Exhibit A16-6

Effects of Wind Turbines on Property Values in Rhode Island

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Executive Summary

This study assesses of the effect that onshore wind turbines have on nearby property values in Rhode Island. The state of Rhode Island established the RIWINDS program in 2006 to promote the development of wind energy in the state, with the goal of meeting 15% of the state's electrical consumption with wind energy. Yet progress towards that goal has been slow. Wind energy proposals commonly meet with strong opposition despite widespread public support for wind energy in the abstract, and a major source of opposition that is commonly articulated is a concern that wind turbines may adversely affect property values. As a consequence, it is important to assess the extent to which wind turbines affect transaction prices of nearby properties.

Methodology

The study estimates the effect of wind towers on property prices using the Hedonic Price technique. The Hedonic method is a statistical approach that uses extensive data on property transactions to identify the extent to which transaction prices are affected by various characteristics of the properties and their surroundings. Characteristics of the property include such factors as the size of the house, size of the lot, number of bedrooms, number of bathrooms, among other characteristics of the property. Neighborhood characteristics might include factors such as ocean views, crime rates, nearby industrial developments, among others. The key factor for purposes of this study is the effect, if any, that nearby wind turbines have on property prices.

This study uses data from 48,554 single-family, owner-occupied housing transactions within five miles of turbine sites in Rhode Island over the time period from January 2000 to February 2013. Of these transactions, 3,254 are for properties that are within one mile of the wind turbine, and it is these observations that are critical for estimating the impacts. If wind turbines have an adverse impact on property transaction prices, then we should find that transactions for properties that are located closer to the wind turbine (e.g., within ½ mile) should sell for systematically lower prices than those located further from the wind turbine (e.g., 3 to 5 miles), after controlling for other characteristics of the various properties and their surroundings.

In addition to distance to the wind tower, we also consider other factors related to the wind turbine that could influence effects on property values. First, one might expect a larger wind turbine to have a greater effect on values of nearby properties than would a smaller wind tower, all else equal. Second, some properties may be located near a wind turbine, but potential effects might be mitigated because the view and/or the sound from the wind turbine might be blocked, in whole or in part, by topography or other obstructions, such as trees or large buildings. Third, one might expect that a wind turbine might have a larger impact on property values in a location that is otherwise pristine, as compared to a location that is already highly industrialized prior to construction of the wind turbine. We carry out analyses of these factors by augmenting our housing price sales data with information on size of wind towers, GIS data on the land use categories in the surroundings and site visits to 1,354 properties located closest to wind turbines.

We estimate the effects of wind towers considering three periods: transactions that occurred prior to any consideration of the wind tower at a particular site, transactions occurring after public announcement but before construction begins, and transactions occurring after construction. We employ a difference-in-differences approach, which compares before-and-after price differentials for properties near wind turbines with price differentials for other properties in the same time period and in the same general area, but that are located further away from a wind turbine. The advantage of this approach is it corrects for events in housing markets that have no connection to the wind turbine, but that occurred in the same time period. For example, housing prices might be generally be increasing over the time period in question, or prices might be declining, as during the crash in housing prices that occurred starting in 2006. These factors are general trends that vary over time, but will have the same effect on transactions prices for houses close a wind turbine and houses in the same general area but are further from the wind turbine. As a consequence, the difference-in-differences approach corrects for these kinds of unrelated factors whose timing may just have happened to coincide with construction of the wind turbine.

Results and Conclusions

Across a wide variety of specifications, the results indicate that wind turbines have no statistically significant impact on house prices. For houses within a half mile of a turbine, the point estimate of price change for properties within ½ mile relative to properties 3-5 miles away

is -0.2%. So our best estimate is wind towers have no virtually effect on prices of nearby properties.

But by the very nature of any statistical analysis, exact measures of price changes are not constructed. Rather, statistical analyses are based on “confidence intervals”, where the analyst might conclude they are 90% sure that any effect on housing prices would fall within some particular range. Our principle finding is that the best estimate is that there is no price effect, and we can say with 90% level of confidence if there is a price effect, it is roughly 5.2% or less. Thus, while we cannot conclude for sure that there is no effect on housing prices, there is no statistical evidence of a large, adverse effect.

One challenge in estimating the effects of wind turbines on housing prices is that most wind turbines were built within the past few years, and there are relatively few property sales in the immediate vicinity of wind turbines (or for that matter, at other specific locations) in such a short time period. We expect that the precision of estimates will increase over time, as more transactions occur. Hence, we recommend that that the analysis be repeated in a few years when a more robust data set with additional property transactions become available.

1. Introduction

Society is highly dependent on high polluting and nonrenewable fossil fuels that constitute roughly 80% 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, aesthetic 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 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 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 on property transactions. We construct a data set of 48,554 single-family, owner-occupied transactions within five miles of a turbine site over the time range

January 2000 to February 2013. Furthermore, 3,254 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 major 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 affects 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 1,354 properties that transacted after construction that are within two miles of a turbine to assess the extent of view of the turbine.[2]

[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.

Across a wide variety of specifications, the results indicate that wind turbines have no negative statistical impacts on house prices, in either the post public announcement phase or post construction phase. 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. 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 unfettered views of a turbine. A repeat sales model corroborates these results.

The literature examining the impacts of wind turbines on property values is still in its infancy. 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 1,202 observed transactions, both before and after construction, but the model they estimate constrains the effect of construction to be constant across distance and the effect of distance to be constant across time.

Fortunately, better 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 et al, 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 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, bedrooms, etc.; the neighborhood attributes such as the condition of nearby homes, the crime rate, quality of schools, etc.; and environmental attributes such as air

quality, adjacent open space, ocean views, etc. 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 (Lucas 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 treatment has 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:

$$\begin{aligned}\ln(p_i) = &\sum_{k=2}^{D} \alpha_k \, dist_{ki} + \beta_1 PAPC_i + \beta_2 PC_i \\ &+ \sum_{k=2}^{D} \gamma_{1k} dist_{ki} PAPC_i + \sum_{k=2}^{D} \gamma_{2k} dist_{ki} PC_i \\ &+ X_i' \delta + \varepsilon_i \qquad (1)\end{aligned}$$

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. α_k measures the PA (i.e., pre-treatment) difference in housing prices for distance band k relative to distance ring 1. β_1 and β_2 measure the change in housing prices for distance band 1 (the control group) in the PAPC and PC time periods, respectively. γ_{1k} and γ_{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 controls 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.

[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.

Within the framework of Equation (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:

$$\ln(p_{it}) = \alpha_i + \beta_1 PAPC_{it} + \beta_2 PC_{it} + \sum_{k=2}^{D} \gamma_{1k} dist_{ki} PAPC_{it} + \sum_{k=2}^{D} \gamma_{2k} dist_{ki} PC_{it} + X'_{it}\delta + \varepsilon_{it} \quad (2)$$

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 Equation (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 γ_{1k} and γ_{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 remainder 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 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. Figure 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. Figure 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, bathrooms 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 turbine, as well as the distance to the coast. 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

[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 (2013a) 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.

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

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 Equation (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).[6] Sales price seems well balanced, as do most of the covariates with the exception of Fireplace and Distance

[6] 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.

from the coast, both of which exceed 0.25, which is considered to be a limit for covariate balance. 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 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

Equation (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 1,354 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 percentage of the blade spinning diameter visible: no view (0%), minor (1-30%), moderate (31-60%), high (61-90%), extreme (91-100%). 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. Figure 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 dramatically 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 α_k in Equation (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 9.0% less than those houses 3-5 miles away from the future site. 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 β_1 and β_2 in Equation (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 β_1 and β_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 γ_{1k} and γ_{2k} in Equation (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. 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. While a smaller confidence band would be ideal, we can rule out large negative impacts, such as -10% or more, that are routinely hypothesized by opponents of wind development. 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 with 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 Equation (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 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. 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. 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 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 (2013b) 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.[7] 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.

[7] 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.

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Figure 1: Spatial distribution of sales and turbines

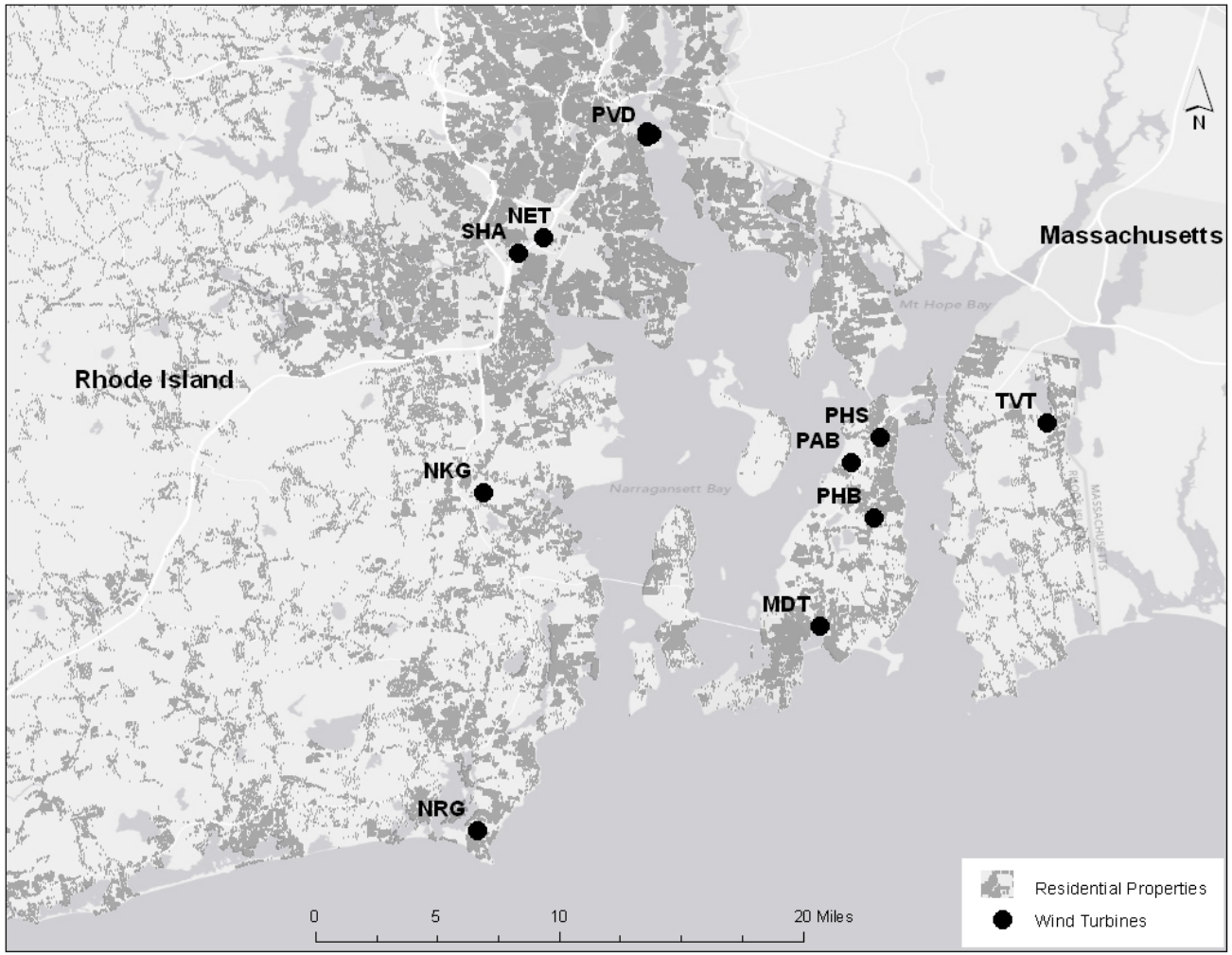

Figure 2: Proximity bands, viewshed, and shadow flicker, for post construction transactions around Portsmouth High School wind turbine

Table 1: Wind turbine characteristics for Rhode Island sample

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

Notes: 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.

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

Distance Interval (miles)	PA	PAPC	PC	**TOTAL**
0 - 0.5	435 1.2%	75 1.0%	74 1.4%	584 1.2%
0.5 - 1	1979 5.5%	353 4.9%	338 6.4%	2670 5.5%
1 - 2	6120 17.0%	1180 16.3%	942 17.8%	8242 17.0%
2 - 3	10116 28.1%	1877 25.9%	1599 30.3%	13592 28.0%
3 - 5	17375 48.2%	3765 51.9%	2326 44.1%	23466 48.3%
TOTAL	36025 100%	7250 100%	5279 100%	48554 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 miles	Pre-announcement 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	48554	17375	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.

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 mile)				
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		48554	48554	48554
R-squared		0.751	0.759	0.760
Akaike Information Criterion		12468.5	10933.5	10801.5

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. *, **, and *** indicate significance at 10%, 5% and 1%, respectively.

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		21414	21414
Unique houses		9618	9618
R-squared		0.897	0.898
Akaike Information Criterion		-12939.7	-13058.9

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. *, **, and *** indicate significance at 10%, 5% and 1%, respectively.

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		23776	23776	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.

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		10932.3	10800.4	10814.8

Notes: See notes to Table 4. The sample size in all columns is 48554. 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 0-0.5 mile distance band and time period are displayed.