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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 3,254 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.

Keywords: wind energy; hedonic valuation; viewshed; Rhode Island
JEL codes: Q42, Q51, R31

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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, 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, 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 2000 to February 2013. Further, 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 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 1,354 properties that transacted after construction and are within two miles of a turbine to assess the extent of view of the turbine.[2]

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[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 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 1,202 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 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 (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 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:

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

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 k^{th} 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

[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

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 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:

$$\begin{aligned}\ln(p_{it}) = {} & \alpha_i + \beta_1 PAPC_{it} + \beta_2 PC_{it} \\ & + \sum_{k=2}^{D} \gamma_{1k} dist_{ki} PAPC_{it} + \sum_{k=2}^{D} \gamma_{2k} dist_{ki} PC_{it} \\ & + X_{it}'\delta + \varepsilon_{it} \qquad (2)\end{aligned}$$

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

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.

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, 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

[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.

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 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

[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.

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 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 a`nd 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

[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.

visible and the degree of dominance it had on the landscape: no view (0%), minor (1-30%), moderate (31-60%), high (61-90%), 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. 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 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.[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 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.

[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 were a problem, our results would likely be biased downwards making it more likely to find a negative effect.

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.[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 warrants 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

[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.

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. 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 generates 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.

[11] http://www.epa.gov/cleanenergy/energy-resources/calculator.html

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 dataset 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. 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 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.

[12] http://www.epa.gov/climatechange/EPAactivities/economics/scc.html

[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.

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.

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[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.

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Figure 1: Spatial distribution of sales and turbines

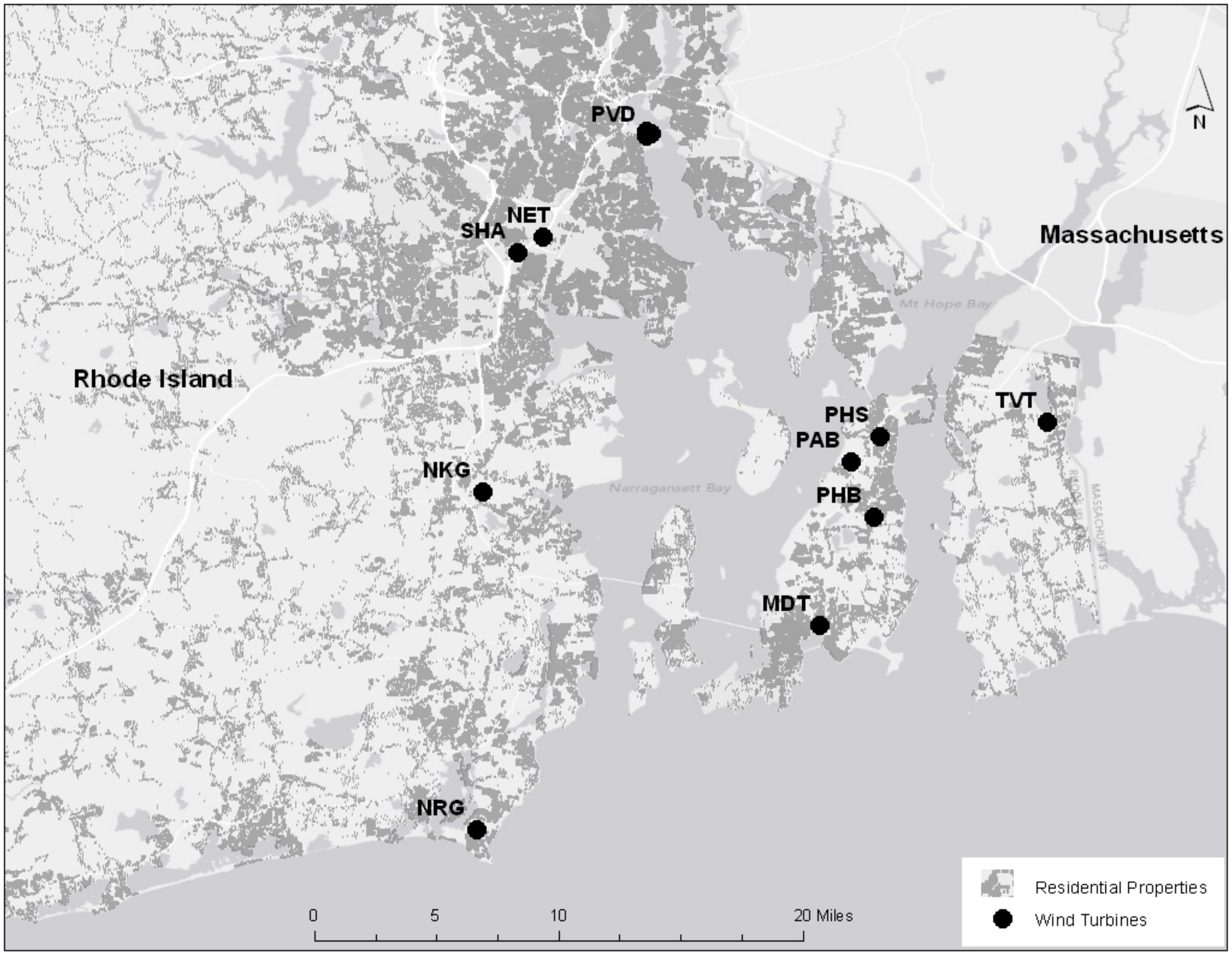

Figure 2: Proximity bands, viewshed, and shadow flicker, for post construction transactions around Portsmouth High School wind turbine

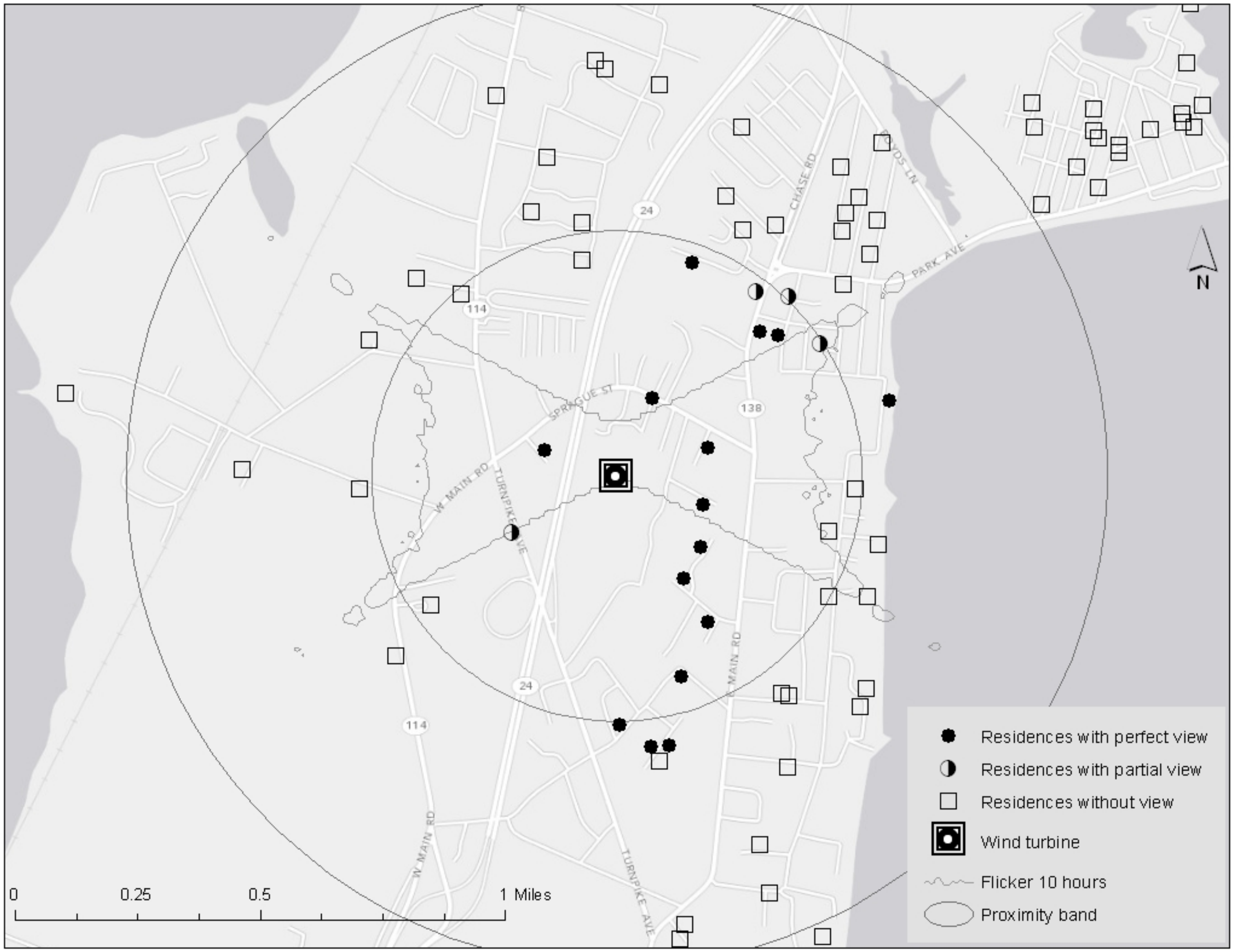

Table 1: Wind turbine characteristics for Rhode Island sample

Name	Abbreviation (match with Figure 1)	Nameplate capacity	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.

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.

Relationship between Wind Turbines and Residential Property Values in Massachusetts

A Joint Report of University of Connecticut and Lawrence Berkeley National Laboratory

January 9, 2014

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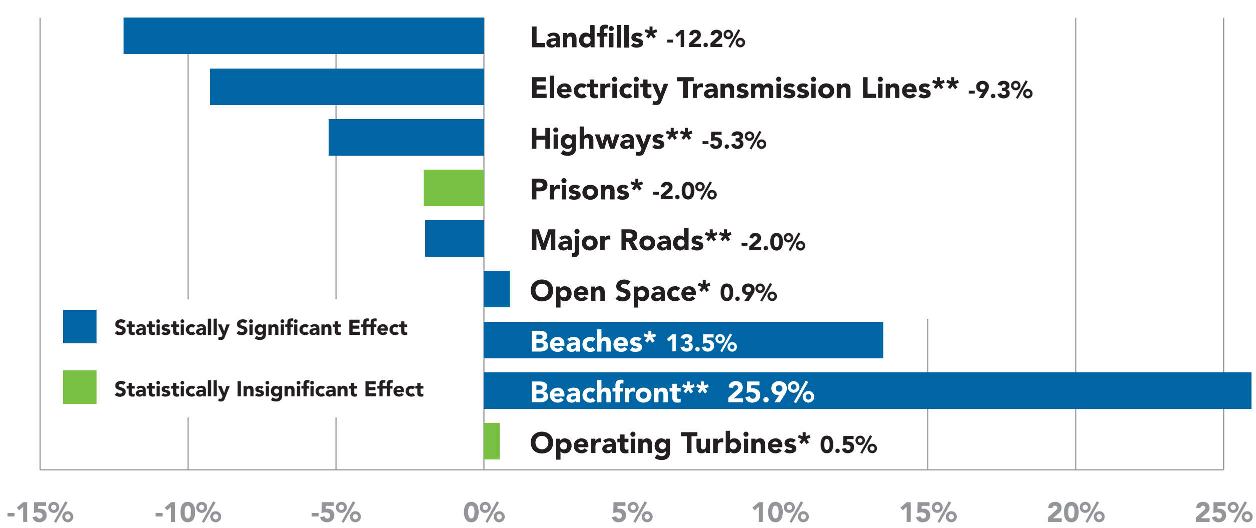
CONTENTS

EXECUTIVE SUMMARY

This study investigates a common concern of people who live near planned or operating wind developments: How might a home's value be affected by the turbines? Previous studies on this topic, which have largely coalesced around non-significant findings, focused on rural settings. Wind facilities in urban[1] locations could produce markedly different results. Nuisances from turbine noise and shadow flicker might be especially relevant in urban settings, where negative features, such as landfills or high voltage utility lines, have been shown to reduce home prices. To determine if wind turbines have a negative impact on property values in urban settings, this report analyzed more than 122,000 home sales, between 1998 and 2012, that occurred near the current or future location of 41 turbines in densely-populated Massachusetts communities.

The results of this study do not support the claim that wind turbines affect nearby home prices. Although the study found the effects from a variety of negative features (such as electricity transmission lines and major roads) and positive features (such as open space and beaches) generally accorded with previous studies, the study found no net effects due to the arrival of turbines in the sample's communities. Weak evidence suggests that the announcement of the wind facilities had a modest adverse impact on home prices, but those effects were no longer apparent after turbine construction and eventual operation commenced. The analysis also showed no unique impact on the rate of home sales near wind turbines. These conclusions were the result of a variety of model and sample specifications detailed later in this report.

Figure 1: Summary of Amenity, Disamenity and Turbine Home Price Impacts



*Distance to MA Homes: * within 1/2 mile; ** within 500 feet*

1 The term "urban" in this document includes both urban and suburban areas.

OVERVIEW

Wind power generation has grown rapidly in recent decades. In the United States, wind development centered initially on areas with relatively sparse populations in the Plains and West. Increasingly, however, wind development is occurring in more populous, urbanized areas, prompting additional concerns about the effects of wind turbine construction on residents in those areas.

One important concern is the potential for wind turbines to create a "nuisance stigma"—due to turbine-related noise, shadow flicker, or both—that reduces the desirability and thus value of nearby homes. Government officials who are called on to address this issue need additional reliable research to inform regulatory decisions, especially for understudied populous urban areas. Our study helps meet this need by examining the relationship between home prices and wind facilities in densely-populated Massachusetts.

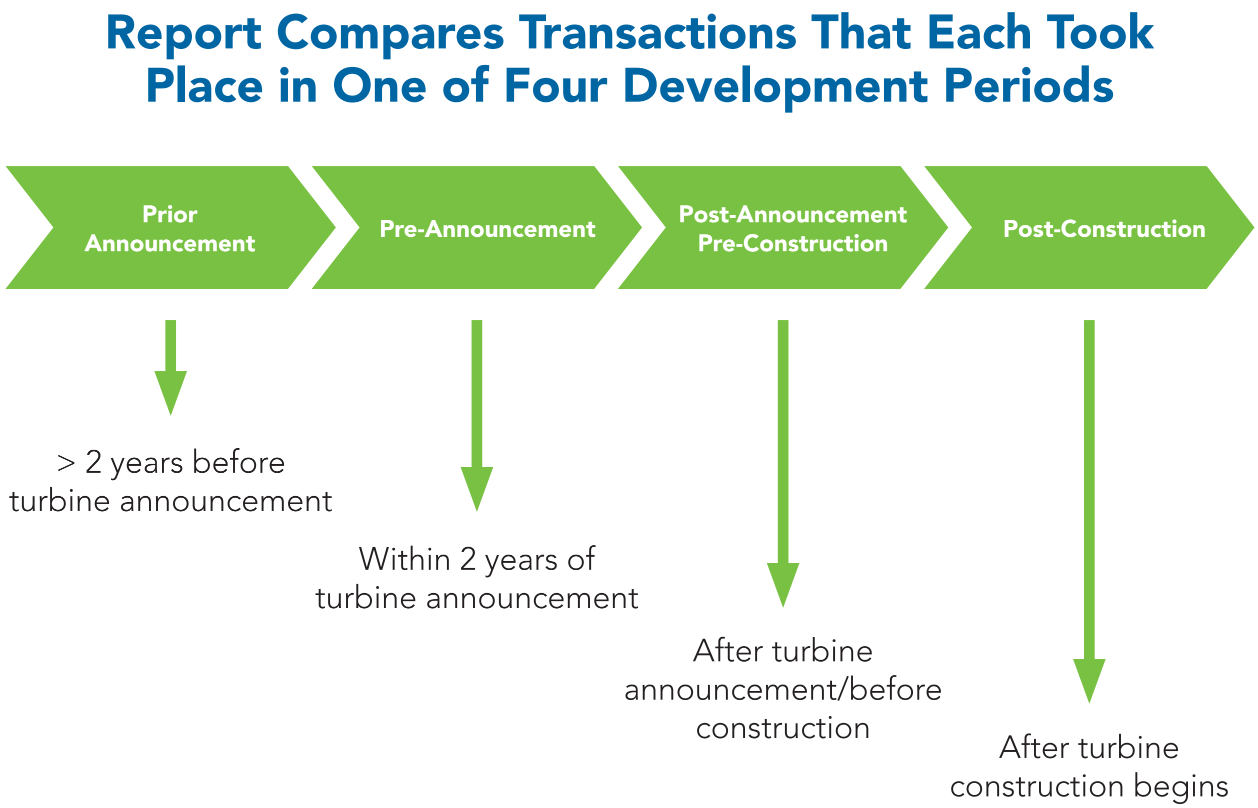
A variety of methods can be used to explore the effects of wind turbines on home prices. Statistical analysis of home sales, using a hedonic model, is the most reliable methodology because it (a) uses actual housing market sales data rather than perceptions of potential impacts; (b) accounts for many of the other, potentially confounding, characteristics of the home, site, neighborhood and market; and (c) is flexible enough to allow a variety of potentially competing aspects of wind development and proximity to be tested simultaneously. Previous studies using this hedonic modeling method largely have agreed that post-construction home-price effects (i.e., changes in home prices after the construction of nearby wind turbines) are either relatively small or sporadic. A few studies that have used hedonic modeling, however, have suggested significant reductions in home prices after a nearby wind facility is announced but before it is built (i.e., post-announcement, pre-construction) owing to an "anticipation effect." Previous research in this area has focused on relatively rural residential areas and larger wind facilities with significantly greater numbers of turbines.

This previous research has done much to illuminate the effects of wind turbines on home prices, but a number of important knowledge gaps remain. Our study helps fill these gaps by exploring a large dataset of home sales occurring near wind turbine locations in Massachusetts. We analyze 122,198 arm's-length single-family home sales, occurring between 1998 and 2012, within 5 miles of 41 wind turbines in Massachusetts. The home sales analyzed in this study occurred in one of four periods based on the development schedule of the nearby turbines (see Figure 2).[2] To estimate the effect proximity to turbines has on home sale prices, we employ a hedonic pricing model in combination with a suite of robustness tests[3] that explore a variety of different model specifications and sample sets, organized around the following five research questions:

2 The analysis focuses on the 41 turbines in Massachusetts that are larger than 600 kilowatt and that were operating as of November 2012.

3 These tests included a comparison of a "base" model to a set of different models, each with slightly different assumptions, to explore the robustness of the study's findings.

Figure 2: Wind Turbine Development Periods Studied



Q1) Have wind facilities in Massachusetts been located in areas where average home prices were lower than prices in surrounding areas (i.e., a "pre-existing price differential")?

Q2) Are post-construction (i.e., after wind-facility construction) home price impacts evident in Massachusetts and how do Massachusetts results contrast with previous results estimated for more rural settings?

Q3) Is there evidence of a post-announcement/pre-construction effect (i.e., an "anticipation effect")?

Q4) How do impacts near turbines compare to the impacts of amenities and disamenities also located in the study area, and how do they compare with previous findings?

Q5) Is there evidence that houses near turbines that sold during the post-announcement and post-construction periods did so at lower rates (i.e., frequencies) than during the pre-announcement period?

The study makes five major unique contributions:

1. It uses the largest and most comprehensive dataset ever assembled for a study linking wind facilities to nearby home prices.[4]

2. It encompasses the largest range of home sale prices ever examined.[5]

3. It examines wind facilities in urban areas (with relatively high-priced homes), whereas previous analyses have focused on rural areas (with relatively low-priced homes).

4. It largely focuses on wind facilities that contain fewer than three turbines, while previous studies have focused on large-scale wind facilities (i.e., wind farms).

5. Our modeling approach controls for seven environmental amenities and disamenities in the study area, allowing the effect of wind facilities to be compared directly to the effects of these other factors.

The models perform exceptionally well given the volatility in the housing market during the study period, with an adjusted-R^2 of approximately 0.80[6] and highly statistically significant[7] and appropriately signed controlling parameters (e.g., square feet, acres, and age of home at the time of sale). The amenity and disamenity variables (proximity to beaches, open space, electricity transmission lines, prisons, highways, major roads, and landfills) are significant in a large portion of the models and appropriately signed—indicating that the models discern a strong relationship between a home's environment and its selling price—and generally accord with the results of previous studies. To test whether the results of the analysis would change if the model was specified in a different way, or run using a differently-specified dataset, we ran a suite of robustness tests. The results generated from the robustness tests changed very little, suggesting that our approach is not dependent on the model specification or the data selection.

The results do not support the claim that wind turbines affect nearby home prices. Despite the consistency of statistical significance with the controlling variables, statistically significant results for the variables focusing on proximity to operating turbines are either too small or too sporadic to be apparent. Post-construction home prices within a half mile of a wind facility are 0.5% higher than they were more than 2 years before the facility was announced (after controlling for

4 Four of the most commonly cited previous studies (Carter, 2011; Heintzelman and Tuttle, 2012; Hinman, 2010; and Hoen et al., 2011) analyzed a *combined total* of 23,977 transactions, whereas the present study analyzes more than five times that number.

5 Existing studies analyzed the impact of wind turbines on homes with a median price of less than \$200,000, whereas the current study examines houses with a median price of \$265,000 for the 122,198 observations located within 5 miles of a wind turbine (with values ranging from \$40,200 to \$2,495,000).

6 In statistics, the coefficient of determination, denoted R^2 (pronounced "R squared"), indicates how well data points fit a line, curve or, in our case, a regression estimation. An R^2 of 1 indicates that the regression line perfectly fits the data.

7 Statistical significance allows one to gauge how likely sample data are to exhibit a definitive pattern rather than, instead, have occurred by chance alone. Significance is denoted by a *p*-value (or "probability" value) which can range between 0 and 1. A very low *p*-value, for example <0.001, is considered highly unlikely (in this case with a probability of less than 0.1%) to have occurred by chance. In general, an appropriate *p*-value is chosen by the researchers consistent with the area of research being conducted, under which results are considered "significant" and over which are considered "non-significant". For the purposes of this research, a *p*-value of 0.10 or below is considered "statistically significant", with *p*-values between 0.10 and 0.05 being "weakly statistically significant", between 0.05 and 0.01 being "significant", and below 0.01 being "highly statistically significant".

What Is a Hedonic Pricing Model?

Hedonic pricing models are frequently used by economists and real estate professionals to assess the impacts of house and community characteristics on property values by investigating the sales prices of homes. A house can be thought of as a bundle of characteristics (e.g., number of square feet, number of bathrooms, the size of the parcel). When a price is agreed upon by a buyer and seller there is an implicit understanding that those characteristics have value. When data from a large number of residential transactions are available, the individual marginal contribution to the sales price of each characteristic for an average home can be estimated with a hedonic regression model. Such a model can statistically estimate, for example, how much an additional bathroom adds to the sale price of an average home. A particularly useful application of the hedonic model is to value non-market goods—goods that do not have transparent and observable market prices. For this reason, the hedonic model is often used to derive value estimates of amenities such as wetlands or lake views, and disamenities such as proximity to and/or views of high voltage transmission lines, roads, cell phone towers, landfills. It should be emphasized that the hedonic model is not typically designed to appraise properties (i.e., to establish an estimate of the market value of one home at a specified point in time) as would a bank appraisal, which would generally be only applicable to that particular home. Instead, the typical goal of a hedonic model is to accurately estimate the marginal contribution of individual or groups of characteristics across a set of homes, which, in general, allows stakeholders to understand if widely applicable relationships exist.

market inflation/deflation). This difference is not statistically significant. Post-announcement, pre-construction home prices within a half mile are 2.3% lower than their pre-announcement levels (after controlling for inflation/deflation), which is also a non-significant difference, though one of the robustness models suggests weak evidence that wind-facility announcement reduced home prices. An additional tangential, yet important, result of the analysis is the finding of a statistically significant "pre-existing price differential": prices of homes that sold more than 2 years before a future nearby wind facility was announced were 5.1% lower than the prices of comparable homes farther away from the future wind location. This indicates that wind facilities in Massachusetts are associated with areas where land values are lower than the surrounding areas, and, importantly, this "pre-existing price differential" needs to be accounted for in order to correctly measure the "post construction" impact of the turbines. Finally, our analysis finds no evidence of a lower rate (i.e., frequency) of home sales near the turbines.

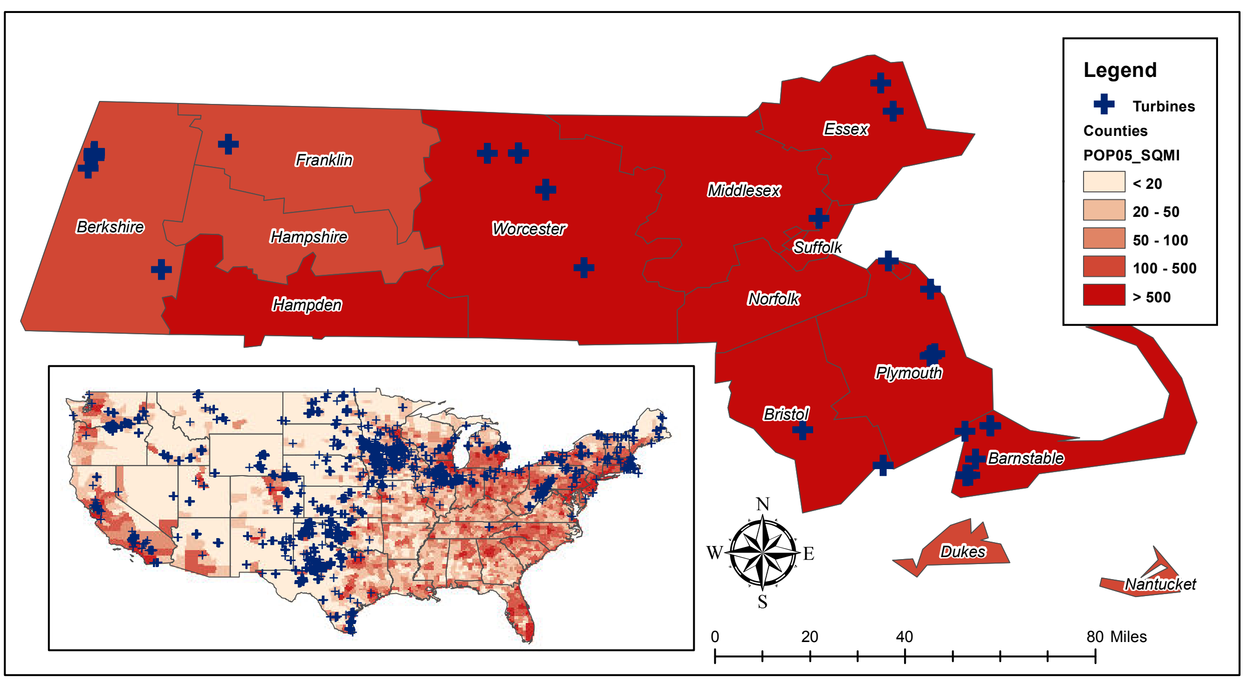
As discussed in the literature review, the effects of wind turbines may be somewhat context specific. Nevertheless, the stability of the results across models and across subsets of the data, and the fact that they agree with the results of existing literature, suggests that the results may be generalizable to other U.S. communities, especially where wind facilities are located in more urban settings with relatively high-priced homes. These results should inform the debate on actual impacts to communities surrounding turbines. Additional research would augment the results of this study and previous studies, and our report concludes with recommendations for future work.

1. INTRODUCTION

Growing concern about global climate change and energy security are prompting reconsideration of how energy—particularly electricity—is generated, transmitted, and consumed in the United States and across the globe (Ekins, 2004; Devine-Wright, 2008; Pasqualetti, 2011). Internationally, greater use of renewable wind energy to mitigate the threat of climate change has broad-based support, primarily because, once facilities are constructed, wind power emits no greenhouse gases (Hasselmann et al., 2003; Watson, 2003; Jager-Waldau and Ossenbrink, 2004). Many jurisdictions have set ambitious renewable energy goals, targeting 20% to 33% of their electricity to be generated by renewable sources by 2020 (see for example, the European Union target of 20% EU, 2012 and California's updated RPS goal of 33%). Wind energy offers several advantages over other low-emission alternatives such as nuclear power and large-scale hydropower projects, but the siting of wind projects remains controversial in many countries (Firestone and Kempton, 2007; Moragues-Faus and Ortiz-Miranda, 2010; Nadai and van der Horst, 2010; Wolsink, 2010).

Figure 3: Map of Massachusetts Turbines included in study (through November 2012) and U.S. Wind Turbines through 2011 and population densities

Population Density in US and Massachusettes (2005 pop per sq. mile)



Source: Lawrence Berkeley National Laboratory, FAA, Ventyx, US Census Bureau, MassCEC

In the United States, large-scale wind installations have tended to be built in sparsely populated locations in the Plains and West (Figure 3). Given that many existing turbines have been located in fairly rural areas, opposition to wind power has largely been attributed to concerns about the transformation of natural landscapes into "landscapes of power" (Pasqualetti et al., 2002 p. 3). Some have extended this place-based perspective and framed the wind-energy debate as being a new kind of environmental controversy, which divides environmentalists of different persuasions who attach contrasting priority to global and local concerns (see for example Warren et al., 2005). Others have delved more deeply into the discourse surrounding renewable energy projects in general, and wind-energy projects specifically, and pointed out that, depending on the narrative, they can be portrayed as representing either development or conservation, localization or globalization (van der Horst and Vermeylen, 2011).

Regardless of what is driving community attitudes towards wind power, government at all spatial scales needs to navigate the complex political terrain of introducing public policies that reduce carbon emissions and fossil fuel dependency in ways that simultaneously protect private property rights and meet with the community's approval (Jepson et al., 2012; Slattery et al., 2012). As such, one of the roles of government is to support independent research to characterize and communicate the potential impacts that public policy decisions, for example for wind facilities, may have on the price of surrounding private property. Existing studies of the effect that wind turbines have had on the price of residential properties have tended to focus on large-scale wind farms located in rural settings, because this is where the majority of projects have been developed. To date, no large-scale studies have focused on smaller-scale facilities in more urban settings, but Massachusetts affords such an opportunity. Massachusetts also has relatively high-priced homes near turbines compared to homes near turbines in other, less urban parts of the country.

Massachusetts has regions with substantial wind resources and strong policies that support the adoption of clean energy. Its first utility-scale (600 kW and larger) wind turbine was installed in Hull in 2001. Since then, wind generation capacity has increased substantially. As of January 2013, Massachusetts had 42 wind projects larger than 100 kW, consisting of 78 individual turbines totaling 99 MW of capacity. This compares to less than 3 MW in Rhode Island and Connecticut combined (Wiser and Bolinger, 2012). Turbines have been located in a variety of settings across the state, including the mountainous Berkshire East Ski Resort, heavily urbanized Charlestown, and picturesque Cape Cod. The average gross population density surrounding the Massachusetts turbines (approximately 416 persons per square mile, based on 2005 population levels and turbines as of 2012) far exceeds the national average of approximately 11 persons per square mile around turbines (Hoen, 2012).

In this study, we analyze the effect of Massachusetts' wind turbines larger than 600 kilowatts (kW) of rated capacity on nearby home prices to inform the debate about the siting and operation of smaller-scale, wind projects across a broad range of land use types in high-home-value areas of the United States. Our study makes five major unique contributions:

1. It uses the largest and most comprehensive dataset ever assembled for a study linking wind facilities to nearby home prices.[8]

2. It encompasses the largest range of home sale prices ever examined.[9]

3. It examines wind facilities in areas across a range of land use and zoning types from rural to urban/industrial (with relatively high-priced homes), whereas previous analyses have focused on rural areas (with relatively low-priced homes).

4. It largely focuses on wind facilities that contain fewer than three turbines, while previous studies have focused on large-scale wind facilities.

5. Our modeling approach controls for seven environmental amenities and disamenities in the study area, allowing the effect of wind facilities to be compared directly to the effects of these other factors.

The remainder of this report is organized as follows. The next section (Section 2) reviews literature related to public opposition to and support for wind turbines, the hypothetical stigmas associated with turbines near homes, policies and guidelines which address the siting and operation of wind facilities, ways to quantify whether turbines are a disamenity, and the impact on home values of other types of environmental amenities and disamenities—followed by a discussion of gaps in the literature. Section 3 presents our empirical analysis, including descriptions of the study area, data, methods, and results. The final section (Section 4) discusses the findings, provides preliminary conclusions, and offers suggestions for future research.

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8 Four of the most commonly cited previous studies (Carter, 2011; Heintzelman and Tuttle, 2012; Hinman, 2010; and Hoen et al., 2011) analyzed a *combined total* of 23,977 transactions, whereas the present study analyzes more than five times that number.

9 Existing studies analyzed the impact of wind turbines on homes with a median price of less than $200,000, whereas the current study examines houses with a median price of $265,000 for the 122,198 observations located within 5 miles of a wind turbine (with values ranging from $40,200 to $2,495,000) and a median price for the 312,674 observations located within 10 miles of a wind turbine of $287,000 (with values ranging from $41,100 to $2,499,000).

2. LITERATURE REVIEW

2.1 Public Acceptance of and Opposition to Wind Energy

Wind energy is one of the fastest growing sources of power generation in the world, and public and political support for it are generally strong (Ek, 2005; Graham et al., 2009). Despite this strong support, the construction of wind projects provokes concerns about local impacts (Toke et al., 2008; Jones and Eiser, 2009; Devine-Wright and Howes, 2010; Jones and Eiser, 2010; Moragues-Faus and Ortiz-Miranda, 2010; Wolsink, 2010; Pasqualetti, 2011). Thus, some researchers have studied the factors shaping public attitudes toward wind energy and renewable energy technologies in general (see for example Devine-Wright, 2005; Firestone and Kempton, 2007; Pedersen et al., 2007; Wolsink, 2007; Devine-Wright, 2009; Jones and Eiser, 2009; Devine-Wright and Howes, 2010; Jones and Eiser, 2010; Swofford and Slattery, 2010; Brannstrom et al., 2011; Devine-Wright, 2011). Others have downplayed the importance of local opposition to wind energy in hindering wind's expansion, pointing instead to hindrances related to institutional barriers, such as how wind energy projects are funded, and the heavy handedness of "legislate, announce, defend" approaches to siting turbines (Wolsink, 2000).

In the early stages of wind development, opposition to wind turbines was often simplistically conceptualized as NIMBY-ism, with NIMBY ("not in my backyard") referring to people opposing the local installation of technologies they otherwise support in principle (Devine-Wright, 2005; Wolsink, 2007; Devine-Wright, 2009). More recently, researchers have suggested that the factors shaping public sentiment towards renewable energy technologies are much more complex than the concept of NIMBY-ism suggests. Of note is the quantitative research aimed at understanding public attitudes towards wind farms in the Netherlands conducted by Wolsink (2007). His work, and the work of others (e.g., Devine-Wright, 2012), which is grounded in theories from social psychology, found that public attitudes towards wind projects were shaped by perceptions of risk and equity. Based on these findings, Wolsink concluded that a collaborative—rather than a "top-down"—approach to siting wind farms was the most likely to produce positive outcomes. These findings were echoed in an examination of public attitudes towards wind turbine construction in Sheffield, England, where researchers found little evidence of NIMBY-ism in respondents living close to proposed developments compared to a control group (Jones and Eiser, 2009). Rather, opposition could be attributed to uncertainty regarding the details of the facilities being constructed, which underscores the importance of continued and responsive community involvement in siting wind turbines.

Some researchers have studied whether communities are more accepting of wind turbines if the facilities are community owned (Warren and McFadyen, 2010). Comparing attitudes towards wind farms on two islands in Scotland, one community owned and one not, the researchers discovered that residents near the community owned facilities had a much more positive perception of the facilities. Locals affectionately referred to their wind turbines as "The Three

Dancing Ladies," which the researchers interpreted as indicating the positive psychological effects of community ownership. Warren and McFadyen (2010) concluded that a change of development model towards community ownership could improve public attitudes towards wind farms in Scotland.

Another strand of research has focused on community perceptions before and after wind-facility construction. Some studies showed that local people become more supportive of wind facilities after they have been constructed (Wolsink, 2007; Eltham et al., 2008; Walker et al., 2010) and that the degree of support increases with proximity to the facilities (Braunholtz and MORI, 2003; Warren et al., 2005; Slattery et al., 2012).

2.2 Hypothetical Stigmas Associated with Wind Turbines

To understand the basis of public opposition to wind facilities, researchers have hypothesized the existence of three types of stigma that might be associated with these facilities (Hoen et al., 2011). An "area stigma" would be a concern that wind-turbine construction will alter the rural sense of place; this resonates with the suggestion made by Pasqualetti et al. (2002) that people object to the creation of "landscapes of power." This is distinct from a "scenic vista stigma," the possible concern that homes might be devalued because of the view of a wind facility. Finally, a "nuisance stigma" would be associated with people located near turbines who might be affected by the turbines' noise and shadow flicker,[10] which fade quickly with distance. Our study focuses on the potential existence of a nuisance stigma by searching for turbine-related impacts on the sale of homes located a short distance away. However, if they exist, the effects of all three stigma types hypothetically could interact, and all are described briefly below.

The spatial and temporal combinations of community and wind-facility characteristics that might produce one or more of these stigmas are not entirely clear. Theoretically, an area stigma would have the largest geographic impact, although its exact reach would depend on the spatial distribution and types of land use in the surrounding area. In their comprehensive analysis, Hoen et al. (2009, 2011) were unable to uncover area stigma effects across their large set of U.S. wind facilities. Recent research has suggested, however, that this type of stigma depends on the "place identity" of local residents (Pedersen et al., 2007; Devine-Wright, 2009; Devine-Wright and Howes, 2010). For those who view the countryside as a place for economic activity and technological development or experimentation, which is potentially consistent with the locations studied in Hoen et al. (2009, 2011), wind turbines might not carry a stigma because they could represent a new use for the land, and the turbine sounds and sights might be insignificant in the context of existing machinery and land practices. Conversely, rural residents who view the countryside as a place for peace and restoration might oppose turbines even if they do not live near them. The "place identity" of the landscape likely varies among wind facility- locations and among individuals in those locations, making some local residents more accepting of turbines than others.

Acceptance of turbines might also relate to their economic benefits. For example, a study in West Texas and Iowa found that community members had positive impressions of large-scale wind facilities built to generate long-term social and economic benefits, including creation of a local industry that

10 Shadow flicker occurs when the sun is behind rotating turbine blades and produces an intermittent shadow.

brought jobs and increased property values as well as increased tax revenue that benefited the community and schools (Slattery et al., 2012; Kahn, 2013). These findings conform to other research suggesting that equitable distribution of economic benefits is a key method of increasing local support for turbines (Pasqualetti et al., 2002) and that the perception of how tax benefits will be shared locally can influence people's acceptance of wind projects (Toke, 2005; Brannstrom et al., 2011). Economic factors appear to be more of a consideration where the economy is perceived to be in decline (Toke et al., 2008); this finding is echoed in studies of other environmental disamenities that show that communities are more willing to accept facilities if jobs are associated with them (Braden et al., 2011). Many of these studies were conducted in rural areas, thus their findings may not be generalizable to more urban settings, where community reactions might be entirely different.

Similarly, if a scenic vista stigma exists, it might have different levels of impact depending on wind-facility locations, the place identity of nearby residents, and the distance of residents from the turbines. Hoen et al. (2009, 2011) meticulously examined effects from views of turbines at many different spatial scales and predicted levels of impacts in rural areas, but they found no evidence of impacts to support the scenic vista stigma claim. However, an urban setting might connote different landscape values and therefore generate different reactions to turbines and produce different effects on home values. For example, Sims et al. (2008) found weak evidence that a house's orientation to a wind facility (and therefore the prominence of the view of the turbines) affected its sales price in Cornwall, United Kingdom, an area of relatively high population.[11]

11 As of 2011, Cornwall had a population density of 390 persons per square mile. (See http://en.wikipedia.org/wiki/Cornwall)

More than the other stigma types, any potential wind-related nuisance stigma would depend on the close proximity of residents to turbines and likely would have the most constrained spatial scale. Two studies in Germany evaluated more than 200 participants living near wind turbines with regard to shadow flicker exposure, stress, behaviors, and coping and found that stress levels and annoyance increased the closer people were to wind turbines in all directions (Pohl et al., 1999, 2000). Similarly, wind turbine noise, which is less direction dependent than shadow flicker, might have an even greater impact on stress levels. Studies have shown that residents experience genuine annoyance and stress responses to "normal" turbine noise levels (Pedersen and Waye, 2007), perceiving the noise as an intrusion into their space and privacy, especially at night (van den Berg, 2004; Pedersen et al., 2007) and when the turbines can be seen (Pedersen and Waye, 2007). Governments around the world have addressed potential turbine-related nuisances via regulations and guidelines, which are discussed in the next subsection.

2.3 Policies and Guidelines Which Address the Siting and Operation of Wind Facilities

Noise is the most prominent potential nuisance associated with wind turbines and thus has been the focus of much regulatory effort. The quality and magnitude of sound produced by turbines results from the complex interaction of numerous variables, such as the size and design of the turbine as well as the wind speed and direction, temperature gradients that affect wind turbulence, and vertical and directional wind shear (Hubbard and Shepherd, 1991; Berglund et al., 1996; Oerlemans et al., 2006; Pedersen et al., 2010; Bolin et al., 2012; Wharton and Lundquist, 2012). For practical purposes, governments, both here in the U.S. and abroad, at a variety of spatial scales have tended to adopt setback metrics for the distance between a wind turbine and housing as a proxy for noise limits (NARUC, 2012). Very few countries have mandatory turbine setback distances beyond what would be required for safety in the event of a collapse (and therefore 1-1.5 times the turbines' height), nor do they often impose mandatory limits to shadow flicker; they do often have mandatory or, at least, stronger regulation of noise.

Although there is no worldwide standard limit for noise associated with wind turbines (Haugen, 2011), many European countries base their regulations on recommended noise limits published by the World Health Organization (WHO) Regional Office for Europe (WHO, 2011). The WHO recommends noise limits of 40 (A-weighted) decibels dB(A) for the average nighttime noise outside a dwelling, which translates to a noise limit of 30 dB(A) inside a bedroom.[12] These limits are based on noise levels that do not harm a person's sleep. Above these limits, it is believed, people have a lower amount and quality of sleep, which can lead to major health issues (WHO, 2011).

In the United States, turbine sound and setback regulation is limited: only "a handful of states have published setback standards, sound standards, or both" (NARUC, 2012, p. 15). Ten states have published voluntary guidelines for wind siting and zoning, and five have published model ordinances intended to guide local governments. Similar to other countries, required or recommended setbacks vary widely from state to state, both in terms of the distances cited and the legal weight they carry (some are formal limits while others are merely guidelines).

In Massachusetts, the Model Wind Bylaw and the Massachusetts Department of Environmental Protection (MADEP) Noise Policy provide guidelines and regulatory standards respectively for the siting and operation of wind facilities to address public safety and minimize local impacts. The former provides some guidance on setbacks from the nearest existing residential or commercial structure using a multiple (e.g., 3 times) of blade tip height (BTH) (i.e., the hub height plus the length of the blade) as a means to determine the project specific setback.[13] However, all of the wind turbines in the state have been permitted at the local level, with varying degrees of adherence to the guidance, while still others were permitted prior to the Model Bylaw's preparation, and still others have had few structures near the turbines from which to setback. Therefore, in practice, setbacks to the nearest structure have varied from as much as 4,679 feet (0.89 miles, 24.4 x BTH) to as little as 520 feet (0.1 miles, 1.3 x BTH), with an average Massachusetts project being 1,925 feet (0.36 miles, 5.9 x BTH) (Studds, 2013).[14] Because, in part, of the variety of ways in which the guidelines have been applied, setbacks remain one of the more controversial aspects of wind-facility siting. Also, adding to the controversy are the results of one recent study of two wind facilities in Maine that claimed noise effects are experienced as far as 1.4 kilometers (4,590 feet, 0.87 miles) from the turbines (Nissenbaum et al., 2012).

12 A-weighted decibels abbreviated to dBa, dBA or dB(a), are an expression of the relative loudness of sounds in air as perceived by the human ear. In the A-weighted system, the decibel values of sounds at low frequencies are reduced, compared with unweighted decibels, in which no correction is made for audio frequency (http://whatis.techtarget.com)

13 MA EEA/DOER Model Wind Bylaw. Accessed on 1/23/12 from: http://www.mass.gov/eea/docs/doer/gca/wind-not-by-right-bylaw-june13-2011.pdf. The Executive Office of Environmental Affairs, Department of Environmental Quality Engineering, Division of Air Quality Control, "DAQC Policy 90-001," February 1, 1990.

14 These setbacks do not include structures of participating landowners, that either might own the turbine, or are being compensated by the turbine owner.

Finally, in response to noise concerns, wind-technology developers are investigating numerous ways to suppress noise including passive noise reduction blade designs, active aerodynamic load control, new research on inflow turbulent and turbine wakes, low-noise brake linings, and cooling fan noise mufflers (Leloudas et al., 2009; Wilson et al., 2009; Barone, 2011; Petitjean et al., 2011), some of which have been shown to lower annoyance when applied (Hoen et al., 2010; Hessler, 2011). How these strategies might eventually affect setback and noise regulations and guidelines is unclear.

For the purposes of this study, suffice it to say that wind turbine setbacks vary, and they are often smaller than the distances at which (at least some) turbine noise effects have been claimed to exist. If a resulting nuisance stigma exists near turbines, it should be reflected in nearby home prices. By evaluating the relationship between wind turbines and home prices this study might help inform appropriate setbacks and noise recommendations in Massachusetts.

2.4 Methods to Quantify Whether Wind Turbines are a Disamenity

If a wind turbine near homes does produce a meaningful stigma, it could be considered a disamenity similar to other disamenities such as proximity to electricity transmission lines and major roads. A variety of research techniques can be used to determine the impact of wind energy projects on residential properties, including homeowner surveys, expert surveys (such as interviewing real estate appraisers), and statistical analysis of property transactions using cases studies or the well-established method of hedonic modeling (see e.g., Jackson, 2003). The latter technique is firmly established in the literature as the most reliable approach to determining the impact of a particular development on property prices, because it (a) uses transactions data that reflect actual sales in the housing market rather than perceptions of potential impacts; (b) controls for a set of potentially confounding home, site, neighborhood and market influences; and, (c) is flexible enough to allow a variety of potentially competing aspects of wind development and proximity to be tested simultaneously (Jackson, 2001).

An extensive meta-analysis of studies that had quantified the effect of environmental amenities and disamenities found that the use of case study techniques provide larger estimates of property losses associated with environmental disamenities than regression studies using hedonic models (Simons and Saginor, 2006). Simons and Saginor attributed this differential to the fact that case studies may be subjective based on the case researcher, and they argue that case study observations may even have been chosen because of their dramatic, atypical conditions. Surveys, which were generally based on respondents' estimates of impacts, were considered to suffer from similar bias due to the subjectivity of respondents and their potential lack of effect-estimation expertise.

The hedonic-modeling approach is based on the idea that any property's sales price is composed of a bundle of attributes, including the characteristics of the individual property and its location (Rosen, 1974). Sales can be compared to one another, taking into account the effects of time (i.e., inflation/deflation), to determine the value of any specific attribute (Butler, 1982; Clapp and Giaccotto, 1998; Jackson, 2001; Simons and Saginor, 2006; Jauregui and Hite, 2010; Kuminoff et al., 2010; Zabel and Guignet, 2012).

The approach has been used extensively to quantify the effects of public policies (specifically infrastructure) on home prices by examining the value associated with being close to a facility before and after it was constructed (see Atkinson-Palombo, 2010 and the extensive references therein). If the particular initiative being studied (for example, a transportation facility) is perceived as an amenity, it would be expected to increase property values, all else being equal. If the initiative is perceived as a disamenity, it would be expected to decrease property values. This hedonic method measures average impacts across the study area and therefore can help policy makers understand costs and benefits at a broad scale.

Our study uses the hedonic-modeling approach to quantify the effect of wind facilities on home values. This involves creating a statistical model with an expression of home price as the dependent variable and independent variables consisting of factors that influence home price. These independent variables include features of the specific housing unit, locational characteristics, a variable that represents distance to a wind turbine at discrete stages of the construction process, and various controls such as the time when a transaction took place to account for changes in the housing market over time (inflation and deflation). If a wind turbine creates a disamenity, then house prices closer to the turbine would be expected to decline (all else being equal) compared to their values before the turbine was installed and compared to the prices of houses farther away that sold during the same period.

The peer-reviewed, published studies that used hedonic modeling largely agree in finding non-significant post-construction effects (i.e., non-significant effects on home prices occurring after construction of wind turbines) (Sims et al., 2008; Hoen et al., 2011; Heintzelman and Tuttle, 2012), implying that average impacts in their study areas were either relatively small or sporadic near existing turbines. Three academic studies found similar results (Hoen, 2006; Hinman, 2010; Carter, 2011). The geographic extent of these studies varied from single counties (Hoen, 2006; Hinman, 2010; Carter, 2011), to three counties in New York (Heintzelman and Tuttle, 2012), to eight states (Hoen et al., 2011), showing that results have been robust to geographic scale. Although the academic and peer-reviewed literature has largely focused on post-construction impacts, some studies have found evidence of pre-construction yet post-announcement impacts (Hinman, 2010; Hoen et al., 2011; Heintzelman and Tuttle, 2012). This "anticipation effect" (Hinman, 2010) correlates with surveys of residents living near wind facilities that have found that once wind turbines are constructed, residents are more supportive of the facilities than they were when the construction of that facility was announced (Wolsink, 2007; Sims et al., 2008). Analysis of home prices related to other disamenities (e.g., incinerators) also has shown anticipation effects and post-construction rebounds in prices (Kiel and McClain, 1995).

2.5 General Literature on the Effects of Amenities and Disamenities on House Prices

While wind turbines are typically limited to high-wind-resource areas, disamenities such as highways, overhead electricity transmission lines, power plants, and landfills are ubiquitous in urban and semi-rural areas, and they have been the focus of many studies. This more established "disamenity literature" (see for example, Boyle and Kiel, 2001; Jackson, 2001; Simons and Saginor, 2006) helps frame the expected level of impact around turbines. For example, adverse home-price effects near electricity transmission lines, a largely visual disturbance, have ranged from 5% to 20%, fading quickly with distance and disappearing beyond 200 to 500 feet, and even in some cases, when afforded with access to the transmission line corridor, home-price effects have found to be positive signaling net benefits over costs of transmission line proximity (e.g., Des Rosiers, 2002). Landfills, which present smell and truck-activity nuisances and potential health risks from groundwater contamination, have been found to decrease adjacent property values by 13.7% on average, fading by 5.9% for each mile a home is further away for large-volume operations (that accept more than 500 tons per day). Lower-volume operations decreased adjacent property values by 2.7% on average, fading by 1.3% per mile, with 20% to 26% of the lower-volume landfills not significantly impacting values at all (Ready, 2010). Finally, a review of literature investigating impacts of road noise on house prices, which might be analogous to noise from turbines, found price decreases of 0.4% to 4% for houses adjacent to a busy road compared to those on a quiet street (see for example Bateman et al., 2001; Day et al., 2007; Kim et al., 2007; Andersson et al., 2010).

Community amenities also have been well studied. Open space (i.e., publicly accessible areas that are available for recreational purposes) has been found to increase surrounding prices (Irwin, 2002; Anderson and West, 2006a); Anderson and West estimated those premiums to be 0.1% to 5%, with an average of 2.6% for every mile that a home is closer to the open space. Proximity to (and access to and views of) water, especially oceans, has been found to increase values (e.g., Benson et al., 2000; Bond et al., 2002); for example, being on the waterfront increased values by almost 90% (Bond et al., 2002).

Although much of the literature on community perceptions of wind turbines suggests that local residents may see turbines as a disamenity, this is not always the case. As discussed above, perceptions about wind turbines are shaped by numerous factors that include the size of the turbine(s) or project, the sense of place of the local residents, the manner in which the planning process is conducted, and the ownership structure. In contrast to disamenities universally disliked by local residents (as discussed above), some literature suggests that wind turbines could be considered amenities (i.e., a positive addition to the community), particularly if benefits accrue to the local community. Thus, whether wind turbines increase or decrease surrounding home prices—and by how much—remains an open question.

The evidence discussed above suggests that any turbine-related disamenity impact likely would be relatively small, for example, less than 10%. If this were the case, tests to discover this impact would require correspondingly small margins of error, which in turn requires large amounts of data. Yet much of the literature has used relatively small numbers of transactions near turbines. For example, the largest dataset studied to date had only 125 post-construction sales within 1 mile of the turbines (Hoen et al., 2009, 2011), while others contained far fewer post-construction transactions within 1 mile: Heintzelman and Tuttle (*n* ~ 35), Hinman (*n* ~ 11), and Carter (*n* ~ 41). Although these numbers of observations might be adequate to examine large impacts (e.g., greater than 10%), they are less likely to discover smaller effects because of the size of the corresponding margins of error. Larger datasets of transactions would allow smaller effects to be discovered. Using results from Hoen at al. (2009) and the confidence intervals for the various fixed-effect variables in that study, we estimated the numbers of transactions needed to find effects of various sizes. Approximately 50 transactions are needed to find an effect of 10% or greater, 200 to find an effect of 5%, 500 to find an effect of 3.5%, and approximately 1,000 to find a 2.5% effect.

Additionally, there is evidence that wind facilities are sited in areas where property prices are lower than in surrounding areas—what we are referring to as a "pre-existing price differential". For example, Hoen et al. (2009) found significantly lower prices (-13%) for homes that sold more than 2 years prior to the wind facilities' announcements and were located within 1 mile of where the turbines were eventually located, as compared to homes that sold in the same period and were located outside of 1 mile. Hinman (2010) found a similar phenomenon that she labeled as a "location effect." To that end, Sims and Dent (2007), after their examination of three locations in Cornwall, United Kingdom, commented that the research "highlighted to some extent, wind farm developers are themselves avoiding the problem by locating their developments in places where the impact on prices is minimized, carefully choosing their sites to avoid any negative impact on the locality" (p. 5). Thus, further investigation of whether wind facilities are associated with areas with lower home values than surrounding areas would be worthwhile. It is important to emphasize that any "pre-existing price differential" does not exist because of the turbines, but instead is likely the result of the fact that wind turbines may be located in areas of relative disamenity. For example, in Massachusetts, wind turbines have typically been co-located with industrial facilities such as waste water treatment plants. While we included seven different amenities and disamenities in our model, we could not include all of them because of a lack of accurate data, especially for waste water treatment plants and industrial sites that may have been co-located with wind turbines. Some of the "pre-existing price differential" may therefore be attributable to other disamenities that have not been included in the model. Regardless of the reason, any "pre-existing price differential" needs to be taken into account in order to accurately calculate the net impacts that wind turbines may have on property prices.

Finally, there have been claims that the home sales rate (i.e., sales volume) near existing wind turbines is far lower than the rate in the same location before the turbines' construction and the rate farther away from the turbines, because homeowners near turbines cannot find buyers (see sales volume discussion in Hoen et al., 2009). Obviously, many homes near turbines have sold, as recorded in the literature. If it were true that homeowners near turbines have *chosen* to sell less often because of very low buyer bids, then sales that did take place near turbines should be similarly discounted on average, but evidence of large discounts has not emerged from the academic literature (as discussed above). Moreover, homes farther away from turbines would be taken off the market for similar reasons (sellers do not get offers they accept), thus the comparison group is potentially affected in a similar way. In any case, although Hoen et al. (2009) found no evidence of lower sales volumes near turbines, further investigations of this possible phenomenon using different datasets are warranted.

2.6 Gaps in the Literature

This literature review suggests several knowledge gaps that could be studied further: exploring wind turbine impacts on home prices in urban settings, where the "sense of place" might be different than in the previously studied rural areas; examining post-announcement/pre-construction impacts; testing for relatively small impacts using large datasets; determining whether wind facilities are sited in areas with lower home values; examining turbine impacts in concert with impacts from other disamenities and amenities; and investigating whether home sales volumes are different near existing wind turbines. Our study seeks to address each of these areas.

3. EMPIRICAL STUDY

Because of Massachusetts' density of urban homes near enough to wind turbines to produce potential nuisance effects, our study analyzes Massachusetts data to address gaps in knowledge about turbine effects on home prices. Specifically, the study seeks to answer the following five questions:

Q1) Have wind facilities in Massachusetts been located in areas where average home prices were lower than prices in surrounding areas (i.e., a "pre-existing price differential")?

Q2) Are post-construction (i.e., after wind-facility construction) home price impacts evident in Massachusetts, and how do Massachusetts results contrast with previous results estimated for more rural settings?

Q3) Is there evidence of a post-announcement/pre-construction effect (i.e., an "anticipation effect")?

Q4) How do impacts near turbines compare to the impacts of amenities and disamenities also located in the study area, and how do they compare with previous findings?

Q5) Is there evidence that houses near turbines that sold during the post-announcement and post-construction periods did so at lower rates (i.e., frequencies) than during the pre-announcement period?

The following subsections detail the study's hedonic-modeling process and base model, the extensive robustness tests used to determine the sensitivity of the base model, the study data, and the results.

3.1 Hedonic Base Model Specification

The price of a home can be expressed as follows:

$$P = f(L, N, A, E, T)$$

where L refers to lot-specific characteristics, N to neighborhood variables, A to amenity/disamenity variables, E to wind-turbine variables, and T to time-dependent variables.

Following from this basic formula, we estimate the following customarily used (see, e.g., Sirmans et al., 2005) semi-log base model to which the set of robustness models are compared.

$$\ln(P) = \beta_0 + \sum \beta_1 L \bullet D + \beta_2 N + \sum \beta_3 A \bullet D + \sum \beta_4 E \bullet D + \sum \beta_5 T + \varepsilon'$$

An explanation of this formula is as follows:

The dependent variable is the log of sales price (P).

L is the vector of lot-specific characteristics of the property, including living area (in thousands of square feet); lot size (in acres); lot size less than 1 acre (in acres if the lot size is less than 1, otherwise 1); effective age (sale year minus either the year built or, if available, the most recent renovation date); effective age squared; and number of bathrooms (the number of full bathrooms plus the number of half bathrooms multiplied by 0.5).

D is the nearest wind turbine's development period in which the sale occurred (e.g., if the sale occurred more than 2 years before the nearest turbine's development was announced, less than 2 years before announcement, after announcement but before construction, or after construction).

N is the U.S. census tract in which the sale occurred.

A is the vector of amenity/disamenity variables for the home, including the amenities: if the home is within a half mile from open space; is within 500 feet or is within a half mile but outside 500 feet of a beach; and, disamenities: is within a half mile of a landfill, and/or prison; and is within 500 feet of an electricity transmission line, highway and/or major road.[15]

T is the vector of time variables, including the year in which the sale occurred and the quarter in which the sale occurred.

E is a binary variable representing if the home is within a half mile from a turbine, and

ε is the error term.[16]

β_0, β_1, β_2, β_3, β_4, β_5 are coefficients for the variables.

The vectors of lot-specific and amenity/disamenity variables are interacted with the development period for three reasons: 1) to allow the covariates to vary over the study period, which will, for example, allow the relationship of living area and sale price to be different earlier in the study period, such as more than 2 years before announcement, than it is later in the study period, such as after construction of the nearest turbine;[17] 2) to ensure that the variables of interest do not absorb any of this variation and therefore bias the coefficients; and 3) to allow the examination of the amenity/disamenity variables for subsets of the data.[18]

The distance-to-the-nearest-turbine variable specified in the base model is binary: one if the home is within a half mile of a turbine and zero if not. The distance can be thought of as the distance, today, when all the turbines in the state have been built. Obviously, for some homes, such as those that sold before the wind facility was announced, there was no turbine nearby at the time of sale, so in those cases the distance variable represents the distance to where the turbine eventually was built. By interacting this distance variable with the turbine development period, we are able to examine how the distance effects might change over the periods and whether or not there was a pre-existing price differential between homes located near turbines and

15 Each of the amenity/disamenity variables are expressed as a binary variable: 1 if "yes," 0 if "no."

16 The error term (i.e., "unexplained variation" or "residual value") defines the portion of the change in the dependent variable (in this case the log of sale price) that cannot be explained by the differences in the combined set of independent variables (in this case the size and age of the home, the number of bathrooms, etc.). For example, a large portion of one's weight can be explained by one's gender, age and height, but differences (i.e., unexplained variation) in a sample of people's weight will still exist for random reasons. Regardless of how well a model performs, some portion of unexplained variation is expected.

17 As discussed in greater detail in the results, the coefficients for the variables of interest are quite small in magnitude, and therefore even a relatively small change in the size of the coefficients can be problematic to the correct interpretation of the results. Moreover, the lot-specific and amenity/disamenity variables vary over the development periods, further reinforcing the need to interact them with period. The results for the wind turbine variables presented herein are robust to alternative specifications without these interactions.

18 While the coefficients associated with the amenity/disamenity variables interacted with the facility development periods are not particularly meaningful, creating the subsets enables examination of the data represented by the different wind turbine development periods and shows how stable the amenity/disamenity variables are within these subsets of data.

those farther away that existed even before the turbines were announced.

Further, we used a binary variable as opposed to other forms used to capture distance. For example, other researchers investigating wind turbine effects have commonly used continuous variables to measure distance such as linear distance (Sims et al., 2008; Hoen et al., 2009), inverse distance (Heintzelman and Tuttle, 2012; Sunak and Madlener, 2013), or mutually exclusive non-continuous distance variables (Hoen et al., 2009; Hinman, 2010; Carter, 2011; Hoen et al., 2011; Heintzelman and Tuttle, 2012; Sunak and Madlener, 2013). We preferred the binary variable because we believe the other forms have limitations. Using the linear or inverse continuous forms necessarily forces the model to estimate effects at the mean distance. In some of these cases those means can be quite far from the area of expected impact. For example, Heintzelman and Tuttle (2012) estimated an inverse distance effect using a mean distance of over 10 miles from the turbines, while Sunak and Madlener (2013) used a mean distance of approximately 1.9 miles. Using this approach makes the model less able to quantify the effect near the turbines, where they are likely to be stronger. More importantly, this method encourages researchers to extrapolate their findings to the ends of the distance curve, near the turbines, despite having few data in this distance band. This was the case for Heintzelman and Tuttle (2010), who had less than 10 sales within a half mile in the two counties where effects were found and only a handful of sales in those counties after the turbines were built. Yet they extrapolated their findings to a quarter mile and even a tenth of a mile, where they had very few, if any, cases. Similarly, Sunak and Madlener (2013) had only six (post-construction) sales within a half mile, yet they extrapolated their findings to this distance band.

One method to avoid using a single continuous function to describe effects at all distances is to use a spline model, which breaks the distances into continuous groups (Hoen et al., 2011), but this still imposes some structure on the data that might not actually exist. By far the most transparent method is to use binary variables for discrete distances that therefore impose only slight structure on the data (Hoen et al., 2009; Hinman, 2010; Hoen et al., 2011). Although this method has been used in existing studies, because of a paucity of data, margins of error for the estimates were large (e.g., 7% to 10% for Hoen et al. 2011). However, as discussed above, the extensive dataset for Massachusetts allows this approach to be taken while maintaining relatively small margins of error. Moreover, although others have estimated effects for multiple distance bins out to 5 or 10 miles, we have focused our estimates on the group of homes that are within a half mile of a turbine—although other groups, such as those within a quarter of a mile and between one half and one mile, are explored in the robustness models. The homes within a half mile of turbines are most likely to be impacted and are, therefore, the first and best place to look for impacts. Further, we use the entire group of homes outside of a half mile as the reference category, which gives us a large heterogeneous comparison group and therefore one that is likely *not* correlated with omitted variables—although we also explore other comparison groups in the robustness tests.

3.2 Robustness Tests

Models are built on assumptions and therefore practitioners often test those assumptions by trying multiple model forms. As was the case for this research, a "base" model is compared to a set of "robustness" models, each with slightly different assumptions, to explore the robustness of the study's findings.

The suite of robustness tests explored changes in: 1) the spatial extent at which both the effect and the comparable data are specified; 2) the variables used to describe fixed effects; 3) the screens that are used to select the final dataset as well as outliers and influencers; 4) the inclusion of spatially and temporally lagged variables to account for the presence of spatial autocorrelation; and 5) the inclusion of additional explanatory variables that are not populated across the whole dataset. Each will be described below.

3.2.1 Varying the Distance to Turbine

The base model tests for effects on homes sold within a half mile of a turbine (and compares the sales to homes located outside of a half mile and inside 5 miles of a turbine). Conceivably, effects are stronger the nearer homes are to turbines and weaker the further they are away—because that roughly corresponds to the nuisance effects (e.g., noise and shadow flicker) that we are measuring—but the base model does not explore this. Therefore, this set of robustness models investigates effects within a quarter mile as well as between a half and 1 mile. It is assumed that effects will be larger within a quarter mile and smaller outside of a half mile.

Additionally, the basis of comparison could be modulated as well. The base model compares homes within a half mile to those outside of a half mile and inside of 5 miles, most of which are between 3 and 5 miles. Conceivably, homes immediately outside of a half mile are also affected by the presence of the turbines, which might bias down the comparison group and therefore bias down the differences between it and the target group inside of a half mile. Therefore, two additional comparison groups are explored: 1) those outside of a half mile and inside of 10 miles, and 2) those outside of 5 miles and inside of 10 miles. It is assumed that effects from turbines are not experienced outside of 5 miles from the nearest turbine.

3.2.2 Fixed Effects

A large variety of neighborhood factors might influence a home price (e.g., the quality of the schools, the crime rate, access to transportation corridors, local tax rates), many of which cannot be adequately measured and controlled for in the model specifically. Thus, practitioners use a "fixed effect" to adjust prices based on the neighborhood, which accounts for all the differences between neighborhoods simultaneously. Examples of these fixed effects, moving from larger and less precise geographic areas to smaller and more precise areas are: zip code; census tract; and, census block group.

The base model uses census tract boundaries as the geographic extent of fixed effects, aiming to capture "neighborhood" effects throughout the sample area. Because this delineation is both arbitrary (a census tract does not necessarily describe a neighborhood) and potentially too broad (multiple neighborhoods might be contained in one census tract), the census block group is used in a robustness test. This is expected to allow a finer adjustment to the effects of individual areas of the sample and therefore be a more accurate control for neighborhood effects. The drawback is that the variables of interest (e.g., within a half mile and the development-period variables) might vary less within the block group, and therefore the block group will absorb the effects of the turbines, biasing the results for the variables of interest.

3.2.3 Screens, Outliers, and Influencers

As described below, to ensure that the data used for the analysis are representative of the sample in Massachusetts and do not contain exceptionally high- or low-priced homes or homes with incorrect characteristics, a number of screens are applied for the analysis dataset. To explore what effect these screens have on the results, they are relaxed for this set of robustness tests. Additionally, a selection of outliers (based on the 1 and 99 percentile of sale price) and influencers (based on a Cook's Distance of greater than 1[19]) might bias the results, and therefore a model is estimated with them removed.

3.2.4 Spatially and Temporally Lagged Nearest-Neighbor Data

The value of a given house is likely impacted by the characteristics of neighboring houses (i.e., local spatial spillovers, defined empirically as W_x) or the neighborhood itself. For example, a house in a neighborhood with larger parcels (e.g., 5 acres lots), might be priced higher than an otherwise identical home in a neighborhood with smaller parcels (e.g., 1 acre lots).

If statistical models do not adequately account for these spatial spillovers, the effects are relegated to the unexplained component of the results contained in the error term, and therefore the other coefficients could be biased. If this occurs, then the error terms exhibit spatial autocorrelation (i.e., similarity on the basis of proximity). Often, in the hedonic literature, more concern is paid to unobserved (and spatially correlated) neighborhood factors in the model.[20]

A common approach for controlling for the unobserved neighborhood factors is to include neighborhood fixed effects (see for example Zabel and Guignet, 2012), which is the approach we took in the base model. To additionally control for the characteristics of neighboring houses a model can be estimated that includes spatial lags of their characteristics as covariates in the hedonic model, as is done for this robustness test. Neighboring houses are determined by a set of *k*-nearest neighbors (*k*, in this case, equals 5), though alternative methods could have been used (Anselin, 2002). Further, although dependence often focuses on spatial proximity, it is also likely that sales are "temporally correlated," with nearby houses selling in the same period (e.g., within the previous 6 months) being more correlated than nearby houses selling in earlier periods (e.g., within the previous 5 years). To account for both of these possible correlations, we include a spatially and temporally lagged set of *k*-nearest neighbor data in a robustness model.

These spatially and temporally lagged variables were created using the set of the five nearest neighbors that sold within the 6 months preceding the sale of each house. These variables contained the average living area, lot size, age, and age squared of the "neighbors."

19 According to Cook, R. D. (1977) Detection of Influential Observations in Linear Regression. Technometrics. 19(1): 15-18.

20 LeSage and Pace (2009) have argued that including an expression of neighboring observations (i.e., a spatial lag, know as Wy) of the dependent variable (i.e., sale price) in the model is appropriate for dealing with these omitted variables. They show that spatially dependent omitted variables generate a model that contains spatial lags of the dependent and exogenous variables, known as the spatial Durbin model (Anselin, 1988). Ideally, we would have estimated these models, but this was not possible because of computing limitations.

3.2.5 Inclusion of Additional Explanatory Variables

Although the base model includes a suite of controlling variables that encompasses a wide range of home and site characteristics, the dataset contains additional variables not fully populated across the dataset that might also help explain price differences between homes. They include the style of the home (e.g., cape, ranch, colonial) and the type of heat the home has (e.g., forced air, baseboard, and steam). Therefore, an additional robustness model is estimated that includes these variables but uses a slightly smaller dataset for which these variables are fully populated.

Combined, it is assumed that the set of robustness tests will provide additional context and possibly bound the results from the base model. We now turn to the data used for the analysis.

3.3 Data Used For Analysis

To conduct the analysis, a rich set of four types of data was obtained from a variety of sources in Massachusetts, including 1) wind turbine data, 2) single-family-home sale and characteristic data, 3) U.S. Census data, and 4) amenities and disamenities data. From these, three other sets of variables were created: distance-to-turbine data, time-of-sale period relative to announcement and construction dates of nearby turbines, and spatially and temporally lagged nearest-neighbor characteristics. Each is discussed below.

3.3.1 Wind Turbines

Using data from the Massachusetts Clean Energy Center (MassCEC), every wind turbine in Massachusetts that had been commissioned as of November 2012 with a nameplate capacity of at least 600 kW was identified and included in the analysis. This generated a dataset of 41 turbines located in a variety of settings across Massachusetts, ranging in scope from a single turbine to a maximum of 10 turbines, with blade tip heights ranging from 58.5 meters (192 feet) to 390 meters (1,280 feet), with an average of approximately 120 meters (394 feet) (Table 1 and Figure 4). Spatial data for every turbine (e.g., x and y coordinates), derived from MassCEC records and a subsequent visual review of satellite imagery, were added, and wind turbine announcement and construction dates were populated by MassCEC. Announcement date is assumed to be the first instance when news of the projects enters the public sphere via a variety of sources including a news article, the filing of a permit application, or release of a Request for Proposals. Dates were identified in consultation with project proponents, developers or using Google News searches.

3.3.2 Single-Family-Home Sales and Characteristics

A set of arm's-length, single-family-home sales data for all of Massachusetts from 1998 to November 2012 was purchased from the Warren Group.[21] Any duplicate observations, cases where key information was missing (e.g., living area, lot size, year built), or observations where the data appeared to be erroneous (e.g., houses with no bathrooms) were removed from the dataset. These data included the following variables (and are abbreviated as follows in parentheses): sale date (*sd*), sale price (*sp*), living

21 See http://www.thewarrengroup.com/. The Warren Group identified all transactions that were appropriate for analysis. As discussed later, we used additional screens to ensure that they were representative of the population of homes. Single-family homes, as opposed to multi-family or condominiums, were selected because condos and multi-family properties constitute different markets and are generally not analyzed together (Goodman and Thibodeau, 1998; Lang, 2012).

Table 1: List of Locations, Key Project Metrics and Dates of Massachusetts Turbines Analyzed

Project Name	Number of Turbines	Capacity per Turbine (kW)	Project Nameplate Capacity (MW)	Blade Tip Height (meters)	Announcement Date	Construction Date	Commission Date	Wastewater or Water Treatment	Industrial Site	Landfill	Located at a School
Berkshire East Ski Resort	1	900	0.9	87	12/16/08	7/12/10	10/31/10				
Berkshire Wind	10	1500	15	118.5	1/12/01	6/1/09	5/28/11				
Fairhaven	2	1500	3	121	5/1/04	11/1/11	5/1/12	X			
Falmouth Wastewater 1	1	1650	1.65	121	4/1/03	11/1/09	3/23/10	X			
Falmouth Wastewater 2	1	1650	1.65	121	11/1/09	4/5/10	2/14/12	X			
Holy Name Central Catholic Jr/Sr HS	1	600	0.6	73.5	9/21/06	3/21/08	10/4/08				X
Hull 1	1	660	0.66	73.5	10/1/97	11/1/01	12/27/01				X
Hull 2	1	1800	1.8	100	1/1/03	12/1/05	5/1/06			X	
Ipswich MLP	1	1600	1.6	121.5	3/1/03	10/1/10	5/15/11				
Jiminy Peak Mountain Resort	1	1500	1.5	118.5	11/1/05	6/25/07	8/3/07				
Kingston Independence	1	2000	2	123	6/1/06	9/23/11	5/11/12				
Lightolier	1	2000	2	126.5	12/14/06	11/1/11	4/20/12		X		
Mark Richey Woodworking	1	600	0.6	89	11/10/07	11/1/08	2/22/09		X		
Mass Maritime Academy	1	660	0.66	73.5	1/31/05	4/12/06	6/14/06				X
Mass Military Reservation 1	1	1500	1.5	118.5	11/8/04	8/1/09	7/30/10		X		
Mass Military Reservation 2	1	1500	1.5	121	10/1/09	10/1/10	10/28/11		X		
Mass Military Reservation 3	1	1500	1.5	121	10/1/09	10/1/10	10/28/11		X		
Mt Wachusett Community College	2	1650	3.3	121	8/18/08	1/28/11	4/27/11				X
MWRA - Charlestown	1	1500	1.5	111	1/24/10	3/25/10	10/1/11	X			
MWRA - Deer Island	2	600	1.2	58.5	6/1/08	8/1/09	11/15/10	X			
No Fossil Fuel (Kingston)	3	2000	6	125	3/1/10	11/16/11	1/25/12		X		
NOTUS Clean Energy	1	1650	1.65	121	8/31/07	4/1/10	7/28/10		X		
Princeton MLP	2	1500	3	105.5	12/18/99	9/9/09	1/12/10				
Scituate	1	1500	1.5	111	3/15/08	2/15/12	3/15/12	X			
Templeton MLP	1	1650	1.65	118.5	7/24/09	2/1/10	9/1/10				
Williams Stone	1	600	0.6	88.5	1/11/08	5/1/08	5/27/09		X		
Total: 26 projects	**41**							**6**	**8**	**1**	**4**

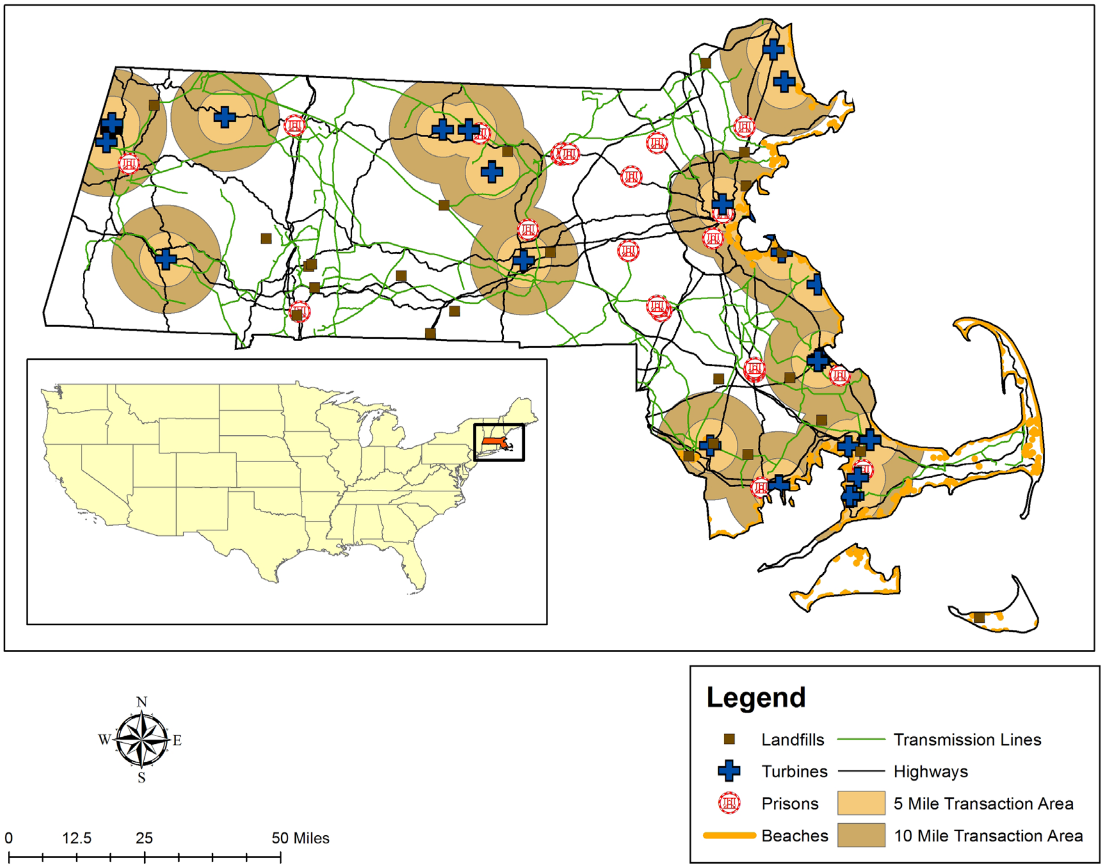
area in thousands of square feet (*sfla1000*), lot size in acres (*acres*), year the home was built (*yb*), most recent renovation year (*renoyear*), the number of full (*fullbath*) and half (*halfbath*) bathrooms, the style of the home (e.g., colonial, cape, ranch) (*style*), the heat type (e.g., forced air, baseboard, steam) (*heat*), and the x and y coordinates of the home.[22] From these, the following variables were calculated: natural log of sale price (*lsp*), sale year (*sy*), sale quarter (*sq*), age of the home at the time of sale ($age = sy - (yb \text{ or } renoyear)$), age of the home at the time of sale squared ($agesqr = age \times age$), lot size less than 1 acre (*acrelt1*), bathrooms ($bath = fullbath + (halfbath \times 0.5)$).[23]

To ensure a relatively homogenous set of data, without outlying observations that could skew the results, the following criteria were used to screen the dataset: sale price between $40,000 and $2,500,000; less than 12 bathrooms or bedrooms; lot size less than 25 acres; and sale price per square foot between $30 and $1,250. As detailed below, these screens

22 The style is used in a robustness test.

23 Geocoding of x-y coordinates can have various levels of accuracy, including block level (a centroid of the block), street level (the midpoint of two ends of a street), address level (a point in front of the house – usually used for Google maps etc.), and house level (a point over the roof of the home). Warren provided x and y coordinates that were accurate to the street level or block level but not accurate to the house level. All homes that were within 2 miles of a turbine were corrected to the house level by Melissa Data. See: www.MelissaData.com. This was important to ensure that accurate measurements of distance to the nearest turbine were possible.

Figure 4: Locations of Massachusetts Wind Turbines Included in Study



were relaxed for a robustness test, and no significant alteration to the results was discovered.

3.3.3 Distance to Turbine

Geographic information system (GIS) software was used to calculate the distance between each house and the nearest wind turbine in the dataset (*tdis*) and to identify transactions within a 10-mile radius of a wind turbine. Transactions inside 5 miles were used for the base model, while those outside of 5 miles were retained for the robustness tests. This resulted in a total of 122,198 transactions within 5 miles of a turbine (and 312,677 within 10 miles of a turbine). Additionally, a binary variable was created if a home was within a half mile of a turbine or not (*halfmile*), which was used in the base model. As discussed above, the robustness models used additional distance variables, including if a home was within a quarter mile of a turbine (*qtrmile*) and if a home was outside a half mile but within 1 mile (*outsidehalf*).

3.3.4 Time of Sale Relative to Announcement and Construction Dates of Nearby Turbines

Using the announcement and construction dates of the turbine nearest a home and the sale date of the home, the facility development period (*fdp*) was assigned one of four values: the sale was more than 2 years before the wind facility was announced

Table 2: Distribution of Transaction Data Across Distance and Period Bins

	prioranc	preanc	postanc-precon	postcon	all periods
0-0.25mile	60	9	14	38	121
	0.04%	*0.02%*	*0.03%*	*0.06%*	*0.04%*
0.25-0.5mile	434	150	210	192	986
	0.25%	*0.39%*	*0.47%*	*0.33%*	*0.32%*
0.5-1mile	3,190	805	813	1,273	6,081
	1.9%	*2.1%*	*1.8%*	*2.2%*	*1.9%*
1-5mile	62,967	14,652	17,086	20,305	115,010
	37%	*38%*	*38%*	*34%*	*37%*
5-10mile	104,188	22,491	26,544	37,256	190,479
	61%	*59%*	*59%*	*63%*	*61%*
Total	**170,839**	**38,107**	**44,667**	**59,064**	**312,677**
	100%	*100%*	*100%*	*100%*	*100%*

(*prioranc*),[24] the sale was less than 2 years before the facility was announced (*preanc*), the sale occurred after facility announcement but prior to construction commencement (*postancprecon*), or the sale occurred after construction commenced (*postcon*). We are assuming that once construction was completed, the turbine went into operation. See Table 2 for the distribution of the 312,677 sales within 10 miles across the distance and period bins.

3.3.5 U.S. Census

Using GIS software, the U.S. Census tract and block group of each home were determined. The tract delineation was used for the base model, and the block group was used for one of the robustness tests. In both cases, the Census designations were used to control for "neighborhood" fixed effects across the sample.

3.3.6 Amenity and Disamenity Variables

Data were obtained from the Massachusetts Office of Geographic Information (MassGIS) on the location of beaches, open space,[25] electricity transmission lines, prisons, highways, and major roads.[26] As discussed above, these variables were included in the model to control for and allow comparisons to amenities and disamenities in the study areas near

24 This first period, more than two years before announcement, was used to ensure that these transactions likely occurred before the community was aware of the development. Often prior to the announcement of the project, wind developers are active in the area, potentially, arranging land leases and testing/measuring wind speeds, which can occur in the two years before an official announcement is made.

25 The protected and recreational open space data layer contains the boundaries of conservation land and outdoor recreational facilities in Massachusetts.

26 Office of Geographic Information (MassGIS), Commonwealth of Massachusetts, Information Technology Division. (www.mass.gov/mgis).

turbines. Based on the data, variables were assigned to each home in the dataset using GIS software. If a home was within 500 feet of a beach, it was assigned the variable *beach500ft*, and if a home was outside of 500 feet but inside of a half mile from a beach it was assigned the variable *beachhalf*. Similarly, variables were assigned to homes within a half mile of a publicly accessible open space with a minimum size of 25 acres (*openhalf*), a currently operating landfill (*fillhalf*), or a prison containing at least some maximum-security inmates (*prisonhalf*). Variables were also assigned to homes within 500 feet of an electricity transmission line (*line500ft*), a highway (*hwy500ft*) or otherwise major road (*major500ft*).[27] Figure 4 shows the location of these amenities and disamenities (except open space and major roads) across Massachusetts.

3.3.7 Spatially and Temporally Lagged Nearest-Neighbor Characteristics

Using the data obtained from Warren Group for the home and site characteristics, x/y coordinates and the sale date, a set of spatially and temporally lagged nearest neighbor variables were prepared to be used in a robustness test. For each transaction the five nearest neighbors were selected that: transacted

Table 3: Summary of Characteristics of Base Model Dataset

Variable	Description	Mean	Std. Dev.	Min	Median	Max
sp	sale price	$322,948	$238,389	$40,200	$265,000	$2,495,000
lsp	log of sale price	12.49	0.60	10.6	12	14.72
sd	sale date	10/19/04	1522	3/3/98	2/6/05	11/23/12
sy	sale year	2004	4	1998	2004	2012
syq	sale year and quarter (e,g., 20042 = 2004, 2nd quarter)	20042	42	19981	20043	20124
sfla1000	square feet of living area (1000s of square feet)	1.72	0.78	0.41	1.6	9.9
acre*	number of acres	0.51	1.1	0.0054	0.23	25
acrelt1*	the number of acres less than one	-0.65	0.31	-0.99	-0.77	0
age	age of home at time of sale	54	42	-1	47	359
agesq	age of home squared	4671	4764	0	3474	68347
bath**	the number of bathrooms	1.9	0.79	0.5	1.5	10.5
wtdis	distance to nearest turbine (miles)	3.10	1.20	0.098	3.2	5
fdp	wind facility development period	1.95	1.18	1	1	4
annacre	average nearest neighbor's acres	0.51	0.93	0.015	0.25	32
annage	average nearest neighbor's age	53.71	30.00	-0.8	52	232
annagesq	average nearest neighbor's agesq	4672	4766	0	3474	68347
annsfla1000	average nearest neighbor's sfla1000	1.72	0.53	0.45	1.6	6.8

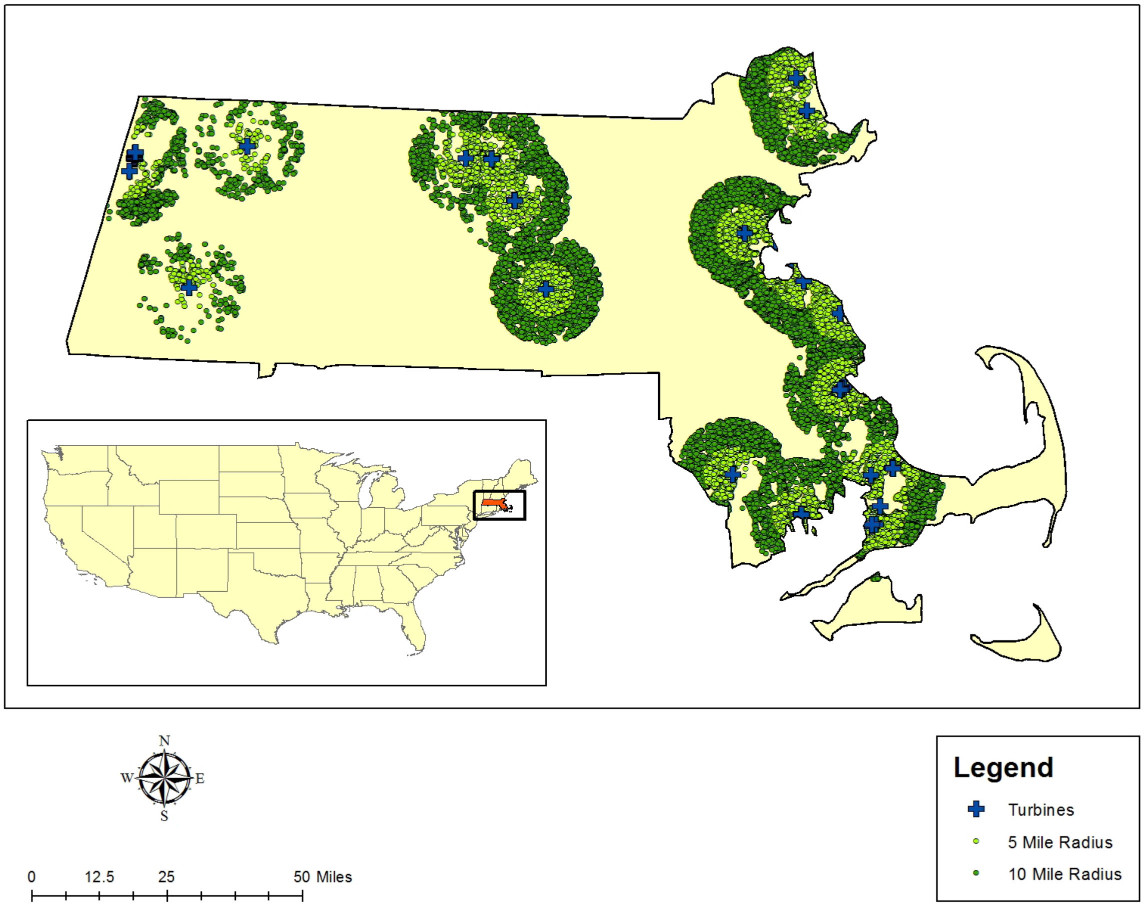
Note: Sample size for the full dataset is 122,198

* Together acrelt1 and acre are entered into the model as a spline function with acrelt1 applying to values from 0 to 1 acres (being entered as values from -1 to 0, respectively) and acre applying to values from 1 to 25 acres.

** Bath is calculated as follows: number of bathrooms + (number of half bathrooms *0.5)

27 Highways and majors road are mutually exclusive by our definition despite the fact that highways are also considered major roads.

Figure 5: Locations of Houses in Relation to Wind Turbines



within the preceding 6 months and were the closest in terms of Euclidian distance. Using those five transactions, average 1000s of square feet of living space (*annsfla1000*), average acres (*annacre*), average age (*annage*), and age squared (*annagesq*) of the neighbors were created for each home. These four variables were used in the robustness test.

3.3.8 Summary Statistics

The base model dataset includes all home sales within 5 miles of a wind turbine, which are summarized in Table 2. The average home in the dataset of 122,198 sales from 1998 to 2012 has a sale price of $322,948, sold in 2004, in the 2nd quarter, has 1,728 square feet of living area, is on a parcel with a lot size of 0.51 acres, is 54 years old, has 1.9 bathrooms, and is 3.1 miles from the nearest turbine. As summarized in Table 2, of the 122,198 sales within 5 miles of a turbine, 7,188 (5.9%) are within 1 mile of a turbine, 1,107 (approximately 0.9%) are within a half mile, and 121 (0.1%) are within a quarter mile. In the post-construction period, 1,503 sales occurred within 1 mile of a turbine, and 230 occurred within a half mile. These totals are well above those collected for other analyses and are therefore ample to discover considerably smaller effects. For example, as discussed in Section 2.5 above, an effect larger than 2.5% should be detectable within 1 mile, and an effect larger than approximately 4% should be detectable within a half mile, given the number of transactions that we are analyzing. Figure 5 shows the spatial distribution of sales throughout the sample area.

3.4 Results

3.4.1 Base Model Results

The base model results for the turbine, amenity, and disamenity variables are presented in Table 4 (with full results in the Appendix). The base model has a high degree of explanatory power, with an adjusted-R^2 of 0.80, while the controlling variables are all highly significant and conform to the *a priori* assumption as far as sign and magnitude (e.g., Sirmans et al., 2006).[28] The model interacts the four wind-facility periods with each of the controlling variables to test the stability of the controlling variables across the periods (and the subsamples they represent) and to ensure that the coefficients for the wind turbine distance variables, which are also interacted with the periods, do not absorb any differences in the controlling variables across the periods.[29] The controlling variables do vary across the periods, although they are relatively stable. For example, each additional thousand square feet of living area adds 21%–24% to a home's value in each of the four periods; the first acre adds 14%–22% to home value, while each additional acre adds 1%–2%; each year a home ages reduces the home's value by approximately 0.2% and each bathroom adds 6%–11% to the value. Additionally, the sale years are highly statistically significant compared to the reference year of 2012; prices in 1998 are approximately 52% lower, and prices in 2005 and 2006 are approximately 31% and 28% higher, after which prices decline to current levels. Finally, there is considerable seasonality in the transaction values. Compared to the reference third quarter, prices in the first quarter are approximately 7% lower, while prices in the second and fourth are about 1%–2% lower (see Appendix for full results).

Similar to the controlling variables, the coefficients for the amenity and disamenity parameters are, for the most part, of the correct sign and within the range of findings from previous studies. For example, being within 500 feet of a beach increases a home's value by 21%-30%, while being outside of 500 feet but within a half mile of a beach increases a home's value by 5%–13%, being within 500 feet of a highway reduces value by 5%–7%, and being within 500 feet of a major road reduces value by 2%–3%. Being within a half mile of a prison reduces value by 6%, but this result is only apparent in one of the periods. Similarly, being within a half mile of a landfill reduces value by 12% in only one of the periods, and being within a half mile of open space increases value by approximately 1% in two of the periods. Finally, being within 500 feet of an electricity transmission line reduces value by 3%-9% in two of the four periods. As noted above, the wind development periods are not meaningful as it relates to the amenity/disamenity variables, because they all likely existed well before this sample period began, and therefore the turbines. That said, they do represent different data groups across the dataset (one for each wind development period), and therefore are illustrative of the consistency of findings for these variables, with beaches, highways and major roads showing very consistent results, while electricity transmission lines, open space, landfills and prisons showing more sporadic results.

Turning now to the variables that capture the effects in our sample, for being within a half mile of a turbine, we find interesting results (see Table

28 All models are estimated using the .areg procedure in Stata MP 12.1 with robust estimates, which corrects for heteroskedasticity. The effects of the census tracts are absorbed. Results are robust to an estimation using the .reg procedure.

29 The results are robust to the exclusion of these interactions, but theoretically we believe this model is the most appropriate, so it is presented here.

Table 4. Selected Results from Base Model

Variables	Description	*Wind Facility Development Period* prioranc	preanc	postanc-precon	postcon
		coefficient	**coefficient**	**coefficient**	**coefficient**
		p-value	*p*-value	*p*-value	*p*-value
halfmile	within a half mile of a wind turbine	**-5.1%*** **	**-7.1%*** **	**-7.4%*** **	**-4.6%***
		0.000	*0.002*	*0.000*	*0.081*
	Net Difference Compared to *prioranc* Period			**-2.3%**	**0.5%**
				0.264	*0.853*
beach500ft	within 500 feet of a beach	**20.8%*** **	**30.4%*** **	**25.3%*** **	**25.9%*** **
		0.000	*0.000*	*0.000*	*0.000*
beachhalf	within a half mile and outside of 500 feet of a beach	**5.3%*** **	**8.8%*** **	**8.7%*** **	**13.5%*** **
		0.000	*0.000*	*0.000*	*0.000*
openhalf	within a half mile of open space	**0.6%** **	**0.1%**	**0.1%**	**0.9%***
		0.021	*0.729*	*0.903*	*0.062*
line500ft	within 500 feet of a electricity transmission line	**-3%*** **	**-0.9%**	**-0.9%**	**-9.3%*** **
		0.001	*0.556*	*0.522*	*0.000*
prisonhalf	within a half mile of a prison	**-5.9%*** **	**2.6%**	**2.8%**	**-2.3%**
		0.001	*0.291*	*0.100*	*0.829*
hwy500ft	within 500 feet of a highway	**-7.3%*** **	**-5.2%*** **	**-3.7%*** **	**-5.3%*** **
		0.000	*0.000*	*0.000*	*0.000*
major500ft	within 500 feet of a major road	**-2.8%*** **	**-2.3%*** **	**-2.5%*** **	**-2%*** **
		0.000	*0.000*	*0.000*	*0.000*
fillhalf	within a half mile of a landfill	**1.8%**	**-0.9%**	**1%**	**-12.2%*** **
		0.239	*0.780*	*0.756*	*0.002*
sfla1000	living area in thousands of square feet	**22.9%*** **	**21.4%*** **	**22.6%*** **	**23.5%*** **
		0.000	*0.000*	*0.000*	*0.000*
acre	lot size in acres	**1.1%*** **	**1.9%*** **	**1.3%*** **	**-0.02%**
		0.000	*0.000*	*0.000*	*0.863*
acrelt1	lot size less than 1 acre	**21.7%*** **	**17.2%*** **	**14.7%*** **	**22.1%*** **
		0.000	*0.000*	*0.000*	*0.000*
age	age of the home at time of sale	**-0.2%*** **	**-0.2%*** **	**-0.2%*** **	**-0.2%*** **
		0.000	*0.000*	*0.000*	*0.000*
agesq*	age of the home at time of sale squared*	**0.6%*** **	**0.5%*** **	**0.6%*** **	**0.8%*** **
		0.000	*0.000*	*0.000*	*0.000*
bath	number of bathrooms	**6.4%*** **	**7.9%*** **	**8.4%*** **	**11.1%*** **
		0.001	*0.556*	*0.522*	*0.000*

Coefficients *represent the percentage change in price for every unit of change in the characteristic. For example, the model estimates that price increases by approximately 23% for every 1000 additional square feet. Coefficient values are reported as percentages, although the actual conversion is 100*(exp(b)-1)% (Halvorsen and Palmquist, 1980). In most cases, the differences between the two are de minimis, though, larger coefficient values would be slightly larger after conversion.*

p-value *is a measure of how likely the estimate is different from zero (i.e., no effect) by chance. The lower the p-value, the more likely the estimate is expected to be different from zero. A p-value of less than 0.10 is considered statistically significant, with higher levels of significance being denoted as follows: * 0.10, ** 0.05, ***0.01.*

** coefficient values are multiplied by 1000 for reporting purposes only*

4). The coefficients for the *halfmile* variable over the four periods are as follows: *prioranc* (sale more than 2 years before the nearest wind turbine was announced) -5.1%, *preanc* (less than 2 years before announcement) -7.1%, *postancprecon* (after announcement but before the nearest turbine construction commenced) -7.4%, and *postcon* (after construction commenced) -4.6%.[30] Importantly, our model estimates that home values within a half mile of a future turbine were lower than in the surrounding area even before wind-facility announcement. In other words, wind facilities in Massachusetts are associated with areas with relatively low home values, at least compared to the average values of homes more than a half mile but less than 5 miles away from the turbines. Moreover, when we determine if there has been a "net" effect from the arrival of the turbines, we must account for this preexisting *prioranc* difference. The net *postancprecon* effect is -2.3% ([-7.4%] - [-5.1%] = -2.3%; *p*-value 0.26). The net *postcon* effect is 0.5% ([-4.6%] - [-5.1%] = 0.5%: *p*-value 0.85).[31] Therefore, after accounting for the "pre-existing price differential" that predates the turbine's development, there is no evidence of an additional impact from the turbine's announcement or eventual construction.

3.4.2 Robustness Test Results

To test and possibly bound the results from the base model, several robustness tests were explored (Section 3.2):

1. Impacts within a quarter mile
2. Impacts between a half and 1 mile
3. Impacts inside of a half mile when data between a half mile and 10 miles were used as a reference category
4. Impacts inside of a half mile when data between 5 miles 10 miles were used as a reference category
5. The inclusion of style (of the home) and heat (type of the home) variables
6. The use of the census block group as the fixed effect instead of census tract
7. Relaxing the screens (e.g., sale price between $40,000 and $2,500,000) used to create the analysis dataset
8. The removal of outliers and influential cases from the analysis dataset
9. The inclusion of spatially/temporally lagged variables to account for the presence of spatial autocorrelation.

Table 5 shows the robustness test results and the base model results for comparison (the robustness models are numbered in the table as they are above). For brevity only the "net" differences in value for the *postancprecon* and *postcon* periods are shown that quantify the *postancprecon* and *postcon* effects after deducting the difference that existed in the Prior period.[32] Throughout the rest of this section, those effects will be referred to as net *postancprecon* and net *postcon*.

There are a number of key points that arise from the results that have implications for stakeholders involved in wind turbine siting. For example, the effects for both the net *postancprecon* and net *postcon* periods for sales within a quarter mile of a turbine are positive and non-significant (which is believed to be a circumstance of the small dataset

30 Although a post-construction effect is shown here and for all other models, a post-operation (after the turbine was commissioned and began operation) effect was also estimated and was no different than this post-construction effect.

31 These linear combinations are estimated using the post-estimation .lincom test in Stata MP 12.1.

32 The full set of robustness results is available upon request.

Table 5: Robustness Results

#	Model Name	n	Adj R^2	Prior Announcement Turbine Effect			"Net" Post Announcement Pre Construction Turbine Effect			"Net" Post Construction Turbine Effect		
				inside 1/4 mile	*inside 1/2 mile*	*between 1/2 and 1 mile*	*inside 1/4 mile*	*inside 1/2 mile*	*between 1/2 and 1 mile*	*inside 1/4 mile*	*inside 1/2 mile*	*between 1/2 and 1 mile*
				coef / *p-value*	**coef** / *p-value*	**coef** / *p-value*	**coef** / *p-value*	**coef** / *p-value*	**coef** / *p-value*	**coef** / *p-value*	**coef** / *p-value*	**coef** / *p-value*
	Base Model	122,198	0.80		**-5.1%***** *0.000*			**-2.3%** *0.264*			**0.5%** *0.853*	
1	Inside 1/4 mile	122,198	0.80	**-5.3%** *0.260*			**12.7%** *0.118*			**0.7%** *0.916*		
2	Between 1/2 and 1 Mile	122,198	0.80		**-5.0%***** *0.000*	**-0.4%** *0.536*		**-2.0%** *0.336*	**1.4%** *0.225*		**1.0%** *0.715*	**1.3%** *0.288*
3	All Sales Out to 10 Miles	312,677	0.82		**-5.8%***** *0.000*			**-3.0%** *0.886*			**1.0%** *0.724*	
4	Using Outside of 5 Miles as Reference	312,677	0.82		**-7.6%***** *0.000*			**1.6%** *0.435*			**1.1%** *0.695*	
5	Including Style & Heat Variables	120,292	0.81		**-3.8%***** *0.004*			**-3.3%** *0.114*			**2.8%** *0.336*	
6	Using Block Group	122,198	0.81		**-3.1%***** *0.024*			**-1.3%** *0.554*			**-2.6%** *0.324*	
7	No Screens	123,555	0.73		**-4.0%***** *0.003*			**-4.6%*** *0.072*			**-0.8%** *0.800*	
8	Removing Outliers and Influencers	119,623	0.79		**-4.3%***** *0.001*			**-2.6%** *0.205*			**0.04%** *0.989*	
9	Including Spatial Variables	122,198	0.80		**-5.3%***** *0.000*			**-1.5%** *0.467*			**1.4%** *0.621*	

*Statistical Significance: * 0.10, ** 0.05, ***0.01. Note: For simplicity, coefficient values are reported as percentages, although the actual conversion is 100*(exp(b)-1)% (Halvorsen and Palmquist, 1980). In most cases, the differences between the two are de minimis, though, larger coefficient values would be slightly larger after conversion.*

in that distance range, see Table 2), providing no evidence of a large negative effect near the turbines. Further, there are weakly significant net *postancprecon* impacts for relaxing the screens (-4.6%), indicating a possible effect associated with turbine announcement that disappears after turbine construction. Finally, and most importantly, no model specification uncovers a statistically significant net *postcon* impact, bolstering the base model results. Moreover, all net *postcon* estimates for homes within a half mile of a turbine fall within a relatively narrow band that equally spans zero (-2.6% to 2.8%), further reinforcing the non-significant results from the base model.

4. DISCUSSION AND CONCLUSIONS

The study estimated a base hedonic model along with a large set of robustness models to test and bound the results. These results are now applied to the research questions listed in Section 3.

4.1 Discussion of Findings in Relation to Research Questions

Q1) Have wind facilities in Massachusetts been located in areas where average home prices were lower than prices in surrounding areas (i.e., a "pre-existing price differential")?

To test for this, we examined the coefficient in the *prioranc* period, in which sales occurred more than 2 years before a nearby wind facility was announced. The -5.1% coefficient for the *prioranc* period (for home sales within a half mile of a turbine compared to the average prices of all homes between a half and 5 miles) is highly statistically significant (p-value < 0.000). This clearly indicates that houses near where turbines eventually are located are depressed in value relative to their comparables further away. Other studies have also uncovered this phenomenon (Hoen et al., 2009; Hinman, 2010; Hoen et al., 2011). If the wind development is not responsible for these lower values, what is?

Examination of turbine locations reveals possible explanations for the lower home prices. Six of the turbines are located at wastewater treatment plants, and another eight are located on industrial sites (Table 1). Some of these locations (for example, Charlestown) have facilities that generate large amounts of hazardous waste regulated by Massachusetts and/or the U.S. Environmental Protection Agency and use large amounts of toxic substances that must be reported to the Massachusetts Department of Environmental Protection.[33] Regardless of the reason for this "pre-existing price differential" in Massachusetts, the effect must be factored into estimates of impacts due to the turbines' eventual announcement and construction, as this analysis does.

Q2) Are post-construction (i.e., after wind-facility construction) home price impacts evident in Massachusetts, and how do Massachusetts results contrast with previous results estimated for more rural settings?

To test for these effects, we examine the "net" *postcon* effects (*postcon* effects minus *prioranc* effects), which account for the "pre-existing price differential" discussed above. In the base model, with a *prioranc* effect of -5.1% and a *postcon* effect of -4.6%, the "net" effect is 0.5% and not statistically significant. Similarly, none of the robustness models reveal a statistically significant "net" effect, and the range of estimates from those models is -2.6% to 2.8%, effectively bounding the results from the base model. Therefore, in our sample of more than 122,000 sales, of which more than 21,808 occurred

33 See, e.g., http://www.mass.gov/anf/research-and-tech/it-serv-and-support/application-serv/office-of-geographic-information-massgis/datalayers/dep-bwp-major-facilities-.html

after nearby wind-facility construction began (with 230 sales within a half mile), no evidence emerges of a *postcon* impact. This collection of *postcon* data within a half mile (and that within 1 mile: n = 1,503) is orders of magnitude larger than had been collected in previous studies and is large enough to find effects of the magnitude others have claimed to have found (e.g., Heintzelman and Tuttle, 2012; Sunak and Madlener, 2012).[34] Therefore, if effects are captured in our data, they are either too small or too sporadic to be identified.

These *postcon* results conform to previous analyses (Hoen, 2006; Sims et al., 2008; Hoen et al., 2009; Hinman, 2010; Carter, 2011; Hoen et al., 2011). Our study differed from previous analyses because it examined sales near turbines in more urban settings than had been studied previously. Contrary to what might have been expected, there do not seem to be substantive differences between our results and those found by others in more rural settings, thus it seems possible that turbines, on average, are viewed similarly (i.e., with only small differences) across these urban and rural settings.

Q3) Is there evidence of a post-announcement/pre-construction effect (i.e., an "anticipation effect")?

To answer this question, we examine the "net" *postancprecon* effect (*postancprecon* effect of -7.4% minus *prioranc* effect of -5.1%), which is -2.3% and not statistically significant. This base model result is bounded by robustness-model *postancprecon* effects ranging from -4.6% to 1.6%. One of the robustness models reveals a weakly statistically significant effect of -4.6% (p-value 0.07) when the set of data screens is relaxed. It is unclear, however, whether these statistically significant findings result from spurious data or multi-collinear parameters, examination of which is outside the scope of this research. Still, it is reasonable to say that these *postancprecon* results, which find some effects, *might* conform to effects found by others (Hinman, 2010), and, to that extent, they *might* lend credence to the "anticipation effect" put forward by Hinman and others (e.g., Wolsink, 2007; Sims et al., 2008; Hoen et al., 2011), especially if future studies also find such an effect. For now, we can only conclude that there is weak and sporadic evidence of a *postancprecon* effect in our sample.

Q4) How do impacts near turbines compare to the impacts of amenities and disamenities also located in the study area, and how do they compare with previous findings?

The effects on house prices of our amenity and disamenity variables are remarkably consistent with a priori expectations and stable throughout our various specifications. The results clearly show that home buyers and sellers accounted for the surrounding environment when establishing home prices. Beaches (adding 20% to 30% to price when within 500 feet, and adding 5% to 13% to price when within a half mile), highways (reducing price 4% to 8% when within 500 feet), and major roads (reducing price 2% to 3% when within 500 feet) affected home prices consistently in all models. Open space (adding 0.6%-0.9% to price when within a half mile), prisons (reducing price 6% when within a half mile), landfills (reducing price 13% when within a half mile) and electricity transmission lines (reducing price 3%-9% when within 500 feet) affected home prices in some models.

34 Though, as discussed earlier, their findings might be the result of their continuous distance specification and not the result of the data, moreover, although Heintzelman & Tuttle claim to have found a *postcon* effect, their data primary occurred prior to construction.

Our disamenity findings are in the range of findings in previous studies. For example, Des Rosiers (2002) found price reduction impacts ranging from 5% to 20% near electricity transmission lines; although those impacts faded quickly with distance. Similarly, the price reduction impacts we found near highways and major roads appear to be reasonable, with others finding impacts of 0.4% to 4% for homes near "noisy" roads (Bateman et al., 2001; Andersson et al., 2010; Blanco and Flindell, 2011; Brandt and Maennig, 2011). Further, although sporadic, the large price reduction impact we found for homes near a landfill is within the range of impacts in the literature (Ready, 2010), although this range is categorized by volume: an approximately 14% home-price reduction effect for large-volume landfills and a 3% effect for small-volume landfills. The sample of landfills in our study does not include information on volume, thus we cannot compare the results directly.

Our amenity results are also consistent with previous findings. For example, Anderson and West (2006b) found that proximity to open space increased home values by 2.6% per mile and ranged from 0.1% to 5%. Others have found effects from being on the waterfront, often with large value increases, but none have estimated effects for being within 500 feet or outside of 500 feet and within a half mile of a beach, as we did, and therefore we cannot compare results directly.

Clearly, home buyers and sellers are sensitive to the home's environment in our sample, consistently seeing more value where beaches, and open space are near and less where highways and major roads are near—with sporadic value distinctions where landfills, prisons and electricity line corridors are near. This observation not only supports inclusion of these variables in the model—because they control for potentially collinear aspects of the environment—but it also strengthens the claim that the market represented by our sample does account for surrounding amenities and disamenities which are reflected in home prices. Therefore, buyers and sellers in the sample should also have accounted for the presence of wind turbines when valuing homes.

Q5) Is there evidence that houses that sold during the post-announcement and post-construction periods did so at lower rates than during the pre-announcement period?

To test for this sales-volume effect, we examine the differences in sales rate in fixed distances from the turbines over the various development periods (Table 2). Approximately 0.29% percent of all homes in our sample (i.e., inside of 10 miles from a turbine) that sold in the *prioranc* period were within a half mile of a turbine. That percentage increases to 0.50% in the *postancprecon* period and then drops to 0.39% in the *postcon* period for homes within a half mile of a turbine. Similarly, homes located between a half mile and 1 mile sold, as a percentage of all sales out to 10 miles, at 1.9% in the *prioranc* period, 1.8% in the *postancprecon* period, and 2.2% in the *postcon* period (and similar results are apparent for those few homes within a quarter mile). Neither of these observations indicates that the rate of sales near the turbines is affected by the announcement and eventual construction of the turbines, thus we can conclude that there is an absence of evidence to support the claim that sales rate was affected by the turbines.[35]

35 This conclusion was confirmed with Friedman's two-way Analysis of Variance for related samples using period as the ranking factor, which confirmed that the distributions of the frequencies across periods was statistically the same.

4.2 Conclusion

This study investigates a common concern of people who live near planned or operating wind developments: How might a home's value be affected by the turbines? Previous studies on this topic, which have largely coalesced around non-significant findings, focused on rural settings. Wind facilities in urban locations could produce markedly different results. Nuisances from turbine noise and shadow flicker might be especially relevant in urban settings where other negative features, such as landfills or high voltage utility lines, have been shown to reduce home prices. To determine if wind turbines have a negative impact on property values in urban settings, this report analyzed more than 122,000 home sales, between 1998 and 2012, that occurred near the current or future location of 41 turbines in densely-populated Massachusetts.

The results of this study do not support the claim that wind turbines affect nearby home prices. Although the study found the effects on home prices from a variety of negative features (such as electricity transmission lines, landfills, prisons and major roads) and positive features (such as open space and beaches) that accorded with previous studies, the study found no net effects due to the arrival of turbines in the sample's communities. Weak evidence suggests that the announcement of the wind facilities had an adverse impact on home prices, but those effects were no longer apparent after turbine construction and eventual operation commenced. The analysis also showed no unique impact on the rate of home sales near wind turbines. These conclusions were the result a variety of model and sample specifications.

4.3 Suggestions for Future Research

Although our study is unparalleled in its methodological scope and dataset compared to the previous literature in the subject area, we recommend a number of areas for future work. Because much of the existing work on wind turbines has focused on rural areas—which is where most wind facilities have been built—there is no clear understanding of how residents would view the introduction of wind turbines in landscapes that are already more industrialized. Therefore, investigating residents' perceptions, through survey instruments, of wind turbines in more urbanized settings may be helpful. Policy-makers may also be interested in understanding the environmental attitudes and perceptions towards wind turbines of people who purchase houses near wind turbines after they have been constructed. Also, our study has aggregated the effects of wind turbines on the price of single-family houses for the study area as a whole. Although the data span an enormous range of sales prices, and contain the highest mean value of homes yet studied, it might be fruitful to analyze impacts partitioned by sales price or neighborhood to discover whether the effects vary with changes in these factors.

Finally, in our study we did not investigate the ownership structure of the turbines (i.e., in Massachusetts some projects benefit town budgets while others are owned by private entities) and assess whether any benefits accrued to surrounding communities, factors that the existing literature suggests are important determinants of community perceptions. This was considered beyond the scope of the existing study, but could be addressed in future research.

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APPENDIX: BASE MODEL FULL RESULTS

	Coef	SE	t	p-value
Intercept	12.15	0.01	1133.88	0.000
within a half mile of a wind turbine				
prioranc	-0.051	0.01	-3.95	0.000
preanc	-0.071	0.02	-3.08	0.002
postancprecon	-0.074	0.02	-4.34	0.000
postcon	-0.046	0.03	-1.74	0.081
Net Difference Compared to prioranc Period—within a half mile of a wind turbine				
postancprecon	-0.023	0.02	-1.12	0.264
postcon	0.005	0.03	0.19	0.853
within 500 feet of a electricity transmission line				
prioranc	-0.030	0.01	-3.41	0.001
preanc	-0.009	0.02	-0.59	0.556
postancprecon	-0.009	0.01	-0.64	0.522
postcon	-0.093	0.02	-4.79	0.000
within 500 feet of a highway				
prioranc	-0.073	0.01	-14.28	0.000
preanc	-0.052	0.01	-4.57	0.000
postancprecon	-0.037	0.01	-4.16	0.000
postcon	-0.053	0.01	-3.95	0.000
within 500 feet of a major road				
prioranc	-0.028	0.00	-12.18	0.000
preanc	-0.023	0.00	-5.05	0.000
postancprecon	-0.025	0.00	-5.43	0.000
postcon	-0.020	0.00	-4.01	0.000
within a half mile of a landfill				
prioranc	0.018	0.02	1.18	0.239
preanc	-0.009	0.03	-0.28	0.780
postancprecon	0.010	0.03	0.31	0.756
postcon	-0.122	0.04	-3.08	0.002
within a half mile of a prison				
prioranc	-0.059	0.02	-3.38	0.001
preanc	0.024	0.02	1.05	0.291
postancprecon	0.028	0.02	1.64	0.100
postcon	-0.020	0.09	-0.22	0.829

	Coef	SE	t	p-value
within 500 feet of a beach				
prioranc	0.208	0.02	12.71	0.000
preanc	0.304	0.03	12.09	0.000
postancprecon	0.253	0.02	12.72	0.000
postcon	0.259	0.02	16.95	0.000
within a half mile and outside of 500 feet of a beach				
prioranc	0.053	0.01	10.07	0.000
preanc	0.088	0.01	10.52	0.000
postancprecon	0.087	0.01	11.99	0.000
postcon	0.135	0.01	17.30	0.000
within a half mile of open space				
prioranc	0.006	0.00	2.31	0.021
preanc	0.001	0.00	0.35	0.729
postancprecon	0.001	0.00	0.12	0.903
postcon	0.009	0.00	1.87	0.062
living area in thousands of square feet				
prioranc	0.229	0.00	86.37	0.000
preanc	0.214	0.01	41.62	0.000
postancprecon	0.226	0.00	48.41	0.000
postcon	0.235	0.01	46.58	0.000
lot size in acres				
prioranc	0.011	0.00	6.67	0.000
preanc	0.019	0.00	6.51	0.000
postancprecon	0.013	0.00	4.17	0.000
postcon	-0.001	0.00	-0.17	0.863
lot size less than 1 acre				
prioranc	0.217	0.01	34.79	0.000
preanc	0.172	0.01	18.45	0.000
postancprecon	0.147	0.01	16.03	0.000
postcon	0.221	0.01	21.71	0.000
age of the home at time of sale				
prioranc	-0.0016	0.00	-21.87	0.000
preanc	-0.0016	0.00	-11.33	0.000
postancprecon	-0.0020	0.00	-13.99	0.000
postcon	-0.0025	0.00	-16.47	0.000

	Coef	SE	t	p-value
age of the home at time of sale squared				
prioranc	0.000006	0.00	28.55	0.000
preanc	0.000005	0.00	17.03	0.000
postancprecon	0.000006	0.00	20.01	0.000
postcon	0.000008	0.00	26.4	0.000
number of bathrooms				
prioranc	0.064	0.00	29.22	0.000
preanc	0.079	0.00	17.98	0.000
postancprecon	0.084	0.00	20.31	0.000
postcon	0.111	0.00	25.54	0.000
sale year				
1998	-0.52	0.007	-73.48	0.000
1999	-0.41	0.007	-58.44	0.000
2000	-0.26	0.007	-37.59	0.000
2001	-0.13	0.007	-18.03	0.000
2002	0.02	0.007	2.33	0.020
2003	0.14	0.007	21.26	0.000
2004	0.24	0.007	37.05	0.000
2005	0.31	0.006	49.32	0.000
2006	0.28	0.006	43.94	0.000
2007	0.23	0.006	37.58	0.000
2008	0.12	0.006	18.43	0.000
2009	0.04	0.006	7.29	0.000
2010	0.04	0.006	6.15	0.000
2011	-0.02	0.006	-3.74	0.000
2012	Omitted			
sale quarter				
1	-0.07	0.002	-28.05	0.000
2	-0.02	0.002	-9.56	0.000
3	Omitted			
4	-0.01	0.002	-3.03	0.002

n	**122,198**
R^2	**0.80**
Adj R^2	**0.80**
F	**2418**

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A Spatial Hedonic Analysis of the Effects of Wind Energy Facilities on Surrounding Property Values in the United States

Ben Hoen, Jason P. Brown, Thomas Jackson, Ryan Wiser, Mark Thayer and Peter Cappers

Environmental Energy Technologies Division

August 2013

This work was supported by the Office of Energy Efficiency and Renewable Energy (Wind and Water Power Technologies Office) of the U.S. Department of Energy under Contract No. DE-AC02-05CH1123.

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Abstract

Previous research on the effects of wind energy facilities on surrounding home values has been limited by small samples of relevant home-sale data and the inability to account adequately for confounding home-value factors and spatial dependence in the data. This study helps fill those gaps. We collected data from more than 50,000 home sales among 27 counties in nine states. These homes were within 10 miles of 67 different wind facilities, and 1,198 sales were within 1 mile of a turbine—many more than previous studies have collected. The data span the periods well before announcement of the wind facilities to well after their construction. We use OLS and spatial-process difference-in-difference hedonic models to estimate the home-value impacts of the wind facilities; these models control for value factors existing before the wind facilities' announcements, the spatial dependence of unobserved factors effecting home values, and value changes over time. A set of robustness models adds confidence to our results. Regardless of model specification, we find no statistical evidence that home values near turbines were affected in the post-construction or post-announcement/pre-construction periods. Previous research on potentially analogous disamenities (e.g., high-voltage transmission lines, roads) suggests that the property-value effect of wind turbines is likely to be small, on average, if it is present at all, potentially helping to explain why no evidence of an effect was found in the present research.

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1. Introduction

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

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

This study helps fill the research gap by collecting and analyzing data from 27 counties across nine U.S. states, related to 67 different wind facilities. Specifically, using the collected data, the study constructs a pooled model that investigates average effects near the turbines across the sample while controlling for the local effects of many potentially correlated independent variables. Property-value effect estimates are derived from two types of models: (1) an ordinary

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

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

least squares (OLS) model, which is standard for this type of disamenity research (see, e.g., discussion in Jackson, 2003; Sirmans et al., 2005), and (2) a spatial-process model, which accounts for spatial dependence. Each type of model is used to construct a difference-in-difference (DD) specification—which simultaneously controls for preexisting amenities or disamenities in areas where turbines were sited and changes in the community after the wind facilities' construction was announced—to estimate effects near wind facilities after the turbines were announced and, later, after the turbines were constructed.[3]

The remainder of the report is structured as follows. Section 2 reviews the current literature. Section 3 details our methodology. Section 4 describes the study data. Section 5 presents the results, and Section 6 provides a discussion and concluding remarks.

2. Previous Literature

Although the topic is relatively new, the peer-reviewed literature investigating impacts to home values near wind facilities is growing. To date, results largely have coalesced around a common set of non-significant findings generated from home sales after the turbines became operational. Previous Lawrence Berkeley National Laboratory (LBNL) work in this area (Hoen et al., 2009, 2011) found no statistical evidence of adverse property-value effects due to views of and proximity to wind turbines after the turbines were constructed (i.e., post-construction or PC). Other peer-reviewed and/or academic studies also found no evidence of PC effects despite using a variety of techniques and residential transaction datasets. These include homes surrounding wind facilities in Cornwall, United Kingdom (Sims and Dent, 2007; Sims et al., 2008); multiple wind facilities in McLean County, Illinois (Hinman, 2010); near the Maple Ridge Wind Facility in New York (Heintzelman and Tuttle, 2011); and, near multiple facilities in Lee County, Illinois (Carter, 2011). Analogously, a 2012 Canadian case found a lack of evidence near a wind facility in Ontario to warrant the lowering of surrounding assessments (Kenney v MPAC, 2012). In contrast, one recent study did find impacts to land prices near a facility in North Rhine-Westphalia, Germany (Sunak and Madlener, 2012). Taken together, these results imply that the

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

PC effects of wind turbines on surrounding home values, if they exist, are often too small for detection or sporadic (i.e., a small percentage overall), or appearing in some communities for some types of properties but not others.

In the post-announcement, pre-construction period (i.e., PAPC), however, recent analysis has found more evidence of potential property value effects: by theorizing the possible existence of, but not finding, an effect (Laposa and Mueller, 2010; Sunak and Madlener, 2012); potentially finding an effect (Heintzelman and Tuttle, 2011)[4]; and, consistently finding what the author terms an "anticipation stigma" effect (Hinman, 2010). The studies that found PAPC property-value effects appear to align with earlier studies that suggested lower community support for proposed wind facilities before construction—potentially indicating a risk-averse (i.e., fear of the unknown) stance by community members—but increased support after facilities began operation (Gipe, 1995; Palmer, 1997; Devine-Wright, 2005; Wolsink, 2007; Bond, 2008, 2010). Similarly, researchers have found that survey respondents who live closer to turbines support the turbines more than respondents who live farther away (Braunholtz and MORI Scotland, 2003; Baxter et al., 2013), which could also indicate more risk-adverse / fear of the unknown effects (these among those who live farther away). Analogously, a recent case in Canada, although dismissed, highlighted the fears that nearby residents have for a planned facility (Wiggins v. WPD Canada Corporation, 2013)

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

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

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

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

It is not clear where wind turbines might fit into these ranges of impacts, but it seems unlikely that they would be considered as severe a disamenity as a large-volume landfill, which present odor, traffic, and groundwater-contamination issues. Low-volume landfills, with an effect near 3%, might be a better comparison, because they have an industrial (i.e., non-natural) quality, similar to turbines, but are less likely to have clear health effects. If sound is the primary concern, a 4% effect (corresponding to road noise) could be applied to turbines, which might correspond to a 10-dBA increase for houses within a half mile of a turbine (see e.g., Hubbard and Shepherd, 1991). Finally, as with transmission lines, if houses are in sight but not within sound distance of turbines, there may be no property-value effects unless those homes are immediately adjacent to the turbines. In summary, assuming these potentially analogous disamenity effects can be entirely transferred, turbine impacts might be 0%–14%, but more likely might coalesce closer to 3%–4%.

Of course, wind turbines have certain positive qualities that landfills, transmission lines, and roads do not always have, such as mitigating greenhouse gas emissions. no air or water pollution, no use of water during the generation of energy, and no generation of solid or hazardous waste that requires permanent storage/disposal (IPCC, 2011). Moreover, wind facilities can, and often do, provide economic benefits to local communities (Lantz and Tegen, 2009; Slattery et al., 2011; Brown et al., 2012; Loomis et al., 2012), which might not be the case for all other disamenities. Similarly, wind facilities can have direct positive effects on local government budgets through property tax or other similar payments (Loomis and Aldeman, 2011), which might, for example, improve school quality and thus increase nearby home values (e.g., Haurin and Brasington, 1996; Kane et al., 2006). These potential positive qualities might mitigate potential negative wind effects somewhat or even entirely. Therefore for the purposes of this research we will assume 3-4% is a maximum possible effect.

The potentially small average property-value effect of wind turbines, possibly reduced further by wind's positive traits, might help explain why effects have not been discovered consistently in previous research. To discover effects with small margins of error, large amounts of data are needed. However, previous datasets of homes very near turbines have been small. Hoen et al. (2009, 2011) used 125 PC transactions within a mile of the turbines, while others used far fewer PC transactions within a mile: Heintzelman and Tuttle (2012) (*n* ~ 35); Hinman (2010) (*n* ~ 11), Carter (2011) (*n* ~ 41), and Sunak and Madlener (2012) (*n* ~ 51). Although these numbers of observations are adequate to examine large impacts (e.g., over 10%), they are less likely to reveal small effects with any reasonable degree of statistical significance. Using results from Hoen et al. (2009) and the confidence intervals for the various fixed-effect variables in that study, estimates for the numbers of transactions needed to find effects of various sizes were obtained.

Approximately 50 cases are needed to find an effect of 10% and larger, 100 cases for 7.5%, 200 cases for 5%, 350 cases for 4%, 700 cases for 3%, and approximately 1,000 cases for a 2.5% effect.[5] Therefore, in order to detect an effect in the range of 3%–4%, a dataset of approximately 350–700 cases within a mile of the turbines will be required to detect it statistically, a number that to-date has not been amassed by any of the previous studies.

As discussed above, in addition to being relatively small on average, impacts are likely to decay with distance. As such, an appropriate empirical approach must be able to reveal spatially diminishing effects. Some researchers have used continuous variables to capture these effects, such as linear distance (Hoen et al., 2009; Sims et al., 2008) and inverse distance (Heintzelman and Tuttle, 2012; Sunak and Madlener, 2012), but doing so forces the model to estimate effects at the mean distance. In some cases, those means can be far from the area of expected impact. For example, Heintzelman and Tuttle (2012) estimated an inverse distance effect using a mean distance of more than 10 miles from the turbines, while Sunak and Madlener (2012) used a mean distance of approximately 1.9 miles. Using this approach weakens the ability of the model to quantify real effects near the turbines, where they are likely to be stronger. More importantly, this method encourages researchers to extrapolate their findings to the ends of the distance curve, near the turbines, despite having few data at those distances to support these extrapolations. This was the case for Heintzelman and Tuttle (2012), who had fewer than 10 cases within a half mile in the two counties where effects were found and only a handful that sold in those counties after the turbines were built, yet they extrapolated their findings to a quarter mile and even a tenth of a mile, where they had very few (if any) cases. Similarly, Sunak and Madlener (2012) had only six PC sales within a half mile and 51 within 1 mile, yet they extrapolated their findings to these distance bands.

One way to avoid using a single continuous function to estimate effects at all distances is to use a spline model, which breaks the distances into continuous groups (Hoen et al., 2011), but this method still imposes structure on the data by forcing the ends of each spline to tie together. A second and more transparent method is to use fixed-effect variables for discrete distances, which imposes little structure on the data (Hoen et al., 2009; Hinman, 2010; Carter, 2011; Hoen et al.,

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

2011). Although this latter method has been used in a number of studies, because of a paucity of data, the resulting models are often ineffective at detecting what might be relatively small effects very close to the turbines. As such, when using this method (or any other, in fact) it is important that the underlying dataset is large enough to estimate the anticipated magnitude of the effect sizes.

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

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

3. Methodology

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

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

3.1. Basic Approach and Models

Our methods are designed to help answer the following questions:

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

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

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

As is common in the literature (Malpezzi, 2003; Sirmans et al., 2005), a semi-log functional form of the hedonic pricing model is used for all models, where the dependent variable is the natural log of sales price. The OLS *half-mile* model form is as follows:

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

where

SP_i represents the sale price for transaction *i*,

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

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

S_i is the state in which transaction *i* occurred,

W_i is the census tract in which transaction *i* occurred,

X_i is a vector of home, site, and neighborhood characteristics for transaction *i* (e.g., square feet, age, acres, bathrooms, condition, percent of block group vacant and owned, median age of block group),[8]

C_i is the county in which transaction *i* occurred,

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

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

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

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

ε_i is a random disturbance term for transaction *i*.

This pooled construction uses all property transactions in the entire dataset. In so doing, it takes advantage of the large dataset in order to estimate an average set of turbine-related effects across all study areas, while simultaneously allowing for the estimation of controlling characteristics at

[8] A “block group” is a US Census Bureau geographic delineation that contains a population between 600 to 3000 persons.

the local level, where they are likely to vary substantially across the study areas.[9] Specifically, the interaction of county-level fixed effects (C_i) with the vector of home, site, and neighborhood characteristics (X_i) allows different slopes for each of these independent variables to be estimated for each county. Similarly, interacting the state fixed-effect variables (S_i) with the sale year and sale winter fixed effects variables (T_i) (i.e., if the sale occurred in either Q1 or Q4) allows the estimation of the respective inflation/deflation and seasonal adjustments for each state in the dataset.[10] Finally, to control for the potentially unique collection of neighborhood characteristics that exist at the micro-level, census tract fixed effects are estimated.[11] Because a pooled model is used that relies upon the full dataset, smaller effect sizes for wind turbines will be detectable. At the same time, however, this approach does not allow one to distinguish possible wind turbine effects that may be larger in some communities than in others.

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

To control for both of these issues simultaneously, we use a difference-in-difference (*DD)* specification (see e.g., Hinman, 2010; Zabel and Guignet, 2012) derived from the interaction of

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

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

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

the spatial (D_i) and temporal (P_i) terms. These terms produce a vector of 11 parameter estimates (β_4) as shown in Table 1 for the *half-mile* models and in Table 2 for the *one-mile* models. The omitted (or reference) group in both models is the set of homes that sold prior to the wind facilities' announcement and which were located more than 3 miles away from where the turbines were eventually located (A3). It is assumed that this reference category is likely not affected by the imminent arrival of the turbines, although this assumption is tested in the robustness tests.

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

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

Table 1: Interactions between Wind Facility Development Periods and Distances – ½ Mile

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

Table 2: Interactions between Wind Facility Development Periods and Distances - 1 Mile

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

3.2. Spatial Dependence

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

In addition to including local fixed effects, spatial econometric methods can be used to help further mitigate the potential impact of spatially omitted variables by modeling spatial dependence directly. When spatial dependence is present and appropriately modeled, more accurate (i.e., less biased) estimates of the factors influencing housing values can be obtained. These methods have been used in a number of previous hedonic price studies; examples include the price impacts of wildfire risk (Donovan et al., 2007), residential community associations (Rogers, 2006), air quality (Anselin and Lozano-Gracia, 2009), and spatial fragmentation of land use (Kuethe, 2012). To this point, however, these methods have not been applied to studies of the impact of wind turbines on property values.

Moran's I is the standard statistic used to test for spatial dependence in OLS residuals of the hedonic equation. If the Moran's I is statistically significant (as it is in our models – see Section 5.1.2), the assumption of spatial independence is rejected. To account for this, in spatial-process models, spatial dependence is routinely modeled as an additional covariate in the form of a spatially lagged dependent variable *Wy*, or in the error structure $\mu = \lambda W\mu + \varepsilon$, where ε is an identically and independently distributed disturbance term (Anselin, 1988). Neighboring criterion determines the structure of the spatial weights matrix *W*, which is frequently based on contiguity, distance criterion, or *k*-nearest neighbors (Anselin, 2002). The weights in the spatial-weights matrix are typically row standardized so that the elements of each row sum to one.

The spatial-process model, known as the SARAR model (Kelejian and Prucha, 1998)[12], allows for both forms of spatial dependence, both as an autoregressive process in the lag-dependent and in the error structure, as shown by:

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

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

Equation (2) is often estimated by a multi-step procedure using generalized moments and instrumental variables (Arraiz et al., 2009), which is our approach. The model allows for the innovation term ε in the disturbance process to be heteroskedastic of an unknown form (Kelejian and Prucha, 2010). If either λ or ρ are not significant, the model reduces to the respective spatial lag or spatial error model (SEM). In our case, as is discussed later, the spatial process model reduces to the SEM, therefore both *half-mile* and *one-mile* SEMs are estimated, and, as with the OLS models discussed above, a similar set of *DD* "net effects" are estimated for the PA, PAPC, and PC periods. One requirement of the spatial model is that the x/y coordinates be unique across the dataset. However, the full set of data (as described below) contains, in some cases, multiple sales for the same property, which consequently would have non-unique x/y coordinates.[13] Therefore, for the spatial models, only the most recent sale is used. An OLS model using this limited dataset is also estimated as a robustness test.

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

3.3. Robustness Tests

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

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

reference category by using transactions more than 2 years PA (as opposed to simply PA) as the reference category. Each of these tests is discussed in detail below.

3.3.1. Outliers and Influential Cases

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

3.3.2. Interacting Sale Year at the County Level

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

3.3.3. Using Only the Most Recent Sales

The dataset for the base OLS models includes not only the most recent sale of particular homes, but also, if available, the sale prior to that. Some of these earlier sales occurred many years prior to the most recent sale. The home and site characteristics (square feet, acres, condition, etc.) used in the models are populated via assessment data for the home. For some of these data, only the most recent assessment information is available (rather than the assessment from the time of sale), and therefore older sales might be more prone to error as their characteristics might have changed since the sale.[14] Additionally, the SEMs require that all x/y coordinates entered into the model are unique; therefore, for those models only the most recent sale is used. Excluding older sales therefore potentially reduces measurement error, and also enables a more-direct comparison of effects between the base OLS model and SEM results.

3.3.4. Using Homes between 5 and 10 Miles as Reference Category

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

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

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

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[14] As discussed in more detail in the Section 4, approximately 60% of all the data obtained for this study (that obtained from CoreLogic) used the most recent assessment to populate the home and site characteristics for all transactions of a given property.

is unbiased, a model is estimated that uses transactions occurring more than 2 years before the wind facilities were announced (and between 3 and 10 miles) as the reference category.

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

4. Data

The data used for the analysis are comprised of four types: wind turbine location data, real estate transaction data, home and site characteristic data, and census data. From those, two additional sets of data are calculated: distance to turbine and wind facility development period. Each data type is discussed below. Where appropriate, variable names are shown in *italics*.

4.1. Wind Turbine Locations

Location data (i.e., x/y coordinates) for installed wind turbines were obtained via an iterative process starting with Federal Aviation Administration obstacle data, which were then linked to specific wind facilities by Ventyx[15] and matched with facility-level data maintained by LBNL. Ultimately, data were collected on the location of almost all wind turbines installed in the U.S. through 2011 (n ~ 40,000), with information about each facility's announcement, construction, and operation dates as well as turbine nameplate capacity, hub height, rotor diameter, and facility size.

4.2. Real Estate Transactions

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

The first source of real estate transaction data was CoreLogic's extensive dataset of U.S. residential real estate information.[16] Using the x/y coordinates of wind turbines, CoreLogic

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

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

The second source of data was the New York Office of Real Property Tax Service (NYORPTS),[18] which supplied a set of arms-length single-family residential transactions between 2001 and 2012 within 10 miles of existing turbines in any New York county in which wind development had occurred prior to 2012. As before, only parcels smaller than 15 acres were included, as were a minimum of 250 transactions and at least one PC transaction within a half mile of a turbine for each New York county. Both CoreLogic and NYORPTS provided the most recent home sale and, if available, the prior sale.

4.3. Home and Site Characteristics

A set of home and site characteristic data was also collected from both data suppliers: 1000s of square feet of living area (*sfla1000*), number of acres of the parcel (*acres*), year the home was built (or last renovated, whichever is more recent) (*yrbuilt*), and the number of full and half bathrooms (*baths*).[19] Additional variables were calculated from the other variables as well: log of 1,000s of square feet (*lsfla1000*),[20] the number of acres less than 1 (*lt1acre)*,[21] age at the time of sale (*age*), and age squared (*agesqr*).[22]

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

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

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

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

Regardless of when the sale occurred, CoreLogic supplied the related home and site characteristics as of the most recent assessment, while NYORPTS supplied the assessment data as of the year of sale.[23]

4.4. Census Information

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

4.5. Distances to Turbine

Using the x/y coordinates of both the homes and the turbines, a Euclidian distance (in miles) was calculated for each home to the nearest wind turbine (*tdis*), regardless of when the sale occurred (e.g., even if a transaction occurred prior to the wind facility's installation).[24] These were then broken into four mutually exclusive distance bins (i.e., groups) for the base *half-mile* models: inside a half mile, between a half and 1 mile, between 1 and 3 miles, and between 3 and 10 miles. They were broken into three mutually exclusive bins for the base *one-mile* models: inside 1 mile, between 1 and 3 miles, and between 3 and 10 miles.

4.6. Wind Facility Development Periods

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

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

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

[23] See footnote 13.

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

of the three facility-development periods (*fdp*) the transaction occurred: *pre-announcement* (PA), *post-announcement-pre-construction* (PAPC), or *post-construction* (PC).

4.7. Data Summary

After cleaning to remove missing or erroneous data, a final dataset of 51,276 transactions was prepared for analysis.[25] As shown in the map of the study area (Figure 1), the data are arrayed across nine states and 27 counties (see Table 4), and surround 67 different wind facilities.

Table 3 contains a summary of those data. The average unadjusted sales price for the sample is $122,475. Other average house characteristics include the following: 1,600 square feet of living space; house age of 48 years[26]; land parcel size of 0.90 acres; 1.6 bathrooms; in a block group in which 74% of housing units are owned, 9% are vacant, and the median resident age is 38 years; located 4.96 miles from the nearest turbine; and sold at the tail end of the PA period.

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

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

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

Figure 1: Map of Transactions, States, and Counties

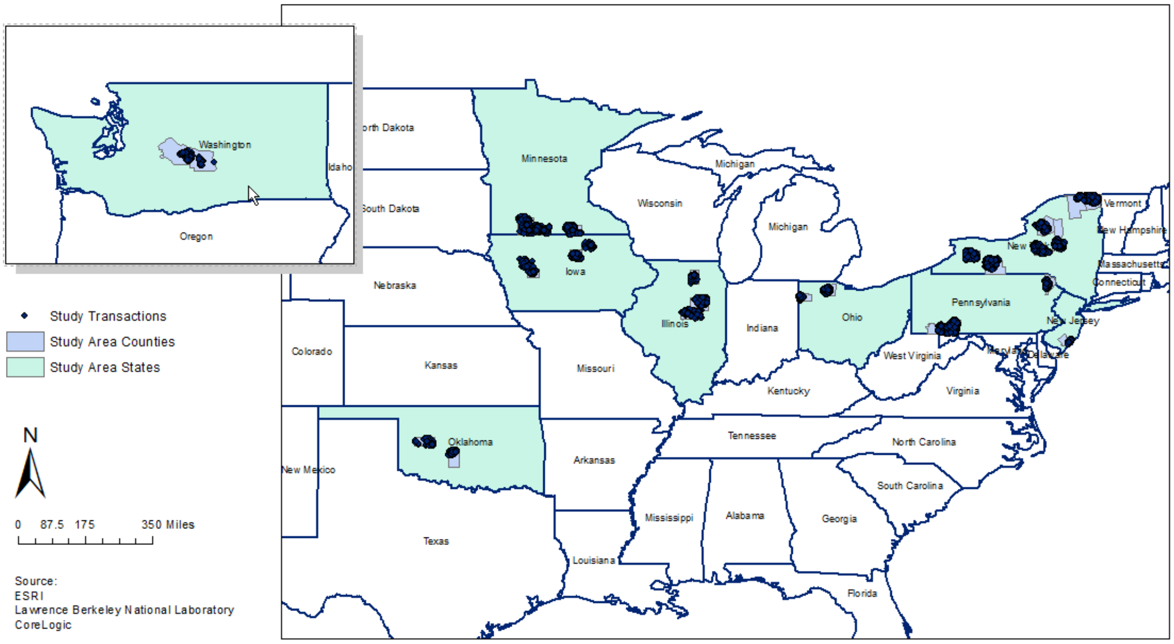

Table 3: Summary Statistics

Variable	Description	Mean	Std. Dev.	Min	Max
sp	sale price in dollars	$ 122,475	$ 80,367	$ 9,750	$ 690,000
lsp	natural log of sale price	11.52	0.65	9.19	13.44
sd	sale date	1/18/2005	1,403 days	1/1/1996	9/30/2011
sy	sale year	2005	3.84	1996	2011
sfla1000	living area in 1000s of square feet	1.60	0.57	0.60	4.50
lsfla1000	natural log of sfla1000	0.41	0.34	-0.50	1.50
acres	number of acres in parcel	0.90	1.79	0.03	14.95
acreslt1*	acres less than 1	-0.58	0.34	-0.97	0.00
age	age of home at time of sale	48	37	-1	297
agesq	age squared	3689	4925	0	88209
baths**	number of bathrooms	1.60	0.64	1.00	5.50
pctowner	fraction of house units in block group that are owned (as of 2000)	0.74	0.17	0.63	0.98
pctvacant	fraction of house units in block group that are vacant (as of 2000)	0.09	0.10	0.00	0.38
med_age	median age of residents in block group (as of 2000)	38	6	20	63
tdis	distance to nearest turbine (as of December 2011) in miles	4.96	2.19	0.09	10.00
fdp***	facility development period of nearest turbine at time of sale	1.94	0.87	1.00	3.00
Note: The number of cases for the full dataset is 51,276					
** acreslt1 is calculated as follows: acres (if less than 1) * - 1*					
*** Some counties did not have bathrooms populated; for those, these variables are entered into the regression as 0.*					
**** fdp periods are: 1, pre-announcement,; 2, post-announcement-pre-construction; and, 3, post-construction.*					

Table 4: Summary of Transactions by County

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

Table 5: Frequency Crosstab of Wind Turbine Distance and Development Period Bins

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

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

Table 6: Wind Facility Summary

	mean	min	25th percentile	median	75th percentile	max
turbine rotor diameter (feet)	262	154	253	253	269	328
turbine hub height (feet)	256	197	256	262	262	328
turbine total height (feet)	388	290	387	389	397	476
turbine capacity (kW)	1637	660	1500	1500	1800	2500
facility announcement year	2004	1998	2002	2003	2005	2010
facility construction year	2007	2000	2004	2006	2010	2011
number of turbines in facility	48	1	5	35	84	150
nameplate capacity of facility (MW)	79	1.5	7.5	53	137	300

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

4.8. Comparison of Means

To provide additional context for the analysis discussed in the next section, we further summarize the data here using four key variables across the sets of development period (*fdp*) and distance bins (*tdis*) used in the *one-mile* models.[27] The variables are the dependent variable log of sale price *(lsp)* and three independent variables: *lsfla100*, *acres*, and *age*. These summaries are provided in Table 7; each sub-table gives the mean values of the variables across the three *fdp* bins and three *tdis* bins, and the corresponding figures plot those values.

The top set of results are focused on the log of the sales price, and show that, based purely on price and not controlling for differences in homes, homes located within 1 mile of turbines had lower sale prices than homes farther away; this is true across all of the three development periods. Moreover, the results also show that, over the three periods, the closer homes appreciated to a somewhat lesser degree than homes located farther from the turbines. As a result, focusing only on the post-construction period, these results might suggest that home prices near turbines are

[27] Summaries for the *half-mile* models reveal a similar relationship, so only the *one-mile* model summaries are shown here.

adversely impacted by the turbines. After all, the logarithmic values for the homes within a mile of the turbines (11.39) and those outside of a three miles (11.72) translate into an approximately 40% difference, in comparison to an 21% difference before the wind facilities were announced (11.16 vs. 11.35).[28] Focusing on the change in average values between the pre-announcement and post-construction periods might also suggest an adverse effect due to the turbines, because homes inside of 1 mile appreciated more slowly (11.16 to 11.39, or 25%) than those outside of 3 miles (11.35 to 11.72, or 45%). Both conclusions of adverse turbine effects, however, disregard other important differences between the homes, which vary over the periods and distances. Similarly, comparing the values of the PA inside 1 mile homes (11.16) and the PC outside of 3 miles homes (11.72), which translates into a difference of 75%, and which is the basis for comparison in the regressions discussed below, but also ignores any differences in the underlying characteristics.

The remainder of Table 7, for example, indicates that, although the homes that sold within 1 mile are lower in value, they are also generally (in all but the PA period) smaller, on larger parcels of land, and older. These differences in home size and age across the periods and distances might explain the differences in price, while the differences in the size of the parcel, which add value, further amplifying the differences in price. Without controlling for these possible impacts, one cannot reliably estimate the impact of wind turbines on sales prices.

In summary, focusing solely on trends in home price (or price per square foot) alone, and for only the PC period, as might be done in a simpler analysis, might incorrectly suggest that wind turbines are affecting price when other aspects of the markets, and other home and sites characteristic differences, could be driving the observed price differences. This is precisely why researchers generally prefer the hedonic model approach to control for such effects, and the results from our hedonic OLS and spatial modeling detailed in the next section account for these and many other possible influencing factors.

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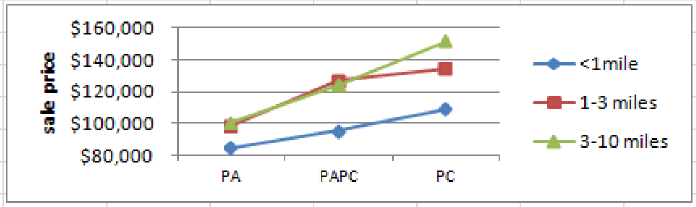
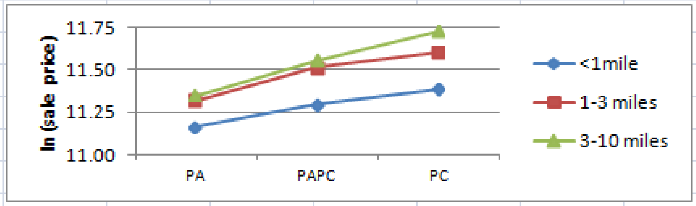
[28] Percentage differences are calculated as follows: exp(11.72-11.39)-1=0.40 and exp(11.35-11.16)-1=0.21.

Table 7: Dependent and Independent Variable Means

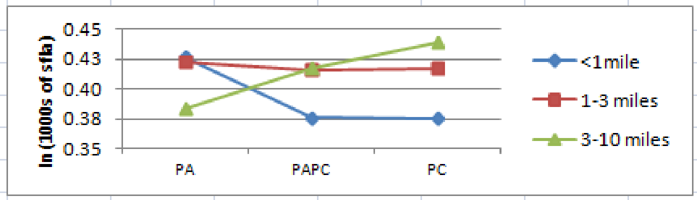
Sale Price	<1mile	1-3 miles	3-10 miles
PA	$ 84,830	$ 98,676	$100,485
PAPC	$ 95,223	$127,054	$124,532
PC	$109,133	$134,647	$151,559



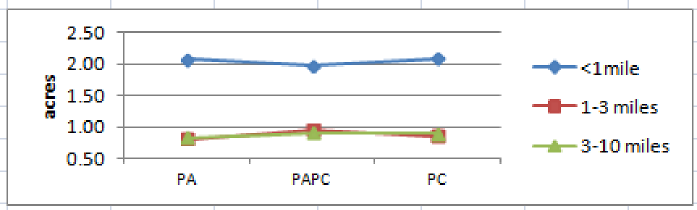
Log of Sale Price	<1mile	1-3 miles	3-10 miles
PA	11.16	11.32	11.35
PAPC	11.30	11.52	11.56
PC	11.39	11.61	11.72



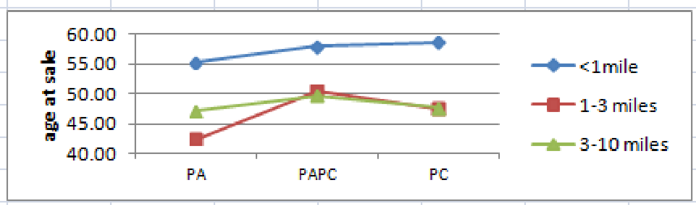
Log of Square Feet (in 1000s)	<1mile	1-3 miles	3-10 miles
PA	0.43	0.42	0.38
PAPC	0.38	0.42	0.42
PC	0.38	0.42	0.44



Number of Acres	<1mile	1-3 miles	3-10 miles
PA	2.08	0.80	0.83
PAPC	1.98	0.94	0.90
PC	2.09	0.84	0.89



Age at the Time of Sale	<1mile	1-3 miles	3-10 miles
PA	55.32	42.34	47.19
PAPC	58.01	50.34	49.73
PC	58.63	47.39	47.73



5. Results

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

5.1. Estimation Results for Base Models

Estimation results for the "base" models are shown in Table 8 and Table 9.[29] In general, given the diverse nature of the data, the models perform adequately, with adjusted R^2 values ranging from 0.63 to 0.67 (bottom of Table 9).

5.1.1. Control Variables

The controlling home, site, and block group variables, which are interacted at the county level, are summarized in Table 8. Table 8 focuses on only one of the base models, the *one-mile* OLS model, but full results from all models are shown in the Appendix. [30] To concisely summarize results for all of the 27 counties, the table contains the percentage of all 27 counties for which each controlling variable has statistically significant (at or below the 10% level) coefficients for the *one-mile* OLS model. For those controlling variables that are found to be statistically significant, the table further contains mean values, standard deviations, and minimum and maximum levels.

Many of the county-interacted controlling variables (e.g., *lsfla1000, lt1acre, age, agesqr, baths,* and *swinter*) are consistently (in more than two thirds of the counties) statistically significant (with a p-value < 0.10) and have appropriately sized mean values. The seemingly spurious minimum and maximum values among some of the county-level controlling variables (e.g., *lt1acre* minimum of -0.069) likely arise when these variables in particular counties are highly correlated with other variables, such as square feet (*lsfla1000*), and also when sample size is limited.[31] The other variables (*acres* and the three block group level census variables: *pctvacant, pctowner,* and *med_age*) are statistically significant in 33-59% of the counties. Only one variable's mean value—the percent of housing units vacant in the block group as of the 2000 census (*pctvacant*)—was counterintuitive. In that instance, a positive coefficient was estimated, when in fact, one would expect that increasing the percent of vacant housing would lower prices;

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

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

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

this counter-intuitive effect may be due to collinearity with one or more of the other variables, or possible measurement errors.[32]

The sale year variables, which are interacted with the state, are also summarized in Table 8, with the percentages indicating the number of states in which the coefficients are statistically significant. The inclusion of these sale year variables in the regressions control for inflation and deflation across the various states over the study period. The coefficients represent a comparison to the omitted year, which is 2011. All sale year state-level coefficients are statistically significant in at least 50% of the states in all years except 2010, and they are significant in two thirds of the states in all except 3 years. The mean values of all years are appropriately signed, showing a monotonically ordered peak in values in 2007, with lower values in the prior and following years. The minimum and maximum values are similarly signed (negative) through 2003 and from 2007 through 2010 (positive), and are both positive and negative in years 2003 through 2006, indicating the differences in inflation/deflation in those years across the various states. This reinforces the appropriateness of interacting the sale years at the state level. Finally, although not shown, the model also contains 250 fixed effects for the census tract delineations, of which approximately 50% were statistically significant.

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

Table 8: Levels and Significance for County- and State-Interacted Controlling Variables[33]

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

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

5.1.2. Variables of Interest

The variables of interest, the interactions between the *fdp* and *tdis* bins, are shown in Table 9 for the four base models. The reference (i.e., omitted) case for these variables are homes that sold prior to the wind facilities' announcement (PA) and are located between 3 and 10 miles from the

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

wind turbines' eventual locations. In relation to that group of transactions, three of the eight interactions in the *one-mile* models and four of the 11 interactions in the *half-mile* models produce coefficients that are statistically significant (at the 10% level).

Across all four base models none of the PA coefficients show statistically significant differences between the reference category (outside of 3 miles) and the group of transactions within a mile for the *one-mile* models (OLS: -1.7%, *p*-value 0.48; SEM: -0.02%, *p*-value 0.94)[34] or within a half- or between one-half and one-mile for the *half-mile* models (OLS inside a half mile: 0.01%, *p*-value 0.97; between a half and 1 mile: -2.3%, *p*-value 0.38; SEM inside a half mile: 5.3%, *p*-value 0.24; between a half and 1 mile: -1.8%, *p*-value 0.60). Further, none of the coefficients are significant, and all are relatively small (which partially explains their non-significance). Given these results, we find an absence of evidence of a PA effect for homes close to the turbines (*research question 1*). These results can be contrasted with the differences in prices between within-1-mile homes and outside-of-3-miles homes as summarized in Section 4.8 when no differences in the homes, the local market, the neighborhood, etc. are accounted for. The approximately 75% difference in price (alone) in the pre-announcement period 1-mile homes, as compared to the PC 3-mile homes, discussed in Section 4.8, is largely explained by differences in the controlling characteristics, which is why the pre-announcement distance coefficients shown here are not statistically significant.

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

The results presented above, and in Table 8, include both OLS and spatial models. Prior to estimating the spatial models, the Moran's I was calculated using the residuals of an OLS model that uses the same explanatory variables as the spatial models and the same dataset (only the most recent transactions). The Moran's I statistic (0.133) was highly significant (*p*-value 0.00),

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

which allows us to reject the hypothesis that the residuals are spatially independent. Therefore, there was justification in estimating the spatial models. However, after estimation, we determined that only the spatial error process was significant. As a result, we estimated spatial error models (SEMs) for the final specification. The spatial autoregressive coefficient, lambda (bottom of Table 9), which is an indication of spatial autocorrelation in the residuals, is sizable and statistically significant in both SEMs (0.26, *p*-value 0.00). The SEM models' variable-of-interest coefficients are quite similar to those of the OLS models. In most cases, the coefficients are the same sign, approximately the same level, and often similarly insignificant, indicating that although spatial dependence is present it does not substantively bias the variables of interest. The one material difference is the coefficient size and significance for homes outside of 3 miles in the PAPC and PC periods, 3.3% (*p*-value 0.000) and 3.1% (*p*-value 0.008), indicating there are important changes to home values over the periods that must be accounted for in the later DD models in order to isolate the potential impacts that occur due to the presence of wind turbines.

Table 9: Results of Interacted Variables of Interest: *fdp* and *tdis*

		one-mile	*one-mile*	*half-mile*	*half-mile*
		OLS	SEM	OLS	SEM
fdp	tdis	β (se)	β (se)	β (se)	β (se)
PA	< 1 mile	-0.017	0.002		
		(0.024)	*(0.031)*		
PA	1-2 miles	-0.015	0.008		
		(0.011)	*(0.016)*		
PA	> 3 miles	Omitted	Omitted		
		n/a	*n/a*		
PAPC	< 1 mile	-0.035	-0.038		
		(0.029)	*(0.033)*		
PAPC	1-2 miles	-0.001	-0.033.		
		(0.014)	*(0.018)*		
PAPC	> 3 miles	-0.006	-0.033***		
		(0.008)	*(0.01)*		
PC	< 1 mile	0.019	-0.022		
		(0.026)	*(0.032)*		
PC	1-2 miles	0.044***	-0.001		
		(0.014)	*(0.019)*		
PC	> 3 miles	-0.005	-0.031**		
		(0.010)	*(0.012)*		
PA	< 1/2 mile			0.001	0.053
				(0.039)	*(0.045)*
PA	1/2 - 1 mile			-0.023	-0.018
				(0.027)	*(0.035)*
PA	1-2 miles			-0.015	0.008
				(0.011)	*(0.016)*
PA	> 3 miles			Omitted	Omitted
				n/a	*n/a*
PAPC	< 1/2 mile			-0.028	-0.065
				(0.049)	*(0.056)*
PAPC	1/2 - 1 mile			-0.038	-0.027
				(0.033)	*(0.036)*
PAPC	1-2 miles			-0.001	-0.034.
				(0.014)	*(0.017)*
PAPC	> 3 miles			-0.006	-0.033***
				(0.008)	*(0.009)*
PC	< 1/2 mile			-0.016	-0.036
				(0.041)	*(0.046)*
PC	1/2 - 1 mile			0.032	-0.016
				(0.031)	*(0.035)*
PC	1-2 miles			0.044***	-0.001
				(0.014)	*(0.018)*
PC	> 3 miles			-0.005	-0.031**
				(0.010)	*(0.012)*
lambda			0.247 ***		0.247 ***
			(0.008)		*(0.008)*
*Note: p-values: < 0.1 *, < 0.05 **, <0.01 ***.*					
n		51,276	38,407	51,276	38,407
adj R-sqr		0.67	0.64	0.67	0.64

5.1.3. Impact of Wind Turbines

As discussed above, there are important differences in property values between development periods for the reference group of homes (those located outside of 3 miles) that must be accounted for. Further, although they are not significant, differences between the reference category and those transactions inside of 1 mile in the PA period still must be accounted for if accurate measurements of PAPC or PC wind turbine effects are to be estimated. The DD specification accounts for both of these critical effects.

Table 10 shows the results of the DD tests across the four models, based on the results for the variables of interest presented in Table 9.[35] For example, to determine the net difference for homes that sold inside of a half mile (drawing from the *half-mile* OLS model) in the PAPC period, we use the following formula: PAPC half-mile coefficient (-0.028) less the PAPC 3-mile coefficient (-0.006) less the PA half-mile coefficient (0.001), which equals -0.024 (without rounding), which equates to 2.3% difference,[36] and is not statistically significant.

None of the DD effects in either the OLS or SEM specifications are statistically significant in the PAPC or PC periods, indicating that we do not observe a statistically significant impact of wind turbines on property values. Some small differences are apparent in the calculated coefficients, with those for PAPC being generally more negative/less positive than their PC counterparts, perhaps suggestive of a small announcement effect that declines once a facility is constructed. Further, the inside-a-half-mile coefficients are more negative/less positive than their between-a-half-and-1-mile counterparts, perhaps suggestive of a small property value impact very close to turbines.[37] However, in all cases, the sizes of these differences are smaller than the margins of error in the model (i.e., 90% confidence interval) and thus are not statistically significant. Therefore, based on these results, we do not find evidence supporting either of our two core hypotheses (*research questions 2 and 3*). In other words, there is no statistical evidence that homes in either the PAPC or PC periods that sold near turbines (i.e., within a mile or even a half

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

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

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

mile) did so for less than similar homes that sold between 3 and 10 away miles in the same period.

Further, using the standard errors from the DD models we can estimate the maximum size an average effect would have to be in our sample for the model to detect it (*research question 4*). For an average effect in the PC period to be found for homes within 1 mile of the existing turbines (therefore using the *one-mile* model results), an effect greater than 4.9%, either positive or negative, would have to be present to be detected by the model.[38] In other words, it is highly unlikely that the true average effect for homes that sold in our sample area within 1 mile of an existing turbine is larger than +/-4.9%. Similarly, it is highly unlikely that the true average effect for homes that sold in our sample area within a half mile of an existing turbine is larger than +/-9.0%.[39] Regardless of these maximum effects, however, as well as the very weak suggestion of a possible small announcement effect and a possible small effect on homes that are very close to turbines, the core results of these models show effect sizes that are not statistically significant from zero, and are considerably smaller than these maximums.[40]

[38] Using the 90% confidence interval (i.e., 10% level of significance) and assuming more than 300 cases, the critical t-value is 1.65. Therefore, using the standard error of 0.030, the 90% confidence intervals for the test will be +/-0.049.

[39] Using the critical t-value of 1.66 for the 100 PC cases within a half mile in our sample and the standard error of 0.054.

[40] It is of note that these maximum effects are slightly larger than those we expected to find, as discussed earlier. This likely indicates that there was more variation in this sample, causing relatively higher standard errors for the same number of cases, than in the sample used for the 2009 study (Hoen et al., 2009, 2011).

Table 10: "Net" Difference-in-Difference Impacts of Turbines

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

*Note: p-values: > 10% NS, < 10% *, < 5% **, <1 % ****

5.2. Robustness Tests

Table 11 summarizes the results from the robustness tests. For simplicity, only the DD coefficients are shown and only for the *half-mile* OLS models.[41] The first two columns show the base OLS and SEM *half-mile* DD results (also presented earlier, in Table 9), and the remaining columns show the results from the robustness models as follows: exclusion of outliers and influential cases from the dataset (*outlier*); using sale year/county interactions instead of sale year/state (*sycounty*); using only the most recent sales instead of the most recent and prior sales (*recent*); using homes between 5 and 10 miles as the reference category, instead of homes between 3 and 10 miles (*outside5*); and using transactions occurring more than 2 years before announcement as the reference category instead of using transactions simply *before* announcement (*prior*).

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

The robustness results have patterns similar to the base model results: none of the coefficients are statistically different from zero; all coefficients (albeit non-significant) are lower in the PAPC period than the PC period; and, all coefficients (albeit non-significant) are lower (i.e., less negative/more positive) within a half mile than outside a half mile.[42] In sum, regardless of dataset or specification, there is no change in the basic conclusions drawn from the base model results: there is no evidence that homes near operating or announced wind turbines are impacted in a statistically significant fashion. Therefore, if effects do exist, either the average impacts are relatively small (within the margin of error in the models) and/or sporadic (impacting only a small subset of homes). Moreover, these results seem to corroborate what might be predicted given the other, potentially analogous disamenity literature that was reviewed earlier, which might be read to suggest that any property value effect of wind turbines might coalesce at a maximum of 3%–4%, on average. Of course, we cannot offer that corroboration directly because, although the size of the coefficients in the models presented here are reasonably consistent with effects of that magnitude, none of our models offer results that are statistically different from zero.

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

Table 11: Robustness Half-Mile Model Results

				Robustness OLS Models				
		Base OLS	Base SEM	outlier	sycounty	recent	outside5	prior
fdp	tdis	β (se)	β (se)	β (se)	β (se)	β (se)	β (se)	β (se)
PAPC	< 1/2 mile	-2.3% ^{NS}	-8.1% ^{NS}	-4.7% ^{NS}	-4.2% ^{NS}	-5.6% ^{NS}	-1.7% ^{NS}	0.1% ^{NS}
		(0.060)	*(0.065)*	*(0.056)*	*(0.060)*	*(0.066)*	*(0.060)*	*(0.062)*
PAPC	1/2 - 1 mile	-0.8% ^{NS}	2.5% ^{NS}	-1.7% ^{NS}	-2.5% ^{NS}	2.3% ^{NS}	-0.2% ^{NS}	0.4% ^{NS}
		(0.039)	*(0.043)*	*(0.036)*	*(0.039)*	*(0.043)*	*(0.039)*	*(0.044)*
PC	< 1/2 mile	-1.2% ^{NS}	-5.6% ^{NS}	-0.5% ^{NS}	-1.8% ^{NS}	-4.3% ^{NS}	-0.3% ^{NS}	1.3% ^{NS}
		(0.054)	*(0.057)*	*(0.047)*	*(0.054)*	*(0.056)*	*(0.054)*	*(0.056)*
PC	1/2 - 1 mile	6.3% ^{NS}	3.4% ^{NS}	6.2% ^{NS}	3.8% ^{NS}	4.1% ^{NS}	7.1% ^{NS}	7.5% ^{NS}
		(0.036)	*(0.041)*	*(0.033)*	*(0.036)*	*(0.042)*	*(0.036)*	*(0.041)*
*Note: p-values: > 0.1 ^{NS}, < 0.1 *, <0.5 **, <0.01 ****								
	n	51,276	38,407	50,106	51,276	38,407	51,276	51,276
	adj R-sqr	0.67	0.64	0.66	0.67	0.66	0.67	0.67

6. Conclusion

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

Previous published and academic research on this topic has tended to indicate that wind facilities, after they have been constructed, produce little or no effect on home values. At the same time, some evidence has emerged indicating potential home-value effects occurring after a wind facility has been announced but before construction. These previous studies, however, have been limited by their relatively small sample sizes, particularly in relation to the important population of homes located very close to wind turbines, and have sometimes treated the variable for distance to wind turbines in a problematic fashion. Analogous studies of other disamenities—including high-voltage transmission lines, landfills, and noisy roads—suggest that if reductions in property values near turbines were to occur, they would likely be no more than 3%–4%, on average, but to discover such small effects near turbines, much larger amounts of data are needed than have been used in previous studies. Moreover, previous studies have not accounted adequately for potentially confounding home-value factors, such as those affecting home values before wind facilities were announced, nor have they adequately controlled for spatial dependence in the data, i.e., how the values and characteristics of homes located near one another influence the value of those homes (independent of the presence of wind turbines).

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

Across all model specifications, we find no statistical evidence that home prices near wind turbines were affected in either the post-construction or post-announcement/pre-construction periods. Therefore, if effects do exist, either the average impacts are relatively small (within the margin of error in the models) and/or sporadic (impacting only a small subset of homes). Related, our sample size and analytical methods enabled us to bracket the size of effects that would be detected, if those effects were present at all. Based on our results, we find that it is *highly unlikely* that the actual average effect for homes that sold in our sample area within 1 mile of an existing turbine is larger than +/-4.9%. In other words, the average value of these homes could be as much as 4.9% higher than it would have been without the presence of wind turbines, as much as 4.9% lower, the same (i.e., zero effect), or anywhere in between. Similarly, it is highly unlikely that the average actual effect for homes that sold in our sample area within a half mile of an existing turbine is larger than +/-9.0%. In other words, the average value of these homes could be as much as 9% higher than it would have been without the presence of wind turbines, as much as 9% lower, the same (i.e., zero effect), or anywhere in between.

Regardless of these potential maximum effects, the core results of our analysis consistently show no sizable statistically significant impact of wind turbines on nearby property values. The maximum impact suggested by potentially analogous disamenities (high-voltage transmission lines, landfills, roads etc.) of 3%-4% is at the far end of what the models presented in this study would have been able to discern, potentially helping to explain why no statistically significant effect was found. If effects of this size are to be discovered in future research, even larger samples of data may be required. For those interested in estimating such effects on a more micro (or local) scale, such as appraisers, these possible data requirements may be especially daunting, though it is also true that the inclusion of additional market, neighborhood, and individual property characteristics in these more-local assessments may sometimes improve model fidelity.

7. References

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8. Appendix – Full Results

	OneMile OLS		HalfMile OLS		OneMile SEM		HalfMile SEM	
Variables	**coef**	**se**	**coef**	**se**	**coef**	**se**	**coef**	**se**
Intercept	11.332***	(0.058)	11.330***	(0.058)	11.292***	(0.090)	11.292***	(0.090)
fdp3tdis3_11	-0.017	(0.024)			0.002	(0.031)		
fdp3tdis3_12	-0.015	(0.011)			0.008	(0.016)		
fdp3tdis3_21	-0.035	(0.029)			-0.038	(0.033)		
fdp3tdis3_22	-0.001	(0.014)			-0.033*	(0.017)		
fdp3tdis3_23	-0.006	(0.008)			-0.033***	(0.009)		
fdp3tdis3_31	0.019	(0.026)			-0.022	(0.031)		
fdp3tdis3_32	0.044***	(0.014)			-0.001	(0.018)		
fdp3tdis3_33	-0.005	(0.010)			-0.031***	(0.012)		
fdp3tdis4_10			0.001	(0.039)			0.053	(0.045)
fdp3tdis4_11			-0.023	(0.027)			-0.018	(0.035)
fdp3tdis4_12			-0.015	(0.011)			0.008	(0.016)
fdp3tdis4_20			-0.028	(0.049)			-0.065	(0.056)
fdp3tdis4_21			-0.038	(0.033)			-0.027	(0.036)
fdp3tdis4_22			-0.001	(0.014)			-0.034*	(0.017)
fdp3tdis4_23			-0.006	(0.008)			-0.033***	(0.009)
fdp3tdis4_30			-0.016	(0.041)			-0.036	(0.046)
fdp3tdis4_31			0.032	(0.031)			-0.016	(0.035)
fdp3tdis4_32			0.044***	(0.014)			-0.001	(0.018)
fdp3tdis4_33			-0.005	(0.010)			-0.031***	(0.012)
lsfla1000_ia_car	0.750***	(0.042)	0.749***	(0.042)	0.723***	(0.045)	0.722***	(0.045)
lsfla1000_ia_flo	0.899***	(0.054)	0.900***	(0.054)	0.879***	(0.060)	0.88***	(0.060)
lsfla1000_ia_fra	0.980***	(0.077)	0.980***	(0.077)	0.932***	(0.083)	0.934***	(0.083)
lsfla1000_ia_sac	0.683***	(0.061)	0.683***	(0.061)	0.633***	(0.065)	0.633***	(0.064)
lsfla1000_il_dek	0.442***	(0.037)	0.441***	(0.037)	0.382***	(0.040)	0.38***	(0.040)
lsfla1000_il_liv	0.641***	(0.030)	0.641***	(0.030)	0.643***	(0.046)	0.643***	(0.046)
lsfla1000_il_mcl	0.512***	(0.019)	0.512***	(0.019)	0.428***	(0.029)	0.428***	(0.029)
lsfla1000_mn_cot	0.800***	(0.052)	0.800***	(0.052)	0.787***	(0.077)	0.787***	(0.077)
lsfla1000_mn_fre	0.594***	(0.028)	0.595***	(0.028)	0.539***	(0.031)	0.539***	(0.031)
lsfla1000_mn_jac	0.587***	(0.101)	0.587***	(0.101)	0.551***	(0.102)	0.55***	(0.102)
lsfla1000_mn_mar	0.643***	(0.025)	0.643***	(0.025)	0.603***	(0.029)	0.603***	(0.029)
lsfla1000_nj_atl	0.421***	(0.012)	0.421***	(0.012)	0.389***	(0.014)	0.389***	(0.014)
lsfla1000_ny_cli	0.635***	(0.044)	0.635***	(0.044)	0.606***	(0.045)	0.606***	(0.045)
lsfla1000_ny_fra	0.373***	(0.092)	0.375***	(0.092)	0.433***	(0.094)	0.436***	(0.094)
lsfla1000_ny_her	0.520***	(0.034)	0.520***	(0.034)	0.559***	(0.035)	0.559***	(0.035)
lsfla1000_ny_lew	0.556***	(0.054)	0.556***	(0.054)	0.518***	(0.057)	0.518***	(0.057)
lsfla1000_ny_mad	0.503***	(0.025)	0.503***	(0.025)	0.502***	(0.025)	0.502***	(0.025)
lsfla1000_ny_ste	0.564***	(0.032)	0.564***	(0.032)	0.534***	(0.034)	0.534***	(0.034)
lsfla1000_ny_wyo	0.589***	(0.034)	0.589***	(0.034)	0.566***	(0.034)	0.566***	(0.034)
lsfla1000_oh_pau	0.625***	(0.080)	0.624***	(0.080)	0.567***	(0.090)	0.565***	(0.090)
lsfla1000_oh_woo	0.529***	(0.030)	0.529***	(0.030)	0.487***	(0.035)	0.487***	(0.035)
lsfla1000_ok_cus	0.838***	(0.037)	0.838***	(0.037)	0.794***	(0.046)	0.793***	(0.046)
lsfla1000_ok_gra	0.750***	(0.063)	0.750***	(0.063)	0.706***	(0.072)	0.706***	(0.072)
lsfla1000_pa_fay	0.332***	(0.111)	0.332***	(0.111)	0.335***	(0.118)	0.334***	(0.118)
lsfla1000_pa_som	0.564***	(0.025)	0.564***	(0.025)	0.548***	(0.031)	0.548***	(0.031)
lsfla1000_pa_way	0.486***	(0.056)	0.486***	(0.056)	0.44***	(0.063)	0.44***	(0.063)
lsfla1000_wa_kit	0.540***	(0.073)	0.540***	(0.073)	0.494***	(0.078)	0.494***	(0.078)

	OneMile OLS		HalfMile OLS		OneMile SEM		HalfMile SEM	
Variables	**coef**	**se**	**coef**	**se**	**coef**	**se**	**coef**	**se**
acres_ia_car	0.033	(0.030)	0.033	(0.030)	0.013	(0.032)	0.013	(0.032)
acres_ia_flo	0.050***	(0.014)	0.050***	(0.014)	0.044***	(0.014)	0.044***	(0.014)
acres_ia_fra	-0.008	(0.022)	-0.008	(0.022)	-0.009	(0.022)	-0.009	(0.022)
acres_ia_sac	0.064***	(0.014)	0.064***	(0.014)	0.054***	(0.015)	0.054***	(0.015)
acres_il_dek	0.068**	(0.027)	0.064**	(0.027)	0.055*	(0.029)	0.048*	(0.029)
acres_il_liv	0.023	(0.014)	0.023	(0.014)	0.014	(0.018)	0.014	(0.018)
acres_il_mcl	0.091***	(0.010)	0.091***	(0.010)	0.092***	(0.011)	0.092***	(0.011)
acres_mn_cot	-0.030***	(0.011)	-0.030***	(0.011)	-0.024*	(0.013)	-0.024*	(0.013)
acres_mn_fre	-0.002	(0.007)	-0.002	(0.007)	0.002	(0.008)	0.002	(0.008)
acres_mn_jac	0.019	(0.016)	0.020	(0.016)	0.03*	(0.016)	0.03*	(0.016)
acres_mn_mar	0.020**	(0.008)	0.020**	(0.008)	0.017*	(0.009)	0.017*	(0.009)
acres_nj_atl	-0.041	(0.031)	-0.041	(0.031)	-0.013	(0.026)	-0.013	(0.026)
acres_ny_cli	0.019***	(0.007)	0.019***	(0.007)	0.022***	(0.007)	0.022***	(0.007)
acres_ny_fra	0.009	(0.010)	0.009	(0.010)	0.014	(0.011)	0.014	(0.011)
acres_ny_her	-0.004	(0.008)	-0.004	(0.008)	0.012	(0.008)	0.012	(0.008)
acres_ny_lew	0.014*	(0.008)	0.014*	(0.008)	0.014	(0.009)	0.014	(0.009)
acres_ny_mad	0.021***	(0.003)	0.021***	(0.003)	0.021***	(0.004)	0.021***	(0.004)
acres_ny_ste	0.009*	(0.005)	0.009*	(0.005)	0.007	(0.005)	0.007	(0.005)
acres_ny_wyo	0.016***	(0.004)	0.016***	(0.004)	0.019***	(0.004)	0.019***	(0.004)
acres_oh_pau	-0.010	(0.020)	-0.010	(0.020)	0.01	(0.024)	0.009	(0.024)
acres_oh_woo	-0.007	(0.010)	-0.007	(0.010)	0.002	(0.010)	0.002	(0.010)
acres_ok_cus	-0.037*	(0.019)	-0.037*	(0.019)	-0.034	(0.022)	-0.034	(0.022)
acres_ok_gra	0.014	(0.010)	0.014	(0.010)	0.019*	(0.011)	0.019*	(0.011)
acres_pa_fay	-0.006	(0.023)	-0.006	(0.023)	0.01	(0.023)	0.01	(0.023)
acres_pa_som	0.003	(0.009)	0.004	(0.009)	0.009	(0.010)	0.009	(0.010)
acres_pa_way	0.017**	(0.007)	0.017**	(0.007)	0.024***	(0.007)	0.024***	(0.007)
acres_wa_kit	0.009	(0.010)	0.009	(0.010)	0.014	(0.011)	0.014	(0.011)
acreslt1_ia_car	0.446***	(0.136)	0.448***	(0.136)	0.559***	(0.144)	0.56***	(0.143)
acreslt1_ia_flo	0.436***	(0.112)	0.435***	(0.112)	0.384***	(0.118)	0.383***	(0.118)
acreslt1_ia_fra	0.670***	(0.124)	0.668***	(0.124)	0.684***	(0.139)	0.68***	(0.139)
acreslt1_ia_sac	0.159	(0.115)	0.160	(0.115)	0.222*	(0.123)	0.221*	(0.123)
acreslt1_il_dek	0.278***	(0.066)	0.285***	(0.066)	0.282***	(0.073)	0.294***	(0.073)
acreslt1_il_liv	0.278***	(0.063)	0.276***	(0.063)	0.383***	(0.088)	0.38***	(0.088)
acreslt1_il_mcl	-0.069***	(0.021)	-0.070***	(0.021)	-0.007	(0.032)	-0.007	(0.032)
acreslt1_mn_cot	0.529***	(0.093)	0.529***	(0.093)	0.466***	(0.120)	0.465***	(0.120)
acreslt1_mn_fre	0.314***	(0.053)	0.314***	(0.053)	0.294***	(0.061)	0.293***	(0.061)
acreslt1_mn_jac	0.250*	(0.144)	0.247*	(0.145)	0.169	(0.146)	0.162	(0.146)
acreslt1_mn_mar	0.452***	(0.062)	0.452***	(0.062)	0.461***	(0.069)	0.462***	(0.069)
acreslt1_nj_atl	0.135***	(0.048)	0.135***	(0.048)	0.044	(0.047)	0.043	(0.047)
acreslt1_ny_cli	0.115***	(0.044)	0.115***	(0.044)	0.108**	(0.047)	0.108**	(0.047)
acreslt1_ny_fra	0.118	(0.100)	0.118	(0.100)	0.113	(0.115)	0.113	(0.115)
acreslt1_ny_her	0.364***	(0.047)	0.364***	(0.047)	0.331***	(0.050)	0.332***	(0.050)
acreslt1_ny_lew	0.119*	(0.061)	0.120**	(0.061)	0.117*	(0.067)	0.117*	(0.067)

	OneMile OLS		**HalfMile OLS**		**OneMile SEM**		**HalfMile SEM**	
Variables	**coef**	**se**	**coef**	**se**	**coef**	**se**	**coef**	**se**
acreslt1_ny_mad	0.017	(0.031)	0.018	(0.031)	0.043	(0.032)	0.043	(0.032)
acreslt1_ny_ste	0.100**	(0.042)	0.100**	(0.042)	0.18***	(0.047)	0.18***	(0.047)
acreslt1_ny_wyo	0.144***	(0.035)	0.144***	(0.035)	0.137***	(0.039)	0.137***	(0.039)
acreslt1_oh_pau	0.426***	(0.087)	0.425***	(0.087)	0.507***	(0.120)	0.507***	(0.120)
acreslt1_oh_woo	0.124***	(0.034)	0.124***	(0.034)	0.114***	(0.041)	0.114***	(0.041)
acreslt1_ok_cus	0.103	(0.070)	0.104	(0.070)	0.091	(0.092)	0.093	(0.092)
acreslt1_ok_gra	-0.038	(0.054)	-0.038	(0.054)	-0.065	(0.066)	-0.065	(0.066)
acreslt1_pa_fay	0.403***	(0.153)	0.403***	(0.153)	0.42**	(0.165)	0.42**	(0.164)
acreslt1_pa_som	0.243***	(0.039)	0.243***	(0.039)	0.223***	(0.047)	0.223***	(0.047)
acreslt1_pa_way	0.138**	(0.062)	0.138**	(0.062)	0.108	(0.077)	0.109	(0.077)
acreslt1_wa_kit	0.335**	(0.134)	0.335**	(0.134)	0.342**	(0.164)	0.342**	(0.164)
age_ia_car	-0.013***	(0.001)	-0.013***	(0.001)	-0.011***	(0.001)	-0.011***	(0.001)
age_ia_flo	-0.013***	(0.002)	-0.013***	(0.002)	-0.013***	(0.002)	-0.013***	(0.002)
age_ia_fra	-0.012***	(0.003)	-0.012***	(0.003)	-0.011***	(0.003)	-0.011***	(0.003)
age_ia_sac	-0.013***	(0.003)	-0.013***	(0.003)	-0.011***	(0.003)	-0.011***	(0.003)
age_il_dek	-0.004***	(0.001)	-0.004***	(0.001)	-0.004***	(0.001)	-0.004***	(0.001)
age_il_liv	-0.001	(0.001)	-0.002	(0.001)	-0.003	(0.002)	-0.003	(0.002)
age_il_mcl	-0.004***	(0.001)	-0.004***	(0.001)	-0.006***	(0.001)	-0.006***	(0.001)
age_mn_cot	-0.021***	(0.003)	-0.021***	(0.003)	-0.013***	(0.005)	-0.013***	(0.005)
age_mn_fre	-0.013***	(0.001)	-0.013***	(0.001)	-0.012***	(0.002)	-0.012***	(0.002)
age_mn_jac	-0.018***	(0.005)	-0.018***	(0.005)	-0.018***	(0.005)	-0.018***	(0.005)
age_mn_mar	-0.010***	(0.001)	-0.010***	(0.001)	-0.009***	(0.002)	-0.009***	(0.002)
age_nj_atl	-0.004***	(0.000)	-0.004***	(0.000)	-0.003***	(0.001)	-0.003***	(0.001)
age_ny_cli	-0.005***	(0.001)	-0.005***	(0.001)	-0.005***	(0.001)	-0.005***	(0.001)
age_ny_fra	-0.004	(0.003)	-0.005	(0.003)	-0.005*	(0.003)	-0.005*	(0.003)
age_ny_her	-0.008***	(0.001)	-0.008***	(0.001)	-0.008***	(0.001)	-0.008***	(0.001)
age_ny_lew	-0.008***	(0.001)	-0.008***	(0.001)	-0.009***	(0.001)	-0.009***	(0.001)
age_ny_mad	-0.006***	(0.001)	-0.006***	(0.001)	-0.006***	(0.001)	-0.006***	(0.001)
age_ny_ste	-0.006***	(0.001)	-0.006***	(0.001)	-0.007***	(0.001)	-0.007***	(0.001)
age_ny_wyo	-0.006***	(0.001)	-0.006***	(0.001)	-0.006***	(0.001)	-0.006***	(0.001)
age_oh_pau	0.003	(0.003)	0.003	(0.003)	0.003	(0.004)	0.003	(0.004)
age_oh_woo	0.008***	(0.001)	0.008***	(0.001)	0.01***	(0.001)	0.01***	(0.001)
age_ok_cus	-0.000	(0.002)	-0.000	(0.002)	0.002	(0.003)	0.002	(0.003)
age_ok_gra	-0.000	(0.002)	-0.000	(0.002)	0.001	(0.002)	0.001	(0.002)
age_pa_fay	0.010**	(0.004)	0.010**	(0.004)	0.01**	(0.005)	0.01**	(0.005)
age_pa_som	-0.006***	(0.001)	-0.006***	(0.001)	-0.008***	(0.001)	-0.008***	(0.001)
age_pa_way	0.006***	(0.002)	0.006***	(0.002)	0.007***	(0.002)	0.007***	(0.002)
age_wa_kit	0.010***	(0.003)	0.010***	(0.003)	0.014***	(0.003)	0.014***	(0.003)
agesq_ia_car	0.034***	(0.011)	0.034***	(0.000)	0.022*	(0.012)	0.022*	(0.012)
agesq_ia_flo	0.040***	(0.016)	0.040**	(0.016)	0.044***	(0.016)	0.044***	(0.016)
agesq_ia_fra	0.025	(0.022)	0.025	(0.022)	0.02	(0.023)	0.021	(0.023)
agesq_ia_sac	0.032	(0.022)	0.032	(0.022)	0.025	(0.023)	0.025	(0.023)
agesq_il_dek	0.008	(0.010)	0.008	(0.010)	0.013	(0.012)	0.013	(0.011)
agesq_il_liv	-0.023**	(0.009)	-0.023**	(0.009)	-0.011	(0.014)	-0.011	(0.014)
agesq_il_mcl	0.005	(0.007)	0.005	(0.007)	0.021*	(0.011)	0.021*	(0.011)
agesq_mn_cot	0.109**	(0.043)	0.109**	(0.043)	0.032	(0.069)	0.033	(0.069)
agesq_mn_fre	0.046***	(0.010)	0.045***	(0.010)	0.044***	(0.012)	0.044***	(0.012)
agesq_mn_jac	0.103***	(0.035)	0.104***	(0.035)	0.1***	(0.034)	0.101***	(0.034)
agesq_mn_mar	0.012	(0.012)	0.012	(0.012)	0.006	(0.014)	0.006	(0.014)

	OneMile OLS		HalfMile OLS		OneMile SEM		HalfMile SEM	
Variables	**coef**	**se**	**coef**	**se**	**coef**	**se**	**coef**	**se**
agesq_nj_atl	0.010***	(0.003)	0.010***	(0.003)	0.003	(0.005)	0.003	(0.005)
agesq_ny_cli	0.011*	(0.006)	0.011*	(0.006)	0.011*	(0.006)	0.011*	(0.006)
agesq_ny_fra	-0.011	(0.022)	-0.011	(0.022)	-0.002	(0.020)	-0.002	(0.020)
agesq_ny_her	0.022***	(0.005)	0.022***	(0.005)	0.022***	(0.006)	0.022***	(0.006)
agesq_ny_lew	0.031***	(0.006)	0.031***	(0.006)	0.032***	(0.007)	0.032***	(0.007)
agesq_ny_mad	0.017***	(0.003)	0.017***	(0.003)	0.023***	(0.003)	0.023***	(0.003)
agesq_ny_ste	0.013**	(0.005)	0.013**	(0.005)	0.018***	(0.005)	0.018***	(0.005)
agesq_ny_wyo	0.016***	(0.005)	0.016***	(0.005)	0.017***	(0.005)	0.017***	(0.005)
agesq_oh_pau	-0.044**	(0.022)	-0.045**	(0.022)	-0.043	(0.028)	-0.043	(0.028)
agesq_oh_woo	-0.074***	(0.007)	-0.074***	(0.007)	-0.091***	(0.009)	-0.091***	(0.009)
agesq_ok_cus	-0.091***	(0.019)	-0.091***	(0.019)	-0.113***	(0.026)	-0.113***	(0.026)
agesq_ok_gra	-0.081***	(0.023)	-0.081***	(0.023)	-0.097***	(0.029)	-0.097***	(0.029)
agesq_pa_fay	-0.112***	(0.032)	-0.112***	(0.032)	-0.105***	(0.034)	-0.106***	(0.034)
agesq_pa_som	0.000	(0.008)	0.002	(0.008)	0.016*	(0.009)	0.016*	(0.009)
agesq_pa_way	-0.000***	(0.012)	-0.052***	(0.012)	-0.053***	(0.014)	-0.053***	(0.014)
agesq_wa_kit	-0.000***	(0.027)	-0.097***	(0.027)	-0.132***	(0.031)	-0.132***	(0.031)
bathsim_ia_sac	-0.050	(0.073)	-0.050	(0.073)	-0.082	(0.077)	-0.081	(0.077)
bathsim_il_dek	-0.005	(0.015)	-0.005	(0.015)	0.001	(0.018)	0.001	(0.018)
bathsim_ny_cli	0.090***	(0.025)	0.090***	(0.025)	0.087***	(0.024)	0.087***	(0.024)
bathsim_ny_fra	0.246***	(0.062)	0.245***	(0.062)	0.213***	(0.064)	0.212***	(0.064)
bathsim_ny_her	0.099***	(0.022)	0.099***	(0.022)	0.079***	(0.022)	0.079***	(0.022)
bathsim_ny_lew	0.168***	(0.030)	0.167***	(0.030)	0.142***	(0.031)	0.142***	(0.031)
bathsim_ny_mad	0.180***	(0.014)	0.180***	(0.014)	0.157***	(0.013)	0.157***	(0.013)
bathsim_ny_ste	0.189***	(0.019)	0.189***	(0.019)	0.166***	(0.020)	0.166***	(0.020)
bathsim_ny_wyo	0.107***	(0.021)	0.107***	(0.021)	0.1***	(0.021)	0.1***	(0.021)
bathsim_oh_pau	0.095*	(0.051)	0.095*	(0.051)	0.149***	(0.057)	0.149***	(0.057)
bathsim_oh_woo	0.094***	(0.017)	0.094***	(0.017)	0.092***	(0.019)	0.092***	(0.019)
bathsim_pa_fay	0.367***	(0.077)	0.367***	(0.077)	0.301***	(0.082)	0.302***	(0.082)
bathsim_pa_way	0.082**	(0.036)	0.082**	(0.036)	0.081**	(0.041)	0.081**	(0.041)
pctvacant_ia_car	-2.515*	(1.467)	-2.521*	(1.468)	-2.011	(1.936)	-2.019	(1.937)
pctvacant_ia_flo	0.903	(1.152)	0.921	(1.152)	1.358	(1.409)	1.339	(1.410)
pctvacant_ia_fra	8.887**	(3.521)	8.928**	(3.518)	-2.596	(1.703)	-2.6	(1.703)
pctvacant_ia_sac	0.672	(0.527)	0.673	(0.527)	1.267***	(0.377)	1.266***	(0.377)
pctvacant_il_dek	0.052	(0.639)	0.062	(0.638)	0.037	(0.964)	0.069	(0.961)
pctvacant_il_liv	-0.475	(0.474)	-0.476	(0.474)	-0.699	(0.872)	-0.701	(0.872)
pctvacant_il_mcl	-0.365	(0.397)	-0.366	(0.397)	0.445	(0.670)	0.442	(0.670)
pctvacant_mn_cot	1.072*	(0.592)	1.072*	(0.592)	0.272	(1.039)	0.273	(1.039)
pctvacant_mn_fre	-1.782**	(0.703)	-1.787**	(0.703)	-1.372	(0.965)	-1.384	(0.965)
pctvacant_mn_jac	-1.345	(0.883)	-1.318	(0.884)	-1.285	(1.084)	-1.313	(1.084)
pctvacant_mn_mar	2.178***	(0.502)	2.175***	(0.502)	1.53**	(0.622)	1.528**	(0.622)
pctvacant_nj_atl	-0.054	(0.062)	-0.054	(0.062)	0.096	(0.085)	0.095	(0.085)
pctvacant_ny_cli	0.709***	(0.224)	0.709***	(0.224)	0.842***	(0.251)	0.841***	(0.251)
pctvacant_ny_fra	6.173***	(2.110)	6.104***	(2.113)	0.519	(0.710)	0.499	(0.709)
pctvacant_ny_her	-1.226***	(0.247)	-1.226***	(0.247)	-1.347***	(0.288)	-1.347***	(0.288)
pctvacant_ny_lew	-0.125	(0.127)	-0.125	(0.127)	-0.266*	(0.159)	-0.266*	(0.159)
pctvacant_ny_mad	0.750***	(0.196)	0.752***	(0.196)	0.767***	(0.246)	0.765***	(0.246)
pctvacant_ny_ste	0.280	(0.190)	0.281	(0.190)	0.039	(0.242)	0.04	(0.242)
pctvacant_ny_wyo	0.179*	(0.101)	0.178*	(0.101)	0.225*	(0.119)	0.224*	(0.119)
pctvacant_oh_pau	-1.473	(1.498)	-1.473	(1.499)	-1.341	(1.951)	-1.256	(1.952)

	OneMile OLS		HalfMile OLS		OneMile SEM		HalfMile SEM	
Variables	**coef**	**se**	**coef**	**se**	**coef**	**se**	**coef**	**se**
pctvacant_oh_woo	-0.565	(0.400)	-0.565	(0.400)	-0.304	(0.563)	-0.306	(0.563)
pctvacant_ok_cus	-0.127	(0.358)	-0.140	(0.359)	-0.167	(0.521)	-0.189	(0.521)
pctvacant_ok_gra	1.413*	(0.777)	1.414*	(0.777)	0.537	(1.045)	0.536	(1.045)
pctvacant_pa_fay	0.227	(0.596)	0.229	(0.596)	0.232	(0.807)	0.235	(0.807)
pctvacant_pa_som	0.517***	(0.098)	0.516***	(0.098)	0.562***	(0.138)	0.562***	(0.138)
pctvacant_pa_way	0.445***	(0.156)	0.444***	(0.156)	0.446**	(0.175)	0.446**	(0.175)
pctvacant_wa_kit	-0.076	(0.546)	-0.075	(0.546)	-0.377	(0.282)	-0.377	(0.281)
pctowner_ia_car	-0.225	(0.244)	-0.225	(0.244)	-0.156	(0.324)	-0.156	(0.324)
pctowner_ia_flo	0.579**	(0.238)	0.578**	(0.238)	0.75***	(0.290)	0.75***	(0.290)
pctowner_ia_fra	0.207	(0.310)	0.206	(0.310)	0.172	(0.393)	0.169	(0.393)
pctowner_ia_sac	0.274	(0.585)	0.261	(0.586)	-0.34	(0.545)	-0.345	(0.545)
pctowner_il_dek	0.075	(0.088)	0.073	(0.087)	0.032	(0.123)	0.028	(0.123)
pctowner_il_liv	0.176	(0.140)	0.176	(0.140)	0.265	(0.200)	0.264	(0.200)
pctowner_il_mcl	0.389***	(0.051)	0.388***	(0.051)	0.331***	(0.101)	0.331***	(0.101)
pctowner_mn_cot	0.375***	(0.138)	0.375***	(0.138)	0.609**	(0.254)	0.609**	(0.254)
pctowner_mn_fre	-0.119	(0.090)	-0.120	(0.090)	-0.072	(0.124)	-0.073	(0.124)
pctowner_mn_jac	-0.206	(0.474)	-0.205	(0.474)	-0.175	(0.569)	-0.185	(0.570)
pctowner_mn_mar	0.262***	(0.076)	0.262***	(0.076)	0.151	(0.103)	0.151	(0.103)
pctowner_nj_atl	-0.087**	(0.037)	-0.087**	(0.037)	-0.036	(0.052)	-0.037	(0.052)
pctowner_ny_cli	-0.229	(0.171)	-0.229	(0.171)	-0.305	(0.199)	-0.303	(0.199)
pctowner_ny_fra	2.743*	(1.500)	2.693*	(1.505)	-0.315	(1.447)	-0.398	(1.442)
pctowner_ny_her	0.246***	(0.095)	0.246***	(0.095)	0.213*	(0.109)	0.213*	(0.109)
pctowner_ny_lew	-0.034	(0.185)	-0.034	(0.185)	-0.126	(0.219)	-0.126	(0.219)
pctowner_ny_mad	0.750***	(0.075)	0.750***	(0.075)	0.723***	(0.084)	0.723***	(0.084)
pctowner_ny_ste	0.192	(0.128)	0.191	(0.128)	-0.083	(0.162)	-0.084	(0.162)
pctowner_ny_wyo	-0.089	(0.111)	-0.089	(0.111)	-0.109	(0.138)	-0.108	(0.138)
pctowner_oh_pau	-0.187	(0.347)	-0.185	(0.348)	-1.245***	(0.473)	-1.249***	(0.474)
pctowner_oh_woo	0.263***	(0.092)	0.264***	(0.092)	0.274**	(0.136)	0.274**	(0.136)
pctowner_ok_cus	0.068	(0.104)	0.068	(0.104)	-0.041	(0.146)	-0.043	(0.146)
pctowner_ok_gra	0.271*	(0.159)	0.271*	(0.159)	0.253	(0.217)	0.253	(0.217)
pctowner_pa_fay	-0.413	(1.736)	-0.420	(1.736)	-0.15	(2.037)	-0.165	(2.037)
pctowner_pa_som	0.171	(0.114)	0.170	(0.114)	0.098	(0.173)	0.098	(0.173)
pctowner_pa_way	-0.351	(0.441)	-0.348	(0.441)	-0.251	(0.345)	-0.252	(0.345)
pctowner_wa_kit	0.257	(2.139)	0.259	(2.139)	-0.358	(1.889)	-0.361	(1.890)
med_age_ia_car	0.002	(0.002)	0.002	(0.002)	0.003	(0.003)	0.003	(0.003)
med_age_ia_flo	0.003	(0.002)	0.003	(0.002)	0.004	(0.003)	0.004	(0.003)
med_age_ia_fra	0.066***	(0.015)	0.066***	(0.015)	0.014**	(0.006)	0.014**	(0.006)
med_age_ia_sac	0.028**	(0.014)	0.028**	(0.014)	0.012	(0.010)	0.012	(0.010)
med_age_il_dek	-0.001	(0.002)	-0.001	(0.002)	-0.001	(0.003)	-0.001	(0.003)
med_age_il_liv	-0.004	(0.004)	-0.004	(0.004)	-0.005	(0.005)	-0.005	(0.005)
med_age_il_mcl	-0.006***	(0.002)	-0.006***	(0.002)	-0.006**	(0.003)	-0.006**	(0.003)
med_age_mn_cot	0.017***	(0.005)	0.017***	(0.005)	0.018**	(0.008)	0.018**	(0.008)
med_age_mn_fre	0.012***	(0.002)	0.012***	(0.002)	0.013***	(0.002)	0.013***	(0.002)
med_age_mn_jac	0.013	(0.008)	0.013	(0.008)	0.012	(0.010)	0.012	(0.010)
med_age_mn_mar	0.013***	(0.003)	0.013***	(0.003)	0.012***	(0.003)	0.012***	(0.003)
med_age_nj_atl	0.010***	(0.001)	0.010***	(0.001)	0.016***	(0.002)	0.016***	(0.002)
med_age_ny_cli	0.020***	(0.004)	0.020***	(0.004)	0.02***	(0.004)	0.02***	(0.004)
med_age_ny_fra	-0.517***	(0.198)	-0.511***	(0.198)	0.008	(0.040)	0.01	(0.039)
med_age_ny_her	0.007*	(0.003)	0.007*	(0.003)	0.005	(0.003)	0.005	(0.003)

	OneMile OLS		HalfMile OLS		OneMile SEM		HalfMile SEM	
Variables	**coef**	**se**	**coef**	**se**	**coef**	**se**	**coef**	**se**
med_age_ny_lew	0.013***	(0.005)	0.013***	(0.005)	0.008	(0.005)	0.008	(0.005)
med_age_ny_mad	0.004**	(0.002)	0.004**	(0.002)	0.004*	(0.002)	0.004*	(0.002)
med_age_ny_ste	0.012***	(0.003)	0.012***	(0.003)	0.001	(0.004)	0.001	(0.004)
med_age_ny_wyo	0.008	(0.005)	0.007	(0.005)	0.008	(0.006)	0.008	(0.006)
med_age_oh_pau	0.034***	(0.013)	0.034***	(0.013)	0.019	(0.012)	0.019	(0.012)
med_age_oh_woo	-0.004	(0.003)	-0.004	(0.003)	-0.004	(0.004)	-0.004	(0.004)
med_age_ok_cus	0.004	(0.002)	0.004	(0.002)	0.008**	(0.004)	0.008**	(0.004)
med_age_ok_gra	0.011	(0.009)	0.011	(0.009)	0	(0.006)	0	(0.006)
med_age_pa_fay	0.049	(0.073)	0.049	(0.073)	0.052	(0.095)	0.052	(0.095)
med_age_pa_som	0.008***	(0.002)	0.008***	(0.002)	0.012***	(0.004)	0.012***	(0.004)
med_age_pa_way	-0.005	(0.012)	-0.005	(0.012)	0.002	(0.007)	0.002	(0.007)
med_age_wa_kit	-0.015	(0.095)	-0.015	(0.095)	0.025	(0.034)	0.025	(0.034)
swinter_ia	-0.034**	(0.015)	-0.034**	(0.015)	-0.039***	(0.015)	-0.039***	(0.015)
swinter_il	-0.020**	(0.008)	-0.020**	(0.008)	-0.013	(0.012)	-0.013	(0.012)
swinter_mn	-0.053***	(0.009)	-0.053***	(0.009)	-0.057***	(0.011)	-0.057***	(0.011)
swinter_nj	-0.007	(0.006)	-0.007	(0.006)	-0.008	(0.007)	-0.008	(0.007)
swinter_ny	-0.030***	(0.007)	-0.030***	(0.007)	-0.026***	(0.007)	-0.026***	(0.007)
swinter_oh	-0.048***	(0.012)	-0.048***	(0.012)	-0.055***	(0.014)	-0.055***	(0.014)
swinter_ok	-0.039**	(0.015)	-0.039**	(0.015)	-0.024	(0.018)	-0.024	(0.018)
swinter_pa	-0.025*	(0.015)	-0.025*	(0.015)	-0.02	(0.017)	-0.02	(0.017)
swinter_wa	-0.004	(0.046)	-0.004	(0.046)	0.014	(0.051)	0.013	(0.051)
sy_1996_ia	-0.436***	(0.137)	-0.433***	(0.137)	-0.493***	(0.157)	-0.489***	(0.157)
sy_1996_il	-0.267***	(0.037)	-0.267***	(0.037)	-0.344***	(0.061)	-0.344***	(0.061)
sy_1996_mn	-0.521***	(0.058)	-0.521***	(0.059)	-0.585***	(0.065)	-0.585***	(0.065)
sy_1996_nj	-0.820***	(0.022)	-0.820***	(0.022)	-0.717***	(0.038)	-0.717***	(0.038)
sy_1996_oh	-0.298***	(0.042)	-0.298***	(0.042)	-0.43***	(0.053)	-0.43***	(0.053)
sy_1996_ok	-0.444***	(0.073)	-0.444***	(0.073)	-0.846***	(0.079)	-0.846***	(0.079)
sy_1996_pa	-0.584***	(0.060)	-0.584***	(0.060)	-0.604***	(0.067)	-0.604***	(0.067)
sy_1997_il	-0.242***	(0.036)	-0.242***	(0.036)	-0.234***	(0.052)	-0.232***	(0.052)
sy_1997_mn	-0.445***	(0.055)	-0.445***	(0.055)	-0.535***	(0.060)	-0.535***	(0.060)
sy_1997_nj	-0.791***	(0.021)	-0.791***	(0.021)	-0.686***	(0.038)	-0.686***	(0.038)
sy_1997_oh	-0.302***	(0.043)	-0.302***	(0.043)	-0.39***	(0.053)	-0.39***	(0.053)
sy_1997_pa	-0.458***	(0.057)	-0.458***	(0.057)	-0.51***	(0.066)	-0.51***	(0.066)
sy_1998_ia	-0.442***	(0.078)	-0.441***	(0.078)	-0.633***	(0.099)	-0.634***	(0.099)
sy_1998_il	-0.156***	(0.031)	-0.156***	(0.031)	-0.175***	(0.048)	-0.175***	(0.048)
sy_1998_mn	-0.391***	(0.054)	-0.391***	(0.054)	-0.484***	(0.059)	-0.484***	(0.059)
sy_1998_nj	-0.723***	(0.020)	-0.723***	(0.021)	-0.633***	(0.037)	-0.633***	(0.037)
sy_1998_oh	-0.217***	(0.040)	-0.217***	(0.040)	-0.302***	(0.047)	-0.302***	(0.047)
sy_1998_ok	-0.394***	(0.048)	-0.395***	(0.048)	-0.816***	(0.059)	-0.818***	(0.059)
sy_1998_pa	-0.481***	(0.059)	-0.480***	(0.059)	-0.554***	(0.068)	-0.552***	(0.067)
sy_1998_wa	-0.433***	(0.115)	-0.433***	(0.115)	-0.356**	(0.161)	-0.356**	(0.161)
sy_1999_ia	-0.347***	(0.085)	-0.345***	(0.086)	-0.568***	(0.117)	-0.565***	(0.117)
sy_1999_il	-0.155***	(0.031)	-0.156***	(0.031)	-0.215***	(0.046)	-0.214***	(0.046)
sy_1999_mn	-0.302***	(0.055)	-0.303***	(0.055)	-0.367***	(0.059)	-0.368***	(0.059)
sy_1999_nj	-0.679***	(0.020)	-0.679***	(0.020)	-0.583***	(0.036)	-0.583***	(0.036)
sy_1999_oh	-0.161***	(0.040)	-0.161***	(0.040)	-0.243***	(0.047)	-0.243***	(0.047)
sy_1999_ok	-0.347***	(0.044)	-0.348***	(0.044)	-0.743***	(0.050)	-0.743***	(0.050)
sy_1999_pa	-0.452***	(0.058)	-0.452***	(0.058)	-0.515***	(0.066)	-0.515***	(0.066)
sy_1999_wa	-0.432***	(0.114)	-0.432***	(0.114)	-0.454***	(0.166)	-0.453***	(0.165)

	OneMile OLS		HalfMile OLS		OneMile SEM		HalfMile SEM	
Variables	**coef**	**se**	**coef**	**se**	**coef**	**se**	**coef**	**se**
sy_2000_ia	-0.165	(0.145)	-0.164	(0.146)	-0.246	(0.183)	-0.246	(0.183)
sy_2000_il	-0.088***	(0.031)	-0.088***	(0.031)	-0.172***	(0.045)	-0.171***	(0.045)
sy_2000_mn	-0.148***	(0.051)	-0.149***	(0.051)	-0.224***	(0.053)	-0.224***	(0.053)
sy_2000_nj	-0.565***	(0.020)	-0.565***	(0.020)	-0.461***	(0.036)	-0.462***	(0.036)
sy_2000_oh	-0.098**	(0.041)	-0.098**	(0.041)	-0.161***	(0.047)	-0.16***	(0.047)
sy_2000_ok	-0.330***	(0.050)	-0.331***	(0.050)	-0.748***	(0.059)	-0.749***	(0.059)
sy_2000_pa	-0.394***	(0.057)	-0.395***	(0.057)	-0.478***	(0.067)	-0.478***	(0.067)
sy_2000_wa	-0.463***	(0.115)	-0.463***	(0.115)	-0.403**	(0.160)	-0.402**	(0.160)
sy_2001_ia	-0.334***	(0.065)	-0.332***	(0.065)	-0.435***	(0.066)	-0.433***	(0.066)
sy_2001_il	-0.080**	(0.031)	-0.080***	(0.031)	-0.101**	(0.048)	-0.101**	(0.048)
sy_2001_mn	-0.119**	(0.050)	-0.119**	(0.050)	-0.204***	(0.051)	-0.204***	(0.052)
sy_2001_nj	-0.438***	(0.018)	-0.438***	(0.018)	-0.333***	(0.034)	-0.333***	(0.034)
sy_2001_oh	-0.033	(0.036)	-0.033	(0.036)	-0.078**	(0.040)	-0.078**	(0.040)
sy_2001_ok	-0.250***	(0.041)	-0.251***	(0.041)	-0.648***	(0.044)	-0.648***	(0.044)
sy_2001_pa	-0.402***	(0.055)	-0.402***	(0.055)	-0.446***	(0.063)	-0.447***	(0.063)
sy_2001_wa	-0.378***	(0.122)	-0.378***	(0.122)	-0.275*	(0.163)	-0.275*	(0.163)
sy_2002_ia	-0.130**	(0.059)	-0.128**	(0.059)	-0.264***	(0.064)	-0.261***	(0.064)
sy_2002_il	0.008	(0.030)	0.007	(0.030)	-0.013	(0.043)	-0.013	(0.043)
sy_2002_mn	-0.072	(0.050)	-0.072	(0.050)	-0.138***	(0.051)	-0.139***	(0.051)
sy_2002_nj	-0.330***	(0.019)	-0.330***	(0.019)	-0.195***	(0.035)	-0.195***	(0.035)
sy_2002_ny	-0.307***	(0.020)	-0.307***	(0.020)	-0.342***	(0.020)	-0.342***	(0.020)
sy_2002_oh	-0.022	(0.038)	-0.022	(0.038)	-0.053	(0.042)	-0.053	(0.042)
sy_2002_ok	-0.249***	(0.045)	-0.249***	(0.045)	-0.649***	(0.052)	-0.649***	(0.052)
sy_2002_pa	-0.313***	(0.053)	-0.313***	(0.053)	-0.355***	(0.059)	-0.354***	(0.059)
sy_2002_wa	-0.241**	(0.123)	-0.241**	(0.123)	-0.216	(0.166)	-0.216	(0.166)
sy_2003_ia	-0.195**	(0.081)	-0.194**	(0.081)	-0.311***	(0.085)	-0.314***	(0.084)
sy_2003_il	0.034	(0.030)	0.034	(0.030)	0.021	(0.040)	0.021	(0.040)
sy_2003_mn	0.034	(0.049)	0.034	(0.049)	-0.026	(0.049)	-0.026	(0.049)
sy_2003_nj	-0.119***	(0.017)	-0.119***	(0.017)	0.023	(0.033)	0.023	(0.033)
sy_2003_ny	-0.247***	(0.020)	-0.247***	(0.020)	-0.276***	(0.020)	-0.276***	(0.020)
sy_2003_oh	0.005	(0.036)	0.005	(0.036)	-0.019	(0.039)	-0.019	(0.039)
sy_2003_ok	-0.229***	(0.046)	-0.229***	(0.046)	-0.632***	(0.053)	-0.632***	(0.053)
sy_2003_pa	-0.191***	(0.052)	-0.191***	(0.052)	-0.213***	(0.054)	-0.213***	(0.054)
sy_2003_wa	-0.326***	(0.114)	-0.326***	(0.114)	-0.335**	(0.159)	-0.337**	(0.159)
sy_2004_ia	-0.209***	(0.076)	-0.208***	(0.076)	-0.307***	(0.087)	-0.308***	(0.087)
sy_2004_il	0.087***	(0.029)	0.087***	(0.029)	0.105***	(0.034)	0.105***	(0.034)
sy_2004_mn	0.082*	(0.049)	0.081*	(0.049)	0.036	(0.049)	0.036	(0.049)
sy_2004_ny	-0.179***	(0.019)	-0.179***	(0.019)	-0.2***	(0.020)	-0.2***	(0.020)
sy_2004_oh	0.059	(0.037)	0.059	(0.037)	0.067*	(0.039)	0.067*	(0.039)
sy_2004_ok	-0.143***	(0.041)	-0.143***	(0.041)	-0.511***	(0.044)	-0.511***	(0.044)
sy_2004_pa	-0.146***	(0.052)	-0.146***	(0.052)	-0.145***	(0.053)	-0.145***	(0.053)
sy_2004_wa	-0.144	(0.113)	-0.144	(0.113)	-0.082	(0.152)	-0.081	(0.152)
sy_2005_ia	-0.074**	(0.037)	-0.075**	(0.037)	-0.151***	(0.040)	-0.151***	(0.040)
sy_2005_il	0.125***	(0.027)	0.125***	(0.027)	0.139***	(0.032)	0.138***	(0.032)
sy_2005_mn	0.163***	(0.048)	0.162***	(0.048)	0.12**	(0.048)	0.119**	(0.048)
sy_2005_nj	0.278***	(0.018)	0.278***	(0.018)	0.453***	(0.034)	0.453***	(0.034)
sy_2005_ny	-0.110***	(0.019)	-0.111***	(0.019)	-0.122***	(0.019)	-0.122***	(0.019)
sy_2005_oh	0.112***	(0.036)	0.112***	(0.036)	0.099***	(0.037)	0.098***	(0.037)
sy_2005_ok	-0.018	(0.038)	-0.018	(0.038)	-0.354***	(0.038)	-0.354***	(0.038)

	OneMile OLS		HalfMile OLS		OneMile SEM		HalfMile SEM	
Variables	**coef**	**se**	**coef**	**se**	**coef**	**se**	**coef**	**se**
sy_2005_pa	-0.060	(0.051)	-0.060	(0.051)	-0.058	(0.053)	-0.058	(0.053)
sy_2005_wa	-0.070	(0.111)	-0.070	(0.111)	0.025	(0.153)	0.025	(0.153)
sy_2006_ia	-0.050*	(0.028)	-0.051*	(0.028)	-0.106***	(0.028)	-0.106***	(0.028)
sy_2006_il	0.192***	(0.026)	0.192***	(0.026)	0.215***	(0.030)	0.215***	(0.030)
sy_2006_mn	0.206***	(0.049)	0.206***	(0.049)	0.164***	(0.049)	0.164***	(0.049)
sy_2006_nj	0.340***	(0.017)	0.340***	(0.017)	0.514***	(0.032)	0.514***	(0.032)
sy_2006_ny	-0.066***	(0.019)	-0.066***	(0.019)	-0.073***	(0.019)	-0.073***	(0.019)
sy_2006_oh	0.147***	(0.034)	0.147***	(0.034)	0.144***	(0.035)	0.144***	(0.035)
sy_2006_ok	0.025	(0.039)	0.026	(0.039)	-0.3***	(0.037)	-0.3***	(0.037)
sy_2006_pa	0.008	(0.051)	0.008	(0.051)	-0.001	(0.052)	-0.001	(0.052)
sy_2006_wa	-0.066	(0.131)	-0.066	(0.131)	0.02	(0.160)	0.021	(0.160)
sy_2007_ia	0.013	(0.028)	0.012	(0.028)	-0.019	(0.028)	-0.019	(0.028)
sy_2007_il	0.218***	(0.025)	0.218***	(0.025)	0.251***	(0.028)	0.251***	(0.028)
sy_2007_mn	0.177***	(0.049)	0.177***	(0.049)	0.145***	(0.048)	0.144***	(0.048)
sy_2007_nj	0.297***	(0.017)	0.297***	(0.017)	0.459***	(0.031)	0.459***	(0.031)
sy_2007_ny	-0.020	(0.019)	-0.020	(0.019)	-0.022	(0.019)	-0.022	(0.019)
sy_2007_oh	0.144***	(0.035)	0.143***	(0.035)	0.138***	(0.036)	0.138***	(0.036)
sy_2007_ok	0.149***	(0.037)	0.150***	(0.037)	-0.154***	(0.034)	-0.154***	(0.034)
sy_2007_pa	0.030	(0.051)	0.030	(0.051)	0.067	(0.052)	0.067	(0.052)
sy_2007_wa	0.189*	(0.110)	0.189*	(0.110)	0.209	(0.147)	0.209	(0.147)
sy_2008_ia	0.011	(0.029)	0.010	(0.029)	-0.029	(0.029)	-0.029	(0.029)
sy_2008_il	0.219***	(0.026)	0.218***	(0.026)	0.217***	(0.029)	0.217***	(0.029)
sy_2008_mn	0.149***	(0.050)	0.149***	(0.050)	0.108**	(0.049)	0.108**	(0.049)
sy_2008_nj	0.195***	(0.018)	0.195***	(0.018)	0.35***	(0.032)	0.35***	(0.032)
sy_2008_ny	-0.000	(0.019)	-0.000	(0.019)	-0.008	(0.019)	-0.008	(0.019)
sy_2008_oh	0.084**	(0.036)	0.084**	(0.036)	0.061*	(0.037)	0.061*	(0.037)
sy_2008_ok	0.154***	(0.039)	0.153***	(0.039)	-0.145***	(0.035)	-0.145***	(0.035)
sy_2008_pa	0.044	(0.053)	0.044	(0.053)	0.055	(0.053)	0.056	(0.053)
sy_2008_wa	0.178	(0.117)	0.179	(0.117)	0.326**	(0.148)	0.325**	(0.148)
sy_2009_ia	-0.056	(0.036)	-0.057	(0.036)	-0.102***	(0.036)	-0.102***	(0.036)
sy_2009_il	0.158***	(0.026)	0.158***	(0.026)	0.176***	(0.028)	0.176***	(0.028)
sy_2009_mn	0.104**	(0.051)	0.104**	(0.051)	0.089*	(0.050)	0.089*	(0.050)
sy_2009_nj	0.071***	(0.019)	0.071***	(0.019)	0.238***	(0.032)	0.238***	(0.032)
sy_2009_ny	-0.005	(0.019)	-0.005	(0.019)	-0.013	(0.019)	-0.013	(0.019)
sy_2009_oh	0.036	(0.035)	0.036	(0.035)	0.028	(0.036)	0.028	(0.036)
sy_2009_ok	0.219***	(0.038)	0.219***	(0.038)	-0.102***	(0.034)	-0.101***	(0.034)
sy_2009_pa	0.009	(0.053)	0.010	(0.053)	0.0003	(0.054)	0.0004	(0.054)
sy_2010_ia	0.018	(0.029)	0.017	(0.029)	-0.004	(0.028)	-0.004	(0.028)
sy_2010_il	0.105***	(0.028)	0.105***	(0.028)	0.104***	(0.029)	0.104***	(0.029)
sy_2010_mn	0.181***	(0.050)	0.180***	(0.050)	0.137***	(0.049)	0.137***	(0.049)
sy_2010_nj	0.010	(0.019)	0.010	(0.019)	0.177***	(0.032)	0.178***	(0.032)
sy_2010_ny	0.003	(0.021)	0.003	(0.021)	-0.006	(0.020)	-0.006	(0.020)
sy_2010_oh	-0.017	(0.036)	-0.017	(0.036)	-0.024	(0.036)	-0.024	(0.036)
sy_2010_ok	0.231***	(0.038)	0.231***	(0.038)	-0.074**	(0.033)	-0.074**	(0.033)
sy_2010_pa	0.013	(0.057)	0.013	(0.057)	0.013	(0.057)	0.013	(0.057)
sy_2010_wa	0.207	(0.127)	0.207	(0.127)	0.305*	(0.165)	0.305*	(0.165)
note: *** p<0.01, ** p<0.05, * p<0.1								
N		51,276		51,276		38,407		38,407
Adjusted R^2		0.66		0.66		0.64		0.64