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The windy city: Property value impacts of wind turbines in an urban setting☆

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ABSTRACT

This paper examines the impact of wind turbines on house values in Rhode Island. In contrast to wind farms surrounded by sparse development, in Rhode Island single turbines have been built in relatively high population dense areas. As a result, we observe 48,554 single-family, owner-occupied transactions within five miles of a turbine site, including 3254 within one mile, which is far more than most related studies. We estimate hedonic difference-in-differences models that allow for impacts of wind turbines by proximity, viewshed, and contrast with surrounding development. Across a wide variety of specifications, the results suggest that wind turbines have no statistically significant negative impacts on house prices, in either the post public announcement phase or post construction phase. Further, the lower bound of statistically possible impacts is still outweighed by the positive externalities generated from CO_2 mitigation.

1. Introduction

Society is highly dependent on high polluting and nonrenewable fossil fuels that constitute roughly 80% of our energy supplies. There is increasing recognition that we need to develop new low polluting renewable energy sources, and wind power is among the most promising technologies. As of December 2012, there are over 200,000 wind towers around the world with combined nameplate capacity of nearly 300 GW, and wind energy is among the fastest growing energy sources (Global Wind Energy Council, 2013).

Public opinion polls commonly find a strong majority of respondents indicating support for wind power in general, with up to 90% of respondents voicing support for wind energy (e.g., Firestone and Kempton, 2007; Mulvaney et al., 2013). Despite the stated preference for wind energy in the abstract, proposed wind energy projects frequently meet with fervent opposition by the local community. Numerous reasons have been given for opposition to wind turbines, ranging from adverse effects on birds, bats and other wildlife, esthetic effects by compromising views, annoyance and potentially even health problems related to noise and shadow flicker, and a general industrialization of the landscape. One of the most common concerns voiced by nearby residents is the potential impact of wind towers on property values (Hoen et al., 2011).

Property values are an important issue in and of themselves, but also reflect an accumulation of preferences for the suite of impacts caused by turbines. For example, if wind turbines created adverse effects due to noise, visual disamenities or other nuisance effects, nearby property values would likely reflect these effects. Further, hedonic valuation theory (reviewed in Section 2) suggests that property values should decrease enough such that homeowners are indifferent between living near a turbine or paying more to live far away. Importantly, this disparity in house values can quantify the cost to nearby residents, which is arguably the sum of negative externalities (perhaps excluding wildlife impacts), to be used in cost–benefit analysis of wind energy expansion.

This paper examines the effect of wind turbines on property values in Rhode Island. While Rhode Island is the smallest state in the U.S., it is the second most densely populated. Given this and the fact that 12 turbines have been erected at 10 sites in the past seven years, Rhode Island offers an excellent setting to examine homeowner preferences for wind turbines because there are so many observations. We construct a data set (detailed in Section 3) of 48,554 single-family, owner-occupied transactions within five miles of a turbine site over the time range January

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2000 to February 2013. Further, 3254 of these transactions occur within one mile, and it is these observations that are critical for understanding the impacts.

Beyond sample size, Rhode Island is an excellent case study because turbine development is plausibly exogenous to changes in house prices, unlike many other settings. In Rhode Island, the wind turbines have been sited and built by the state government or private parties, often with opposition from nearby homeowners (Faulkner, 2013). Thus, the possibility that a community collectively decides to build a turbine and such a community may have different house price dynamics is not an issue here. In addition, these are not large-scale wind farm developments and there is no wind industry so-to-speak, so there is essentially no local economic impact through job creation or lease payments to property owners as is the case in Iowa and Texas (Brown et al., 2012; Slattery et al., 2011).[1] Thus, Rhode Island sales prices should offer an unadulterated reflection of homeowner preferences.

Within a hedonic valuation framework, we estimate a difference-in-differences (DD) model. In the most basic model, the treatment group is defined by proximity; we create concentric rings around turbines and regard the set of houses in each distance band as a separate treatment group. We define two distinct treatments. The first is when it is publicly announced that a wind turbine will be built at a specific location; this aspect of the model determines if homeowner's expectations of disamenities affect property values. The second is when the construction of the turbine is completed and measures if the realized disamenity has an effect on property values.

Proximity is a crude measure of the potential impacts of a wind turbine, and we took several additional steps to model likely impacts. We delve into heterogeneous impacts by the size of the turbine and the setting (i.e., industrial or residential area). In addition, we account for the fact that other obstructions such as large buildings or trees might mitigate the effects of a nearby wind tower on particular properties. To do so we physically visited 1354 properties that transacted after construction and are within two miles of a turbine to assess the extent of view of the turbine.[2]

Across a wide variety of cross sectional and repeat sales specifications, the results (discussed in Section 4) suggest that wind turbines have no statistically significant negative impacts on house prices, in either the post public announcement phase or post construction phase. The DD models indicate that turbines are built in less desirable areas to begin with, which is consistent with intuition because several turbines are built near highways or industrial areas. However, even when we isolate residential areas where turbines are likely to contrast most with surroundings, our results still indicate no statistically significant negative price impacts. Further, our results suggest no statistically significant negative impacts to houses with substantial views of a turbine.

Our preferred model indicates that for houses within a half mile of a turbine, the point estimate of price change relative to houses 3–5 miles away is −0.4%. While the standard error of the point estimate is not small (3.8%), we can rule out negative impacts greater than 5.2% with 90% confidence. Further, in Section 5, we quantify the external benefits of wind generation in Rhode Island due to CO_2 mitigation and find that in order to offset the benefits, the price change would need to be greater than 5.8% if considering all turbines, and greater than 12.3% if only considering the industrial sized turbines. Thus, our results indicate that not only do negative externalities appear to be small and insignificant, but even the lower bound of statistically possible impacts is still outweighed by the positive externalities generated from CO_2 mitigation.

The literature examining the impacts of wind turbines on property values is still in its infancy. To date, hedonic studies have focused on large scale wind farms comprised of as many as 150 turbines, as district from our study that examines the case of individual wind turbines, so the disamenities present and resulting valuation may be different. There are several studies that suffer from small sample sizes or unsound econometric modeling. Sims and Dent (2007) used only post construction observations, and Sims et al. (2008) only had 199 observations — all within a half mile of a single wind farm. Neither of these studies use the DD framework, which is essential for controlling for confounding factors, either that exist prior to wind energy development or that affect all houses regardless of turbine construction. This is most evident for Sims and Dent (2007), who show an aerial picture of one of their study wind farms, and between it and the housing development is an already existent, enormous, open pit quarry, which surely could have affected housing prices prior to the wind farm. More recently, Sunak and Madlener (2012) collect 1202 observed transactions, both before and after construction, but the models they estimate constrain either the effect of construction to be constant across distance or the effect of distance to be constant across time.

More complete studies have been carried out recently. Heintzelman and Tuttle (2012) examine impacts of wind farms in three counties of Upstate New York using over 11,000 transactions and a specification that treats distance as a single continuous variable. They do find some significant price effects from proximity, though they are not consistent across counties. Their results imply that a newly built wind farm within a half mile of a property can decrease value by 8–35%. It is important to note, however, that the average distance to a turbine of a transaction in their data is over 10 miles, and they interpolate effects to close proximity. The strongest research to date is a recent report from Hoen et al. (2013), which updates Hoen et al. (2011). They collect over 50,000 transactions within 10 miles of wind farms spanning 27 counties in nine states. They utilize a DD methodology similar to ours with distance bands around the wind farms and both a post announcement and post construction treatment. Similar to our results, Hoen et al. (2013) find no statistical effect of wind turbines on property values. It is important to note that both the Hoen et al. (2013) and Heintzelman and Tuttle (2012) results are for large scale wind farms with as many as 194 turbines, as distinct from our study that examines the case of individual wind turbines.

This paper contributes to the understanding of property value impacts of turbines by providing an econometrically sound analysis with far more observations than all but one existing analysis. Further, we go beyond proximity and offer the most thorough to-date analysis of how impacts may be heterogeneous due to viewshed of a property and size and setting of a turbine. Lastly, because we are working in a single state, we have been able to take part in multiple stakeholder meetings related to wind energy development and gain an understanding of the local perceptions, sentiments, and institutions, which have all informed our analysis. For instance, homeowners feel certain turbines are more odious than others, which suggested we should look for heterogeneous property value effects.

2. Methodology

In the absence of explicit markets, there are generally two approaches that economists use to determine the value of environmental amenities and disamenities: revealed and stated preference methods (e.g., Freeman, 2003). Revealed preference methods use actual choices made by people to infer the value they place on an amenity. Stated preference methods infer values using responses of what individuals would do in a given situation, such as what is the most the individual would pay to participate in an activity rather than go without.

The Hedonic Price Method (HPM) is among the most popular revealed preference methods for determining values of non-market environmental amenities. The Hedonic method is based on the concept that many market commodities are comprised of several bundled attributes, and the market

[1] Two exceptions exist. The owner of the North Kingstown Green Turbine pays $150/year to the dozen or so residents in the same development as the turbine and the Tiverton turbine offsets electricity expenditure to residents of the Sandy Woods Farm community. Only a single transaction in our data set occurred after turbine construction for these houses affected by payments, thus we feel confident that our results are unaffected by payments.

[2] In the appendix, we also examine the property value impacts of shadow flicker, though there are very few observations affected.

prices are determined by their attributes. Applied to residential properties, the price of a property is affected by attributes such as the size of the house, the size of the lot, the number of bathrooms, and bedrooms; the neighborhood attributes such as the condition of nearby homes, the crime rate, and quality of schools; and environmental attributes such as air quality, adjacent open space, and ocean views. The basic idea is that houses with desirable attributes (e.g., an ocean view) will be bid up by potential buyers, and the extent to which prices are bid up depends upon how much buyers value the attribute. If one can estimate the price premium associated with an attribute, one can gain insights into the extent to which potential buyers value an environmental amenity. HPM models have been applied to estimate implicit values associated with a wide range of amenities and disamenities: airport noise (Pope, 2008), crime (Bishop and Murphy, 2011), power plants (Davis, 2011), air quality (Bento et al., 2013), and school quality (Cellini et al., 2010).

This paper applies HPM to the impacts of wind turbines on property values. Within the HPM framework, we estimated a DD model. DD models typically compare treated units to untreated units, both before and after treatments have occurred. There are two modifications to the basic framework for our application. First, treatment is defined by distance and is thus continuous. In order to avoid parametric assumptions, we group houses into D discrete bands of concentric circles surrounding the location of a turbine. The furthest distance band is chosen such that no effect of the wind turbine is expected and serves as the control group. Second, instead of two time periods, we have three: 1) pre-announcement (PA), in which no one knows that a wind turbine will be built nearby, 2) post-announcement pre-construction (PAPC), which is after the public has been made aware that a turbine will be built, but prior to the construction, and 3) post construction (PC). PA is the before treatment time period, and we allow the two treatment periods, PAPC and PC, to have differential impacts on property values, the first based on expectations and the second based on the realized (dis)amenity. The specification is:

$$\begin{aligned}\ln(p_i) = \alpha &+ \sum_{k=2}^{D} \beta_k dist_{ki} + \gamma_1 PAPC_i + \gamma_2 PC_i \\ &+ \sum_{k=2}^{D} \delta_{1k} dist_{ki} PAPC_i + \sum_{k=2}^{D} \delta_{2k} dist_{ki} PC_i \\ &+ X_i' \psi + \varepsilon_i \end{aligned} \tag{1}$$

where p_i is the sales price of transaction i, $dist_{ki}$ is a dummy variable equal to one if transaction i is within the kth distance band, and $PAPC_i$ and PC_i are dummy variables equal to one if transaction i occurs PAPC or PC, respectively. X_i is a set of housing, location, and temporal controls. X_i also includes a constant to capture the omitted group of the 1st distance band in time period PA. Finally, ε_i is the error term.

The coefficients are interpreted as follows. β_k measures the PA (i.e., pre-treatment) difference in housing prices for distance band k relative to distance ring 1. γ_1 and γ_2 measure the change in housing prices for distance band 1 (the control group) in the PAPC and PC time periods, respectively. δ_{1k} and δ_{2k} are the coefficients of interest and measure, for PAPC and PC, respectively, the differential change in property values from the pre-announcement time period for distance band k relative to the change in property values of distance band 1.

The timing of our data, 2000–2013, corresponds to the housing boom and bust. Further, as detailed in the next section, the PAPC and PC periods almost always occur during bust years. Relative to a simple before–after estimate of the impacts of wind turbines on property values using only houses in close proximity, the DD model goes a long way to mitigate spurious correlation creeping into the treatment effect coefficients. To further guard against spurious correlation, we follow the advice of Boyle et al. (2012) and include city by year–quarter fixed effects and an interaction of lot size and its square with city fixed effects and year fixed effects. The city by year–quarter fixed effects flexibly control for the boom and bust in prices for each city separately. The lot size interactions not only allow the value of land to be different in each city, but allow the value to evolve over time with the boom and bust. For more standard reasons, we also include census tract fixed effects and we interact distance from the coast with city. Tract fixed effects capture time invariant locational heterogeneity.[3] Interactions of coast and city allow the value of coastal living to change in different parts of Rhode Island. As with other DD estimators, identification of the treatment effects relies on the assumption that house prices would have changed identically across distance bands in the absence of turbines being built. See Figure A1 in the appendix for suggestive evidence that this assumption is reasonable.

Within the framework of Eq. (1), we additionally estimate models that examine impacts that vary due to type of turbine, turbine surroundings, and viewshed (and shadow flicker, in the appendix).

Finally, we analyze property value impacts of turbines in a repeat sales model. There are many idiosyncratic features of a property that are unobserved by the researcher, and these may lead to omitted variables bias. A repeat sales model that includes property level fixed effects will account for all unobserved property attributes as long as they are time invariant. We estimate the following model:

$$\begin{aligned}\ln(p_{it}) = \alpha_i &+ \gamma_1 PAPC_{it} + \gamma_2 PC_{it} \\ &+ \sum_{k=2}^{D} \delta_{1k} dist_{ki} PAPC_{it} + \sum_{k=2}^{D} \delta_{2k} dist_{ki} PC_{it} \\ &+ X_{it}' \psi + \varepsilon_{it} \end{aligned} \tag{2}$$

where p_{it} is the sales price of unit i at time t, and α_i is a unit-level fixed effect. $dist_{ki}$, $PAPC_{it}$ and PC_{it} are as defined in Eq. (1). Due to their time-invariant nature, property characteristics drop out of X_{it}. However, we still can include lot size and its square interacted with year fixed effects to allow for changes in the value of land through the boom and bust. X_{it} also includes city by year–quarter fixed effects. Identification of δ_{1k} and δ_{2k} (the coefficients of interest) comes from properties that transact in more than one of the three periods (PA, PAPC, PC).

3. Data

3.1. Wind turbines

Table 1 provides information on the 10 sites in Rhode Island that currently have turbines of 100 kW or above. All of these are single turbine sites, with the exception of Providence Narragansett Bay Commission, which has three. There is a wide range in the nameplate generation capacity; four turbines are 100 kW, one at 250 kW, one at 275 kW, one at 660 kW, and five at 1.5 mW. Table 1 also lists the date of public announcement that the wind turbine will be built and the date that construction was complete. The date of public announcement is marked by either an abutter notice or a public forum. The first turbine was built in 2006 and the second not until 2009; the remainders were built in 2011 and 2012. Time period PA is defined as before the announcement date, PAPC defined as between the announcement date and construction completed date, and PC is defined as after the construction completed date.[4] The last column of Table 1 describes the location and

[3] In the spirit of Abbott and Klaiber (2010), one may be concerned that the tract fixed effects and city by year–quarter fixed effects will capture all relevant variation needed for the identification of wind turbines on property values. The spatial scale of influence could reasonably be at the tract level, however, because the tract fixed effects do not vary over time, within tract temporal variation will identify the effect of turbines if there is one. Our intuition is that effects of turbines are much smaller than the scale of a city. Thus, even with the inclusion of city by year–quarter fixed effects will, there will still be within-city variation to identify property value impacts. Further, the five mile radius around each turbine includes 4.1 cities, on average.

[4] Several turbines in our sample were built quite recently, which makes the length of the PC period relatively short in our sample. This could cause problems for estimating true treatment effects if prices are slow to respond to changes in amenities. However, Lang (2012) examines the dynamic path that house prices take responding to changes in air quality (an amenity more difficult to observe), and finds that owner-occupied house prices capitalize changes immediately.

Table 1
Wind turbine characteristics for Rhode Island sample.

Name	Abbreviation (match with Fig. 1)	Nameplate capacity	Height (feet)	Announcement	Construction completed	Comments
Portsmouth Abbey	PAB	660 kW	240	12/15/2004*	3/27/2006	On grounds of a school/monastery; primarily residential surroundings
Portsmouth High School	PHS	1.5 mW	336	4/15/2006*	3/1/2009	On grounds of a public school; primarily residential surroundings
Tiverton Sandywoods Farm	TVT	275 kW	231	7/18/2006	3/23/2012	On grounds of communal residential development; primarily residential surroundings
Providence Narragansett Bay Commission (3 identical turbines)	PVD	1.5 mW each	360	9/26/2007	1/23/2012	On grounds of water treatment facility; mixed industrial/residential surroundings
Warwick New England Tech	NET	100 kW	157	10/9/2008	8/6/2009	On grounds of technical college, next to highway
Middletown Aquidneck Corporate Park	MDT	100 kW	157	4/13/2009	10/9/2009	Mixed residential/commercial surroundings
Narragansett Fishermen's Memorial State Park	NRG	100 kW	157	7/7/2009	9/19/2011	On grounds of state campground; primarily residential surroundings
Portsmouth Hodges Badge	PHB	250 kW	197	5/14/2009	1/4/2012	Mixed residential/commercial/agricultural surroundings
Warwick Shalom Housing	SHA	100 kW	157	8/6/2009	2/2/2011	On grounds of apartment complex, next to highway
North Kingstown Green	NKG	1.5 mW	402	9/15/2009	10/18/2012	Primarily residential surroundings

Notes: Height is hub height plus blade length. Dates of announcement and construction completed were gathered from personal requests for information and newspaper/online sources. Dates marked with * are approximate, sources could only identify a month and year that the announcement was made, and we chose to use the midpoint of the month.

surroundings of each turbine. Of note is that several are in primarily residential areas. Others are in mixed use areas with either industrial or commercial activity, and sometimes coupled with an existing disamenity such as proximity to a highway or water treatment plant. Fig. 1 shows the location of the turbine sites around the state.

One threat to identification could be that turbines are sited in neighborhoods that are strongly in favor of wind energy and that the treatment effect on the treated is substantially different than the average treatment effect (or what the price effect would be if the turbines were randomly placed). With the exception of Tiverton Sandywoods Farm, the turbines have been sited by private or government parties with little to no backing from surrounding neighbors. In fact, several turbines have been sited and erected despite substantial community protest. Given this history, we are not concerned about endogenous placement of turbines threatening identification.

3.2. Housing data

Our housing data include nearly all Rhode Island transactions between January 2000 and February 2013. Fig. 1 displays the location of all transactions in our data in relation to the turbines. The data offer information on sales price, date of transaction, street address, living square feet, lot size, year of construction, number of bedrooms, fell and half bathrooms, and whether or not the unit has a pool, fireplace, air conditioning or view of the water. To get latitude and longitude, we geocoded all addresses to coordinates using the Rhode Island GIS E-911 geolocater.[5] Using GIS, we calculated the Euclidian distance to the nearest eventual turbine site, as well as the distance to the coast.[6] We limit the sample to arm's length transactions of single family homes within 5 miles of an eventual wind turbine site and with a sales price of at least $10,000. This yields 66,487 observations. From that, we drop 385 observations for incomplete data.

One downside to the housing data is that characteristics of the house (bedrooms, bathrooms, square feet, etc.) come from assessor's data and only reflect the current characteristics of the house. If a house was remodeled or a property was split into two or more properties, the data do not capture the characteristics of the property or house before the change. One concern is that "flipped" properties could bias our estimates. To deal with this potential problem, we search the data for properties with multiple sales occurring less than six months apart and drop any sale that occurred prior to the last sale in the set of rapid sales. For example, if we observe a property transact 1/1/2000, 1/1/2005, 2/1/2005, and 1/1/2010, we would drop the 1/1/2000 and 1/1/2005 transactions because the characteristics of the property may be dramatically different for those transactions than what is current. This drops 26.5% of observations, leaving us with a sample of 48,554.

We define five distance bands surrounding turbines needed to estimate Eq. (1): 0–0.5 miles, 0.5–1 miles, 1–2 miles, 2–3 miles, and 3–5 miles. Table 2 presents the distribution of transactions across the bands for the three time periods. For identifying the effect of proximity on prices, we need a substantial number of observations in close range. There are 584 transactions within half a mile, with 75 occurring PAPC and 74 occurring PC, which should be sufficient for identifying an effect if it is there. This table makes clear the benefits of examining wind turbine valuation in a population dense state. In addition, Table 2 gives the proportion of transactions occurring in each distance band for each time period, which can give a sense of whether transaction volume is substantially different for nearby distance intervals in either PAPC or PC. The proportions appear roughly constant across time suggesting neither announcement nor construction affects transaction volume.

Table 3 presents summary statistics for our sample properties. Prices are adjusted for inflation and brought to February 2013 levels using the monthly CPI. The average price in our sample is $305,800. The average lot size is 0.34 acres and the average living area is 1559 square feet. The average distance from the coast is only 1.59 miles (Rhode Island deserves its nickname "The Ocean State"!). Additionally, Table 3 compares houses in the 0–1 mile band to the 3–5 mile band PA to examine differences between the treatment and control group prior to treatment. The last column gives the difference in means divided by the combined standard deviation, which is the best statistic for assessing covariate balance (Imbens and Wooldridge, 2009).[7] Sales price seems well balanced, as do most of the covariates with the exception of Fireplace and Distance from the coast, both of which exceed 0.25, which is considered to be a limit for covariate balance.[8] If the implicit values of these characteristics are different across space or change over time, then the differences in means could be a threat to identification. However, comparing the 0–1 mile band to the 2–3 mile band (not shown), distance to the coast has much better overlap, and both variables have strong overlap comparing

[5] Available at http://www.edc.uri.edu/rigis/.

[6] A house located within 5 miles of two eventual turbine sites is matched only to the nearest turbine site to ensure that a house treated as a control for one turbine is not a treated unit for another turbine.

[7] The problem with the frequently used t-statistic is that, as sample size grows, equivalent means can be rejected even when a covariate is well balanced.

[8] Using voter registration data, we were also able to show that partisanship is similar between the 0–1 mile band and the 3–5 mile band. This further supports the idea that the areas where turbines were sited were not meaningfully different than other areas and the valuation estimates should not be impacted by selection issues.

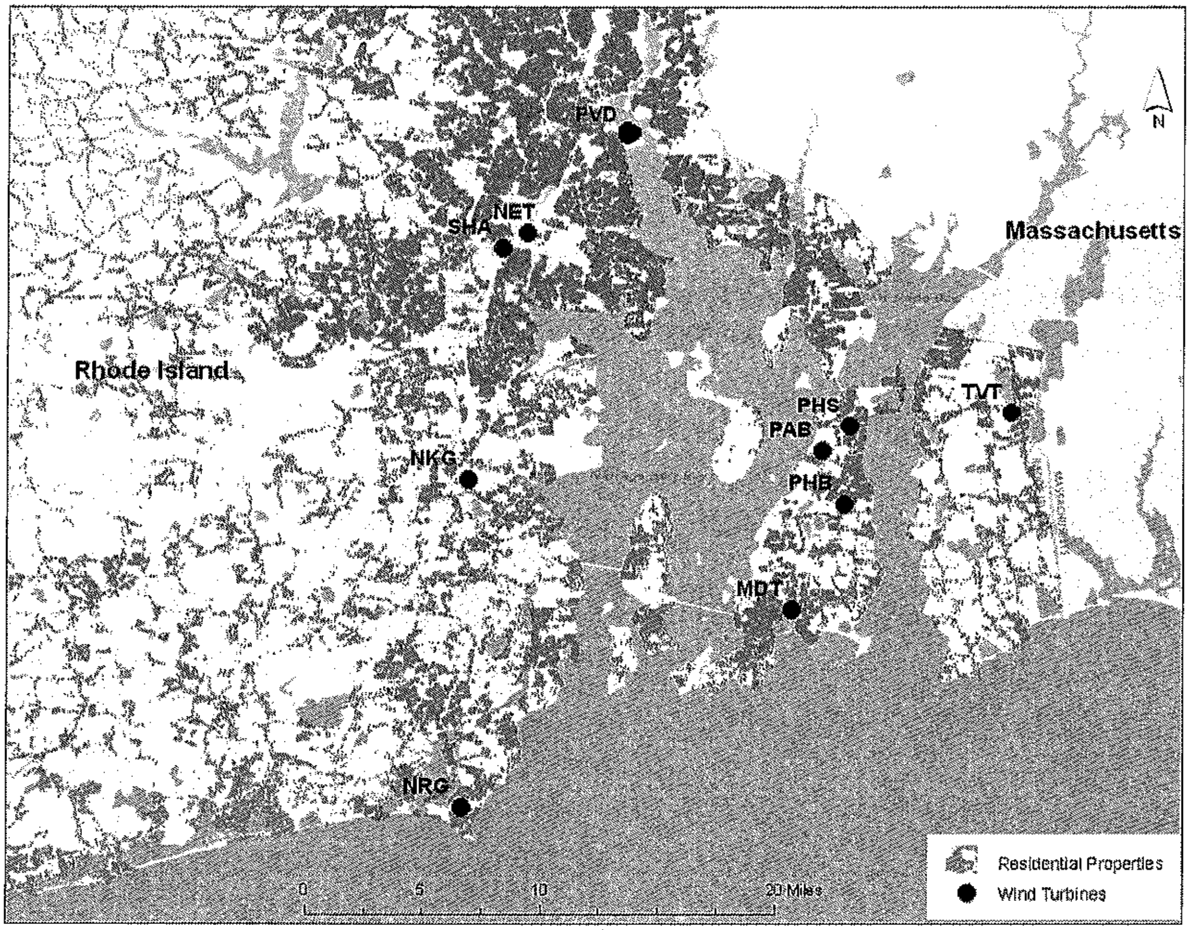

Fig. 1. Spatial distribution of sales and turbines.

the 0–1 mile band to the 1–2 mile band. Thus, the treated units have common support with the spectrum of control units. Further, as explained in Section 2 (following the advice of Boyle et al., 2012), to guard against changing implicit prices affecting the estimated valuation of turbines, we allow the implicit value of lot size and distance from the coast to vary between cities and for lot size to vary over time too.

3.3. Viewshed

Eq. (**1**) examines how house prices change with proximity to a turbine, but proximity is a crude measure for some of the impacts of living near a turbine. One source of heterogeneity in impacts by proximity could come from whether or not residents can actually see the turbine from their property. Unfortunately, we are unable to capture this variation with GIS due to the presence of obstructions such as trees and buildings that might mitigate the impacts of a nearby wind turbine. To overcome this limitation, we completed site visits to all 1354 properties that transacted PC and are within two miles of a turbine. Based on what we could see from the street in front of a given house, plus a bit of walking in both directions (to account for the possibility that a turbine may only be visible from certain parts of the house or backyard), the view was rated into one of five categories based on the proportion of the blade spinning diameter visible and the degree of dominance it had on the landscape: no view (0%), minor (1–30%), moderate (31–60%), high (61–90%), and extreme (91–100%). A view is coded extreme only if the turbine is both nearby and unobstructed. As a consequence, two houses with an unobstructed view of a turbine will be coded differently if the turbine takes up a different amount of view in the horizon, either due to proximity or height of the turbine. While the classification was subjective, a single person did all of the ratings and went to great length to be consistent.

The results of the site visits confirmed substantial heterogeneity in views. Despite Rhode Island's minimal topography, only 0.4% of properties in the 1–2 mile band had any view of the turbine (see Table A1 in the Appendix). Within half a mile, 24.3% have a full view, 13.5% have a partial view, and 63.2% have no view. Fig. 2 illustrates the heterogeneity in viewshed for PC transactions surrounding the Portsmouth High School turbine. While viewshed and proximity are certainly correlated, it is far from a perfect correlation and there are several instances of properties with similar location and different views.

4. Results

Table 4 presents the main DD results on the full sample of transactions. There are three columns that represent three different models that each add additional variables described at the bottom of the table. All three models include housing characteristic controls, detailed further in the notes of the table, and tract fixed effects. The first set of coefficients, corresponding to the τ_k in Eq. (**1**), measure the difference in housing values among the various distance bands relative to the 3–5 mile band. All models suggest that there is a negative premium for living near the eventual site of a wind turbine, prior to an announcement that a wind a turbine will be built. For instance, Model 1 indicates that houses located within half a mile of a future turbine site are worth

Table 2
Transaction counts and proportions by distance and time period.

Distance interval (miles)	PA	PAPC	PC	Total
0–0.5	435	75	74	584
	1.2%	1.0%	1.4%	1.2%
0.5–1	1979	353	338	2670
	5.5%	4.9%	6.4%	5.5%
1–2	6120	1180	942	8242
	17.0%	16.3%	17.8%	17.0%
2–3	10,116	1877	1599	13,592
	28.1%	25.9%	30.3%	28.0%
3–5	17,375	3765	2326	23,466
	48.2%	51.9%	44.1%	48.3%
Total	36,025	7250	5279	48,554
	100%	100%	100%	100%

Notes: 'PA' stands for pre-announcement, 'PAPC' for post-announcement/pre-construction, and 'PC' for post-construction. The percentages are the proportion of all transactions for a given time period occurring in that distance band.

Table 3
Housing summary statistics.

Variable	Full sample	Pre-announcement		
		0–1 mile	3–5 miles	Difference/std. dev.
Price (000s)	305.8	330.8	323.4	0.03
Lot size (acres)	0.34	0.35	0.41	−0.06
Living area (square feet)	1559	1567	1600	−0.04
Bedrooms	3.03	3.07	3.03	0.06
Full bathrooms	1.49	1.55	1.51	0.06
Half bathrooms	0.45	0.44	0.46	−0.03
Fireplace (1 = yes)	0.31	0.13	0.38	−0.44
Pool (1 = yes)	0.04	0.03	0.05	−0.09
Air conditioning (1 = yes)	0.30	0.25	0.31	−0.15
Distance from coast (miles)	1.59	1.15	1.94	−0.49
Age at time of sale (years)	52.5	46.0	47.3	−0.04
Observations	48,554	17,375	2414	

Notes: Housing prices are brought to February 2013 levels using the monthly CPI. The final column equals the difference in means between the 0–1 mile set and the 3–5 mile set divided by their combined standard deviation.

9.0% less than those houses 3–5 miles away from the future site.[9] This finding implies that turbines are being sited in areas that have lower house prices conditional on property and locational characteristics. This makes sense since several of the turbines are located in less desirable areas, i.e., near the highway or on the grounds of a wastewater treatment facility. The second set of coefficients, which correspond to $\square_1$ and $\square_2$ in Eq. (**1**), measure the change in housing prices for the 3–5 mile distance band in the PAPC and PC time periods, respectively. Across all models, the results suggest that these time periods are associated with lower sales prices relative to PA (due to the crash of the housing market), though given the inclusion of city by year–quarter fixed effects the magnitudes of $\square_1$ and $\square_2$ do not fully reflect the large drop in house prices during those periods. Taken together, the distance and timeline results indicate that a purely cross-sectional or before–after research design would both provide negatively biased estimates of the effect of wind turbines on property values. The DD approach we apply controls for these potential problems.

The third set of coefficients in Table 4 are the DD estimates, corresponding to $\square_{1k}$ and $\square_{2k}$ in Eq. (**1**), which are the estimated treatment effects of PAPC and PC for the various distance bands. The coefficients for the 2–3 mile band are small in magnitude and statistically insignificant. Intuition suggests that 2–3 miles away from a turbine is probably too far for an impact to occur, so observing that these prices closely track those 3–5 miles away gives confidence in the assumption of common trends needed for the DD research design. Moving into closer distance bands, no coefficients are statistically significant and all are small in magnitude. For all models, the Akaike Information Criterion (AIC) is calculated and Model 3 minimizes this statistic, which is the objective, and so we deem Model 3 to be our preferred specification. The point estimates of the treatment effects for this model suggest that for houses within half a mile of a turbine, values decreased 0.4% PAPC and decreased 0.4% PC.[10] The standard error on the PC estimate is 3.8%, which implies a one-sided hypothesis can rule out decreases in prices more than 5.1% with 90% confidence. This implies that the large negative impacts, such as −10% or more, that are routinely hypothesized by opponents of wind development can be ruled out as inconsistent with the data. While the coefficients are statistically insignificant, they are also consistently negative across the three specifications, which warrant updating the models in two or so years when there are more PC transactions. Results are qualitatively similar using distance bands with increment in thirds of a mile within 1 mile, but standard errors double, which leads to a larger range of possible impacts.

4.1. Repeat sales analysis

Table 5 presents results from a repeat sales analysis. Only properties that transact more than once are included in the sample, which decreases the sample by over half. The first column includes city by year–quarter fixed effects (akin to Column 1 in Table 4), and the second column additionally includes lot size-year interactions (akin to Column 3 in Table 4). Model 2 minimizes AIC, but both are presented for completeness and robustness.

Like Table 4, the results suggest that there is no significant difference in price changes between the 2–3 mile band and the 3–5 mile (control) band. In the 0.5–1 mile band, both columns suggest that house prices decreased PAPC, by 5.7% (statistically significant at the 5% level) in Model 2. The point estimates indicate larger impacts PC (−8.1% for Model 2), but are statistically insignificant. In contrast, the 0–0.5 mile band shows statistically insignificant price increases PAPC (8.1% for Model 2). The PC results for the 0–0.5 mile band are nearly identical to Table 4, indicating a 0.0% change in prices with a standard error of 3.7%.

It is difficult to draw conclusions from the results. On the one hand, the 0.5–1 mile band results indicate that turbines could have a negative and large impact on property values. On the other hand, the 0–0.5 mile band results, where the impacts should be strongest, are incongruent with the 0.5–1 mile results. It will be beneficial to update this analysis in two or so years with more PC transactions.

4.2. Heterogeneity by type of turbine and setting

As explained in Table 1, there is substantial heterogeneity among the Rhode Island turbines in terms of size and placement. The turbines range in size from 100 kW to 1.5 mW, and some are located near highways or industrial areas. The estimates presented thus far group all turbines together, but it is possible the price effects are different based on size and surroundings. Intuition suggests that price impacts would be more pronounced for larger turbines and turbines in primarily residential areas where other disamenities do not already exist.

Table 6 presents DD estimates, returning to Eq. (**1**), for subsets of the data based on turbine characteristics. Columns 1 and 2 use only turbines with a capacity of 660 kW or more — these would be considered the industrial sized turbines. Columns 3 and 4 use only turbines in primarily residential areas. Similar to the repeat sales analysis, the large turbine analysis presents mixed evidence of price impacts. The results suggest negative price impacts of 3.6% PC in the 1–2 mile band and positive

[9] Though we are not concerned about endogeneity bias given the manner of turbine development in Rhode Island, this spatial price gradient PA suggests that even if endogeneity was a problem, our results would likely be biased downwards making it more likely to find a negative effect.

[10] A parsimonious model including just housing characteristics and DD variables was also estimated. Results suggested positive impacts of turbines, though we interpret this as a spurious correlation.

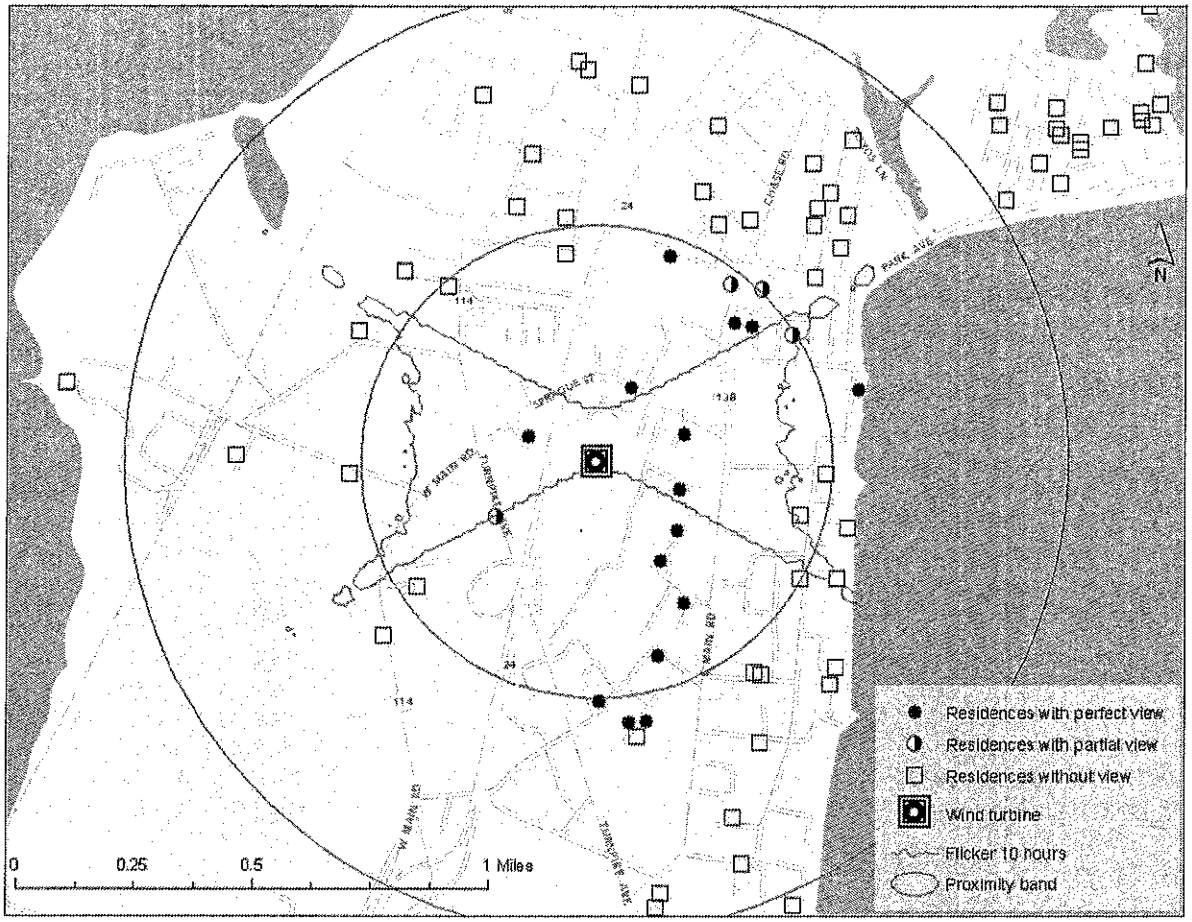

Fig. 2. Proximity bands, viewshed, and shadow flicker, for post construction transactions around Portsmouth High School wind turbine.

impacts of 8.4% PAPC in the 0–0.5 mile band. The point estimates for PC in the 0–0.5 mile band are 4.3%, but insignificant. For the primarily residential locations analysis, all coefficients are statistically insignificant.

4.3. Viewshed

Beyond the size and location of a turbine, another source of heterogeneity is whether or not a house can actually see the turbine, and to what extent. This source of heterogeneity can occur within a group of houses matched to a single turbine, in contrast to the heterogeneity explored in Table 6, which occurs between turbines. Table 7 presents the results of three models exploring the impact of viewshed on prices. Models 1 and 2 match Columns 2 and 3 of Table 4, except additionally include indicator variables for each of the categories of view. Model 3 omits the DD variables from the model, to check if multicollinearity between viewshed and proximity affects coefficients on the viewshed variables. To be clear, only PC sales can be scored higher than 'no view' and the viewshed variables enter as an additive treatment effect, not interactive. Across the three models, the results suggest that view of the turbine has no statistical impact on property values. Further, the point estimates have a non-monotonic relationship with the extent of view and range from −5.2% to 7.9%.

5. Policy perspective

The purpose of this paper is to quantify the negative externalities associated with wind turbine development in a population dense area. While a full cost-benefit analysis of wind energy is well beyond the scope of this paper, it is useful to consider the positive externalities derived from wind generation – specifically, reductions in CO_2 emissions – and weigh these against the negative. The following back-of-the-envelope calculations are not meant to be absolute, but to put perspective on the issue at hand and try to answer the question 'What loss in property values would offset gains from reduced CO_2?'

The turbines that enter this study have a nameplate capacity of 9.085 MW. Using a standard capacity factor of 0.25, we can expect these turbines to generate 19,896 MWh annually. The EPA estimates that each MWh produced in the US generate 0.706 tons of CO_2, which implies that 14,046.7 tons of CO2 are mitigated annually due to these turbines.[11] If the turbines last for 25 years, then a total 351,167 tons of CO_2 will be mitigated over the turbines' lifetimes. The EPA also estimates that the social cost of carbon (the marginal damage expected from each emitted ton of CO_2) is currently \$39, which yields a total monetary benefit of nearly \$13.7 million.[12] If we restrict attention to only the six industrial sized turbines, which have a combined nameplate capacity of 8.16, total monetary benefit is \$12.3 million.

Turning to the cost side, using the full data set there are 910 single family, owner-occupied housing units within half a mile of a turbine site (over ten times what has transacted PC). The average selling price for these houses in 2012–2013 was \$260,162, and so we estimate a total value of this housing stock to be \$236.7 million. In order to offset the benefits, the housing stock would need to decline 5.8% is value. If we again restrict attention to industrial turbine sites only, we find 306 units worth an average of \$327,570 for a total value of \$100.2 million.

[11] http://www.epa.gov/cleanenergy/energy-resources/calculator.html.
[12] http://www.epa.gov/climatechange/EPAactivities/economics/scc.html.

Table 4
Difference-in-differences estimates of the impact of wind turbine proximity on housing prices.

Variables		(1)	(2)	(3)
Distance (relative to 3–5 miles)				
2–3 miles		−0.008	−0.014	−0.014
		(0.023)	(0.023)	(0.023)
1–2 miles		−0.025	−0.030	−0.030
		(0.026)	(0.026)	(0.025)
0.5–1 miles		−0.048	−0.060	−0.059
		(0.022)**	(0.020)***	(0.020)***
0–0.5 miles		−0.090	−0.087	−0.087
		(0.033)**	(0.032)**	(0.032)**
Timeline (relative to PA)				
PAPC		−0.033	−0.035	−0.038
		(0.014)**	(0.014)**	(0.014)**
PC		−0.055	−0.060	−0.058
		(0.020)**	(0.020)***	(0.019)***
Difference-in-differences				
2–3 miles	PAPC	−0.008	−0.009	−0.008
		(0.020)	(0.020)	(0.018)
	PC	0.007	0.008	0.006
		(0.014)	(0.014)	(0.015)
1–2 miles	PAPC	−0.041	−0.040	−0.039
		(0.037)	(0.036)	(0.036)
	PC	−0.002	−0.009	−0.010
		(0.017)	(0.019)	(0.018)
0.5–1 miles	PAPC	−0.029	−0.032	−0.029
		(0.030)	(0.028)	(0.028)
	PC	−0.001	0.003	0.002
		(0.033)	(0.031)	(0.030)
0–0.5 miles	PAPC	−0.009	−0.001	−0.004
		(0.060)	(0.053)	(0.054)
	PC	−0.004	−0.001	−0.004
		(0.042)	(0.039)	(0.038)
City by year-quarter fixed effects		Y	Y	Y
Property–city interactions		N	Y	Y
Property–year interactions		N	N	Y
Observations		48,554	48,554	48,554
R-squared		0.751	0.759	0.760
Akaike Information Criterion		12,468.5	10,933.5	10,801.5

Notes: 'PA' stands for pre-announcement, 'PAPC' for post-announcement/pre-construction, and 'PC' for post-construction. Included in all regressions as control variables are lot size, lot size squared, living area, living area squared, number of bedrooms, full bathrooms, half bathrooms, indicator variables for the presence of a fireplace, pool, air conditioning, view of the water, within 0.25 miles of the coast, and within one mile of the coast, a set of dummy variables for the age of the house at purchase, a set of dummy variables for the subjective condition of the house, and tract fixed effects. Property–city interactions indicate that lot size, its square, and the two coast dummy variables are interacted with a full set of city dummies. Property–year interactions indicate that lot size and its square are interacted with year fixed effects. Standard errors are shown in parentheses and are estimated using the Eicker–White formula to correct for heteroskedasticity and are clustered at the city level.
* Indicates significance at 10%.
** Indicates significance at 5%.
*** Indicates significance at 1%.

These houses would need to decline in value by 12.3% to offset CO_2 benefits.

These calculations indicate two things. First, in Rhode Island, our results suggest that it is statistically improbable that the external benefits of wind generation are outweighed by the external costs to homeowners. Second, if we consider similar calculations for wind farms located in rural areas, it is impossible for prices to depreciate enough to overcome the benefits of CO_2 mitigation.[13]

6. Conclusion

This paper offers an econometrically sound analysis of the effect of wind turbines on property values in Rhode Island. With a sample of 48,554 transactions, we estimate a suite of DD models that examine property impacts due to proximity, viewshed, and type and location of turbine. Because our sample time period includes the housing boom

[13] For example, Hoen et al. (2013) report an average of 12.3 sales within half a mile of wind farm with average capacity of 79 MW. Houses would need to depreciate over 1000% to outweigh the CO_2 mitigation benefits, but this of course is impossible.

Table 5
Difference-in-differences estimates using repeat sales data.

Variables		(1)	(2)
2–3 miles	PAPC	0.017	0.019
		(0.012)	(0.014)
	PC	0.032	0.032
		(0.027)	(0.027)
1–2 miles	PAPC	−0.067	−0.068
		(0.056)	(0.055)
	PC	−0.023	−0.024
		(0.041)	(0.041)
0.5–1 miles	PAPC	−0.058	−0.057
		(0.028)*	(0.027)**
	PC	−0.075	−0.081
		(0.054)	(0.052)
0–0.5 miles	PAPC	0.079	0.081
		(0.068)	(0.074)
	PC	0.006	−0.000
		(0.039)	(0.037)
City by year-quarter fixed effects		Y	Y
Property–year interactions		N	Y
Observations		21,414	21,414
Unique houses		9618	9618
R-squared		0.897	0.898
Akaike Information Criterion		−12,939.7	−13,058.9

Notes: Sample includes only properties that transact more than once during the sample timeframe. Standard errors are shown in parentheses and are estimated using the Eicker–White formula to correct for heteroskedasticity and are clustered at the city level.
* Indicates significance at 10%.
** Indicates significance at 5%.
*** Indicates significance at 1%.

Table 6
Heterogeneity of impacts by turbine size and location.

Variables		Capacity ≥ 660 kW		Primarily residential	
		(1)	(2)	(3)	(4)
2–3 miles	PAPC	0.003	0.002	−0.004	−0.011
		(0.016)	(0.016)	(0.075)	(0.061)
	PC	−0.011	−0.012	−0.045	−0.043
		(0.068)	(0.069)	(0.066)	(0.061)
1–2 miles	PAPC	−0.056	−0.057	0.048	0.046
		(0.053)	(0.052)	(0.037)	(0.031)
	PC	−0.038	−0.036	−0.022	−0.014
		(0.022)*	(0.019)*	(0.068)	(0.063)
0.5–1 miles	PAPC	−0.042	−0.042	0.023	0.022
		(0.041)	(0.038)	(0.048)	(0.036)
	PC	−0.047	−0.047	0.028	0.030
		(0.041)	(0.042)	(0.073)	(0.065)
0–0.5 miles	PAPC	0.084	0.084	−0.028	−0.034
		(0.044)*	(0.044)*	(0.124)	(0.126)
	PC	0.039	0.043	0.073	0.078
		(0.098)	(0.101)	(0.110)	(0.115)
City by year-quarter fixed effects		Y	Y	Y	Y
Property–city interactions		Y	Y	Y	Y
Property–year interactions		N	Y	N	Y
Observations		23,776	23,776	8206	8206
R-squared		0.775	0.776	0.726	0.729
Akaike Information Criterion		7107.2	7021.2	1929.2	1843.8

Notes: See notes to Table 4. The model used in Columns (1) and (3) is identical to that of Column (4) in Table 4, and the model used in Columns (2) and (4) is identical to that of Column (5) in Table 4. Columns (1) and (2) include turbines PAB, PHS, PVD, NKG. Columns (3) and (4) include PAB, PHS, TVT, NRG, NKG.
* Indicates significance at 10%.
** Indicates significance at 5%.
*** Indicates significance at 1%.

Table 7
The impact of viewshed on property values.

Variables		(1)	(2)	(3)
0–0.5 miles	PAPC	−0.001	−0.004	–
		(0.053)	(0.054)	–
	PC	0.007	0.003	–
		(0.061)	(0.059)	–
View of turbine	None (omitted)	–	–	–
		–	–	–
	Minor	0.028	0.021	0.020
		(0.067)	(0.072)	(0.066)
	Moderate	0.079	0.080	0.082
		(0.125)	(0.125)	(0.124)
	High	−0.052	−0.044	−0.042
		(0.177)	(0.172)	(0.144)
	Extreme	−0.019	−0.016	−0.012
		(0.071)	(0.069)	(0.050)
City by year-quarter fixed effects		Y	Y	Y
Property–city interactions		Y	Y	Y
Property–year interactions		N	Y	Y
R-squared		0.759	0.760	0.760
Akaike Information Criterion		10,932.3	10,800.4	10,814.8

Notes: See notes to Table 4. The sample size in all columns is 48,554. The model used in Column (1) is identical to that of Column (4) in Table 4, and the model used in Column (2) is identical to that of Column (5) in Table 4. Column (3) includes all control variables that Column (5) in Table 4, but does not include the interaction terms between proximity bands and time periods (i.e., the difference-in-differences terms). Columns (1) and (2) include all difference-in-difference variables shown in Table 4, though only the interaction between the 0 and 0.5 mile distance band and time period are displayed.

and bust, we control for city-level price fluctuations and allow the implicit value of housing characteristics to vary by year and city, following the advice of Boyle et al. (2012). Broadly, the results suggest that there is no statistical evidence for negative property value impacts of wind turbines. Both the whole sample analysis and the repeat sales analysis indicate that houses within half a mile had essentially no price change PC. These results are consistent with Hoen et al. (2013), who examine impacts of large wind farms in nine states. However, the results are not unequivocal. First, some models do suggest negative impacts; however, these are often incongruent with other coefficient estimates in the same model. Second, many important coefficient estimates have large standard errors. As time goes on and there are more PC transactions observed, we hope to update this analysis and improve accuracy and consistency of the estimates.

In the past (and likely going forward), proposed wind energy projects have been fervently opposed by homeowners surrounding the turbine site. There are several possible reasons why these stated preferences may be different than preferences revealed through housing market choices, such as we found in this analysis. First, stated preference is completely in the abstract and losses and gains are never realized. Hence, people may behave strategically to try and influence outcomes even if they are not willing to pay for it. Lang (2014) finds a similar inconsistency with stated beliefs about climate change and what internet search records reveal about people's interests. Second, wind energy is still relatively new in the United States, especially farms and individual turbines that are in close proximity to residential development. It could be that local opposition is driven by fear of the unknown, but that once reality sets in (i.e., the turbines are built) people care much less. Third, there could be a process of preference-based sorting occurring in the housing market in which people who dislike the turbines move away and those that are indifferent or even enjoy the turbines move near.[14] Importantly, these location shifts of certain homeowners may not affect housing prices if there are enough potential buyers who are indifferent or prefer to live near turbines.

[14] See, for example, Banzhaf and Walsh (2008), who examine preference-based sorting in response to toxic emissions from factories. One anecdote in support of this idea is that we talked with one recent home buyer, an engineer, who enjoyed watching a nearby turbine spin.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2014.05.010.

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