)	(0.001)			
Age Squared	-0.000***	-0.000***	-0.000***			
	(0.000)	(0.000)	(0.000)			
ln(Square Footage of Structure)	0.394***	0.395***	0.392***			
	(0.034)	(0.034)	(0.034)			
ln(Square Footage of Lot)	0.160***	0.161***	0.164***			
	(0.021)	(0.019)	(0.019)			
Garage	0.136***	0.136***	0.136***			
	(0.017)	(0.016)	(0.017)			
Porch	-0.037	-0.038	-0.040			
	(0.025)	(0.025)	(0.025)			
Shed	0.043	0.039	0.040			
	(0.088)	(0.087)	(0.086)			
Carport	-0.001	0.007	0.000			
	(0.077)	(0.078)	(0.075)			
Brick Exterior	0.105***	0.104***	0.104***			
	(0.020)	(0.020)	(0.020)			
Pool	0.023	0.017	0.027			
	(0.085)	(0.085)	(0.085)			
Finished Basement	0.015	0.014	0.015			
	(0.027)	(0.028)	(0.028)			
Attic	0.060	0.060	0.057			
	(0.080)	(0.080)	(0.079)			
Patio	0.009	0.010	0.009			
	(0.025)	(0.025)	(0.025)			
Central Air Conditioning	0.103***	0.103***	0.103***			
	(0.015)	(0.016)	(0.015)			
Log Home	-0.179**	-0.173**	-0.179**			
	(0.074)	(0.074)	(0.075)			
Mobile Home	-0.079	-0.218**	-0.094			
	(0.101)	(0.082)	(0.062)			
Farm Property	0.016	0.018	0.013			
	(0.118)	(0.119)	(0.120)			
Number of Stories	0.251***	0.252***	0.251***			
	(0.017)	(0.016)	(0.016)			
Number of Fireplaces	0.067***	0.067***	0.067***			
	(0.014)	(0.014)	(0.014)			
Number of Baths	0.040**	0.037**	0.038**			
	(0.017)	(0.017)	(0.017)			
ln(Meters to Lakeshore)	0.015	0.013	0.014			
	(0.010)	(0.010)	(0.009)			
ln(Meters to River)	-0.080***	-0.081***	-0.080***			
	(0.025)	(0.026)	(0.026)			
ln(Meters to Nearest Railroad)	0.028**	0.029**	0.031**			
	(0.012)	(0.012)	(0.012)			
ln(Meters to Nearest Highway)	-0.011	-0.012	-0.016			
	(0.018)	(0.019)	(0.019)			
ln(Meters to Nearest Secondary Road	0.009	0.009	0.009			
	(0.008)	(0.008)	(0.008)			
Constant	6.843***	6.516***	6.507***	11.113***	11.131***	11.137***

	(1.075)	(0.387)	(0.375)	(0.118)	(0.117)	(0.118)
Observations	7,185	7,185	7,185	1,903	1,903	1,903
R-squared	0.533	0.536	0.535	0.752	0.756	0.756
Number of Properties	4,134	4,134	4,134	716	716	716

Table 10. Residual Analysis using Announcement and Operational Period Distance Level Dummies. Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

	All-sales	Repeat-Sales
	[2.R]	[4.R]
Dependent Variable	Model 2 Residuals	Model 4 Residuals
Turbine0.5mi*Announce	-0.293*	
	(0.164)	
Turbine0.5mi_1mi*Announce	-0.052	-0.161
	(0.102)	(0.123)
Turbine1mi_1.5mi*Announce	-0.031	0.021
	(0.068)	(0.091)
Turbine1.5mi_2mi*Announce	0.107	0.055
	(0.116)	(0.106)
Turbine2mi_3mi*Announce	0.064	0.062
	(0.074)	(0.064)
Turbine0.5mi*PostOp	-0.167	-0.077
	(0.137)	(0.135)
Turbine0.5mi_1mi* PostOp	-0.286***	-0.230***
	(0.084)	(0.069)
Turbine1mi_1.5mi* PostOp	-0.183**	-0.044
	(0.077)	(0.100)
Turbine1.5mi_2mi* PostOp	-0.397	
	(0.250)	
Turbine2mi_3mi* PostOp	0.158	0.033
	(0.112)	(0.106)
Constant	0.002	0.002
	(0.005)	(0.007)
Observations	7,185	1,903
R-squared	0.004	0.008

Table 11. Results of Unpooled Models, Distance Level Coefficients
Notes: WO is White Oak, TG is Twin Groves, robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

	All-sales	Repeat-Sales
	[2.A]	[4.A]
Dependent Variable	ln(Real Price)	ln(Real Price)
WO_Turbine0.5mi	0.275**	
	(0.109)	
WO_Turbine0.5mi_1mi	0.047	
	(0.111)	
WO_Turbine1mi_1.5mi	0.003	
	(0.109)	
WO_Turbine1.5mi_2mi	0.004	
	(0.118)	
WO_Turbine2mi_3mi	0.047	
	(0.075)	
WO_Turbine0.5mi*Announce	-0.689***	
	(0.045)	
WO_Turbine0.5mi_1mi*Announce	-0.265***	-0.385***
	(0.071)	(0.090)
WO_Turbine1mi_1.5mi*Announce	-0.060***	-0.033
	(0.020)	(0.095)
WO_Turbine1.5mi_2mi*Announce	0.139***	0.067
	(0.029)	(0.129)
WO_Turbine2mi_3mi*Announce	0.040	0.089
	(0.027)	(0.066)
WO_Turbine1mi_1.5mi* PostOp	-0.154***	0.215**
	(0.042)	(0.097)
WO_Turbine1.5mi_2mi* PostOp	-0.336***	
	(0.045)	
WO_Turbine2mi_3mi* PostOp	0.086*	0.001
	(0.044)	(0.091)
TG_Turbine0.5mi	0.153	
	(0.217)	
TG_Turbine0.5mi_1mi	0.095	
	(0.189)	
TG_Turbine1mi_1.5mi	-0.021	
	(0.213)	
TG_Turbine1.5mi_2mi	-0.202	
	(0.422)	
TG_Turbine2mi_3mi	0.028	
	(0.106)	
TG_Turbine0.5mi*Announce	-0.074	
	(0.151)	
TG_Turbine0.5mi_1mi*Announce	-0.098**	-0.490
	(0.043)	(0.471)
TG_Turbine1mi_1.5mi*Announce	-0.076*	0.334*
	(0.040)	(0.183)
TG_Turbine1.5mi_2mi*Announce	-0.126	
	(0.441)	
TG_Turbine0.5mi*PostOp	-0.295**	-0.193*
	(0.142)	(0.113)
TG_Turbine0.5mi_1mi* PostOp	-0.382***	-0.527***
	(0.024)	(0.182)
TG_Turbine1mi_1.5mi* PostOp	-0.212***	-0.100
	(0.054)	(0.314)
TG_Turbine1.5mi_2mi* PostOp	-0.252	
	(0.170)	
TG_Turbine2mi_3mi* PostOp	0.178	0.121
	(0.149)	(0.369)
Constant	6.465***	11.129***
	(0.429)	(0.117)
Observations	7,185	1,903
R-squared	0.536	0.756

Table 12. Estimated Percentage Change across Models

Notes: Missing values are due to lack of observations at that distance level, *** p<0.01, ** p<0.05, * p<0.1

Sample Type	All-sales								Repeat Sales							
Study Area	Mclean County, IL						Franklin County, NY		McLean County, IL						Franklin County, NY	
Model	[2]		[2.B]		[2.C]		*Heintzelman and Tuttle (2012)*		[4]		[4.B]		[4.C]		*Heintzelman and Tuttle (2012)*	
Distance Level	% Δ	Sig.	% Δ	Sig.	% Δ	Sig.	% Δ	Sig.	% Δ	Sig.	% Δ	Sig.	% Δ	Sig.	% Δ	Sig.
Turbine0.5mi*Announce	-33.57	***	-24.65	*	-30.72	***	-25.02	*							-6.33	
Turbine0.5mi_1mi*Announce	-13.06	***	-23.36	***	73.15	***	-34.07	***	-37.81		-40.49	***			-2.63	
Turbine1mi_1.5mi*Announce	-6.95	***	-16.14	***	-14.44	***	-38.85		0.70		0.70		-23.70	***		
Turbine1.5mi_2mi*Announce	9.97		6.29		-28.47	***	14.73		7.04		26.36	**	-61.00	***	-26.10	**
Turbine2mi_3mi*Announce	4.18		9.20		-13.24		27.44	*	9.64		9.75		-18.90		-3.58	
Turbine0.5mi*PostOp	-23.97		-11.04	**	-8.97	*			-13.93		-17.63	*				
Turbine0.5mi_1mi*PostOp	-31.20	***	-30.16	***	131.87	***			-40.43	***	-36.05	*				
Turbine1mi_1.5mi*PostOp	-19.27	***	-19.27	***	-15.04	***			-7.60		-0.10		93.20	***		
Turbine1.5mi_2mi*PostOp	-31.41	**	-22.90		-3.15								60.00	***		
Turbine2mi_3mi*PostOp	13.31		14.45	*					7.04		14.80		-2.40			