Wind Turbines, Amenities and Disamenities: A Study of Home Value Impacts in Densely Populated Massachusetts

Authors Ben Hoen and Carol Atkinson-Palombo

Abstract

In this study, we investigate the effect of planned or operating wind turbines on urban home values. Previous studies, which largely produced non-significant findings, focused on rural settings. We analyzed more than 122,000 home sales, between 1998 and 2012, that occurred near 41 turbines in densely populated Massachusetts communities. Although we found the effects from various negative features (such as electricity transmission lines) and positive features (such as open space) generally accorded with previous studies, we found no net effects due to turbines in these communities. We also found no unique impact on the rate of home sales near wind turbines.

Wind energy offers several advantages over other low-emission alternatives such as nuclear power and large-scale hydropower projects but has met with opposition in the United States and many other countries (Firestone and Kempton, 2007; Moragues-Faus and Ortiz-Miranda, 2010; Nadai and van der Horst, 2010). One common concern is that wind turbines constitute a disamenity, which reduces the desirability and hence the price of nearby properties. In the U.S., large-scale wind installations have tended to be built in sparsely populated locations in the Plains and West, so existing studies of the effect of wind turbines on the price of residential properties have tended to focus on large-scale installations located in rural settings. Rural residents have expressed concern about the way in which industrialized large-scale wind farms have transformed the rural sense of place through the creation of ‘‘landscapes of power’’ (Pasqualetti, Gipe, and Righter, 2002, p. 3).

Smaller-scale distributed renewable energy technologies located in and around urbanized areas where energy is being consumed provide an opportunity to reduce transmission costs. However, locating wind turbines in more densely populated areas potentially means that more homes may be affected if the facilities were to constitute a disamenity. 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. Alternatively, people residing in more urbanized settings may have different perceptions about the built and natural environment from those living in rural environments. Despite the growing popularity of smaller-scale energy facilities being built in more urbanized settings, no comprehensive studies have yet been undertaken to identify whether or not wind turbines constitute a disamenity in these locations.

Massachusetts has been especially progressive in its adoption of renewable energies and as of October 2015 had almost 107 MW of installed capacity distributed across 129 separate wind projects. Turbines have been located in a variety of settings including the mountainous Berkshire East Ski Resort, heavily urbanized Charlestown, and coastal Cape Cod. The average gross population density surrounding the Massachusetts turbines of 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.

Accordingly, 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 more densely populated areas of the U.S. Our study makes five major unique contributions to the wind energy property value literature: (1) We use the largest and most comprehensive dataset ever assembled for a study linking wind facilities to nearby home prices in North America. (2) Our study includes the largest range of home sale prices ever examined. (3) We examine 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) We largely focus 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 paper is organized as follows. We begin with a literature review and identification of gaps in the literature that inform our empirical analysis. We then discuss our empirical analysis, including descriptions of the data, methods, and results. We next present the results, and close with a discussion of the findings, conclusions, and suggestions for future research.

Literature

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 (e.g., Graham, Stephenson, and Smith, 2009). Despite this strong support, the construction of wind projects provokes concerns about local impacts (e.g., Devine-Wright, 2012), specifically, turbine-related impacts on homes located a short distance away (Hoen et al., 2011). If wind turbines create such a disamenity, then house prices closer to the turbine would be expected to decline (all else being equal). Therefore, their impact can be examined by investigating nearby house prices after the facility has been erected compared to their values before the turbine was installed, while taking into account the prices of houses farther away that sold during the same period.

The peer-reviewed, published studies that have used hedonic modeling have generally found non-significant post-construction effects (Sims, Dent, and Oskrochi, 2008; Hoen et al., 2011; Hoen et al., 2013; Lang, Opaluch, and Sfinarolakis, 2014; Vyn and McCullough, 2014), or relatively small impacts (Jensen, Panduro, and Lundhede, 2014), implying that average impacts in their study areas were either relatively small or sporadic near existing turbines. Three academic studies found similarly non-significant results (Hoen, 2006; Hinman, 2010; Carter, 2011) while two found relatively small effects (Dröes and Koster, 2015; Gibbons, 2015), and one found a substantial effect (Grieser, Sunak and Madlener, 2015). The geographic extent of the North American studies varied from single county (Hoen, 2006; Hinman, 2010; Carter, 2011; Vyn and McCullough, 2014), to three counties in New York (Heintzelman and Tuttle, 2012), to eight (Hoen et al., 2011) or nine states (Hoen et al., 2013), showing that results have been robust to geographic scale and sample selection. Some studies have found evidence of pre-construction yet post-announcement impacts (Hinman, 2010; Hoen et al., 2011; Heintzelman and Tuttle, 2012).[1] This "anticipation effect" (Hinman, 2010) correlates with surveys of residents living near wind facilities finding that residents are more supportive of the facilities after they have been built than they were when the construction of that facility was announced (Wolsink, 2007; Sims, Dent, and Oskrochi, 2008). This effect is consistent with analyses of home prices related to other disamenities (e.g., incinerators), which have also shown anticipation effects and post-construction rebounds in prices (Kiel and McClain, 1995).

Wind turbines are typically limited to high-wind-resource areas but disamenities such as highways, overhead electricity transmission lines, power plants, and landfills are ubiquitous in urban and semi-rural areas, and have been well studied. This more established "disamenity literature" (e.g., Boyle and Kiel, 2001; Jackson, 2001; Simons and Saginor, 2006) helps both to frame the expected level of impact around turbines and validate whether the coefficients for the amenities and disamenities included in our model are reasonable. 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 (Colwell, 1990; Delaney and Timmons, 1992; Kinnard and Dickey, 2000; Pitts and Jackson, 2007). 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, decreasing by 5.9% for each mile a home is further away for large-volume operations.[2] Lower-volume operations decreased adjacent property values by 2.7% on average, decreasing by 1.3% per mile (Ready, 2010). Finally, studies on the impact of road noise on house prices found price decreases of 0.4% to 4% for houses adjacent to a busy road compared to those on a quiet street [e.g., Bateman, Day, and Lake (2001) and the references therein, and Andersson, Jonsson, and Ogren (2010); Day, Bateman, and Lake (2007); and Kim, Park, and Kweon (2007)].

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, 2006); Anderson and West (2006) 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, Hansen, and Schwartz, 2000; Bond, Seiler, and Seiler, 2002); for example, being on the waterfront increased values by almost 90% (Bond, Seiler, and Seiler, 2002). Although many researchers of the community perceptions of wind turbines suggest that local residents may see turbines as a disamenity, this is not always the case. Some suggest that wind turbines could be considered amenities (i.e., a positive addition to the community), particularly if benefits accrue to the local community (Loomis and Aldeman, 2011; Loomis, Hayden, and Noll, 2012) and therefore might decrease the tax burden for local residents.

The evidence discussed above for other disamenities and for other studies of turbines suggests that any turbine-related disamenity impact likely would be relatively small, for example, less than 10% if it exists at all. If this is the case, tests to discover this impact would require correspondingly small margins of error and hence large amounts of data. Yet much of the North American studies have used relatively small numbers of transactions near turbines. For example, the largest dataset studied to date had only 376 post-construction sales within 1 mile of the turbines (Hoen et al., 2013), while others contained far fewer post-construction transactions within 1 mile: Hoen et al. (2009, 2011) (n = 125); Hinman (2010) ($n \sim 11$); Carter (2011) ($n \sim 41$); Heintzelman and Tuttle (2012) ($n \sim 35$); and Vyn and McCullough (2014) ($n \sim 22$). 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 et 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, research has identified that wind facilities are sited in areas where property prices are lower than in surrounding areas—hereafter referred to as a "preexisting price differential." For example, Hoen et al. (2009) found significantly lower prices (−13%) for homes that sold more than two years prior to the wind facilities' announcements and were located within one 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 termed a "location effect." Thus, further investigation of whether wind facilities are located in areas with lower home values than surrounding areas is warranted. 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)].

Empirical Study

Research Questions

We address the following questions informed by gaps in the literature: (Q1) Have wind facilities in Massachusetts been located in areas where average home prices were lower than prices in surrounding areas (i.e., a "preexisting price differential")?[3] (Q2) Are post-construction (i.e., after wind-facility construction) home price impacts evident in Massachusetts, and how do Massachusetts' results compare to 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 to previous findings? (Q5) Is there evidence that houses near turbines that sold during the post-announcement and post-construction periods do so at lower relative rates (i.e., frequencies) than during the pre-announcement period?

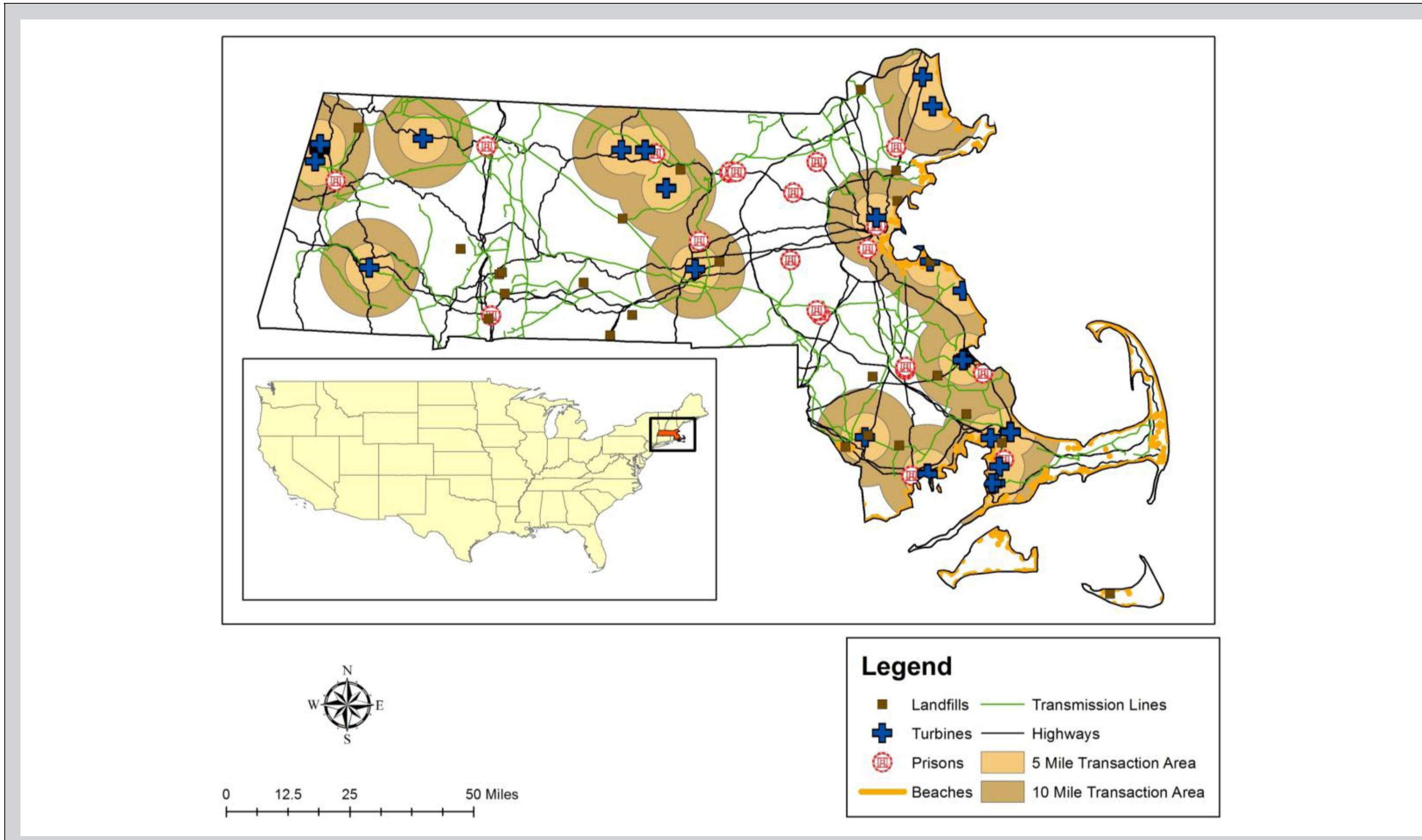
Data

The study uses data from the Massachusetts Clean Energy Center (MassCEC) for 41 wind turbines in Massachusetts that had been commissioned as of November 2012 with a capacity of at least 600 kW.[4] The location of the wind turbines along with other features included in the analysis is shown in Exhibit 1. Data on homes were purchased from the Warren Group[5] and a geographic information system (GIS) was used to calculate the distance of each home to the nearest turbine. Transactions inside five miles were used for the base model, while those outside of five miles were retained for the robustness tests.

Summary Statistics

The base model dataset includes all home sales within five miles of a wind turbine, which are summarized in Exhibit 2.[6] The average home in the dataset of 122,198

Exhibit 1 | Location of Wind Turbines and Amenities and Disamenities in Massachusetts



Sample location detail showing turbines, five- and ten-mile sample areas, and multiple overlapping locations of various amenities and disamenities.

Exhibit 2 | 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	10/19/2004	1522	3/3/1998	2/6/2005	11/23/2012
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 (1,000s of Square Feet)	1.72	0.78	0.41	1.6	9.9
acre[a]	Number of acres	0.51	1.1	0.005	0.23	25
acrelt1[a]	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[b]	The number of bathrooms	1.90	0.79	0.5	1.5	10.5
wtdis	Distance to nearest turbine (miles)	3.10	1.20	0.1	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

Notes: Summary statistics of base model dataset showing a wide range in prices, sizes, ages and distances from turbines of homes in the sample. Sample size for the full dataset is 122,198.

[a] 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.

[b] Bath is calculated as follows: number of bathrooms + (number of half bathrooms *0.5).

Exhibit 3 | Distribution of Transaction Data Across Distance and Period Bins

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

Note: Count of transactions across distance and wind facility development periods showing over 1,000 transactions within a half mile and stable numbers of transactions near turbines over time.

sales from 1998 to 2012 has a sale price of \$322,948, sold in 2004, in the second 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 Exhibit 3, of the 122,198 sales within five miles of a turbine, 7,188 (5.9%) are within one 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 one mile of a turbine, and 230 occurred within a half mile. It is worth noting that although the land area within a quarter mile (~0.2 mile^2) is one-third of that between a quarter mile and a half mile (~0.6 mile^2), the number of transactions (and homes) is approximately one-tenth (121/986 = 0.12). This makes sense because there are regulatory and business practices that, respectively, require and/or encourage utility scale turbines to be set back from homes. Often these setbacks are 1,000 feet or so (NARUC, 2012). Therefore a significant percentage of the usable land around all wind facilities will contain only a few or no homes. That notwithstanding, this sample represents the most densely populated sample studied to date in North America and its density is similar to other "urban" utility scale wind installations elsewhere in the U.S. (in Connecticut, Ohio, and New Jersey). Moreover, the sample of homes studied immediately near the turbines is sufficient to gauge if an effect existed that might be relatively small, as is hypothesized, and especially so if an effect is larger (say, greater than 10%). The mean values for each of the distance bins and development periods for sale price, square feet, age, and acres are provided in Exhibit 4.

Exhibit 4 | Mean Values of Key Variables by Distance and Period Bins

	prioranc	*preanc*	*postanc-precon*	*postcon*	*prioranc*	*preanc*	*postanc-precon*	*postcon*
	Sale Price				Square Feet (in 1000s)			
0–0.5 mile	$256,378	$309,149	$314,337	$332,708	1.784	1.577	1.622	1.582
0.5–1 mile	$288,536	$377,842	$359,003	$385,499	1.744	1.700	1.737	1.715
1–5 mile	$292,258	$361,352	$346,581	$370,096	1.737	1.716	1.719	1.718
	Acre				Age			
0–0.5 mile	0.45	0.40	0.42	0.35	46	46	49	53
0.5–1 mile	0.35	0.36	0.48	0.32	55	57	55	65
1–5 mile	0.51	0.52	0.60	0.47	51	53	54	61

Note: Summary statistics of sale price, square feet, acres, and age of homes that sold across the various wind facility development periods and distance bins showing consistently lower prices of homes near the turbines across all periods and varying levels of acres, square feet and age.

Hedonic Base Model Specification

We estimate the following customarily used (e.g., Sirmans, Lynn, Macpherson, and Zietz, 2005) semi-log base model to which the set of robustness models are compared.

$$\ln(P) = \beta_0 + \sum \beta_1 LD + \beta_2 N + \sum \beta_3 AD + \sum \beta_4 ED + \sum B_5 T + \varepsilon', \quad (1)$$

where the dependent variable is the log of sales price (P), and L is the vector of characteristics of the property including living area (in thousands of square feet); lot size (in acres); lot size less than one acre (in acres if the lot size is less than 1, otherwise 1);[7] 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 development period in which the sale occurred for the nearest wind turbine (e.g., if the sale occurred more than two years before the nearest turbine's development was announced, less than two years before announcement, after announcement but before construction, or after construction). N is the U.S. census tract in which the sale occurred.[8] 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.[9] T is the vector of time variables, including the year in which the sale occurred and the quarter in which the sale occurred.[10] E is a binary variable representing if the home is within a half mile from a turbine, and ε is the error term. β_0, β_1, β_2, β_3, β_4, and β_5 are coefficients for the variables.

The vectors of lot-specific and amenity/disamenity variables are interacted with the development period. This is done for three reasons: (1) to allow the covariates to vary over the study period, which will, for example, allow the relation of living area and sale price to be different earlier in the study period, such as more than two years before announcement, than it is later in the study period, such as after construction of the nearest turbine;[11] (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.[12] 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. 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, Dent, and Oskrochi, 2008; Hoen et al., 2009), inverse distance (Heintzelman and Tuttle, 2012; Vyn and McCullough, 2014; Grieser, Sunak, and Madlener, 2015), or mutually exclusive non-continuous distance variables (Hoen et al., 2009; Hinman, 2010; Carter, 2011; Hoen et al., 2011; Heintzelman and Tuttle, 2012; Hoen et al., 2013; Vyn and McCullough, 2014; Grieser, Sunak, and Madlener, 2015). We preferred the binary variable because we believe the other forms have limitations (although we explore a continuous specification as a robustness test). For example, 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 (Heintzelman and Tuttle, 2012; Grieser, Sunak, and Madlener, 2015). 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 (Heintzelman and Tuttle, 2012; Grieser, Sunak, and Madlener, 2015).

One method to avoid using a single continuous function 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; Heintzelman and Tuttle, 2012; Hoen et al., 2013; Vyn and McCullough, 2014). 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% in 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 five or ten miles, we focus 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 tests. 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.

Robustness Tests

A suite of robustness tests explored changes in: (1) the spatial extent at which both the effect and the comparable data are specified; (2) an alternative representation of distance to turbine as a ‘‘distance decay’’ function; (3) the variables used to describe fixed effects; (4) the screens that are used to select the final dataset, as well as outliers and influencers; (5) a series of tests associated with the suite of disamenity variables; and (6) the inclusion of spatially and temporally lagged variables to account for the presence of spatial autocorrelation. Each is described below and indicates the appropriate model in the results in Exhibit 6.

Varying the Distance to Turbine. In the base model, we test for effects on homes sold within a half mile of a turbine (and compare the sales to homes located outside of a half mile and inside five 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 we do not explore this in the base model. Therefore, this set of robustness models investigates effects within a quarter mile (robustness model a), as well as between a half and one mile (model b). 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. In the base model, we compare homes within a half mile to those outside of a half mile and inside of five miles, most of which are between three and five 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 ten miles (model c), and (2) those outside of five miles and inside of ten miles (model d). It is assumed that effects from turbines are not experienced outside of five miles from the nearest turbine.

Using a "Distance Decay" Effect. The aim of the paper is to specifically examine if effects within a half mile of turbines are apparent, while also examining effects for homes proximate to other amenities and disamenities within the same dataset using the same methods. We have enough data to allow us to do so with a reasonably small margin of error (3%–5%). As a robustness test, we also estimate a model with a distance decay function (1/distance) to capture a decrease in effects with increased distance to the turbines (model e).

Fixed Effects. 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 (model f). 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.

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 dataset. To explore what effect these screens have on the results, they are relaxed for this set of robustness tests (model g). Additionally, a selection of outliers (based on the 1st and 99th percentiles of sale price) and influencers (based on a Cook's distance of greater than 1), (Cook, 1977) might bias the results, and therefore a model is estimated with them removed (model h).

Disamenity Variables. The base model includes a series a binary variables to represent the various disamenities and amenities located near the homes in our dataset, and assumes that any potential disamenity associated with wind turbines would be "over and above" that for the existing disamenities. To account for the possibility that the combined effect of multiple disamenities may not necessarily be additive, and that the disamenity associated with wind turbines may be small compared to other negative externalities, we conducted three separate robustness tests with respect to our disamenity variables. In the first test, we exclude observations where the negative externalities (other than the wind turbines) are present, focusing on a sample that only includes houses close to wind turbines but not close to any other negative externalities (model i). In the second test, we use factor analysis on all of our disamenity variables to create indices of disamenity that are then used in a regression in place of the individual binary variables representing disamenities (model j). In the third analysis, to test for the possibility that there are latent effects that are not being captured with the regression, or that the results are over or understating the effects of the wind turbines, we conduct two separate tests utilizing 2010 census data on household income, education, and employment level and percentage owner-occupied for all of the block groups in the sample area: (1) using *t*-tests, we examine whether census characteristics for block groups close to the turbines are statistically significantly different from those outside of five miles; we find they were not in terms of employment, household income, and education (results not shown); and (2) we include the census variables in our regression model (model k).[13]

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., five-acre lots) might be priced higher than an otherwise identical home in a neighborhood with smaller parcels (e.g., one-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, concern is paid to unobserved (and spatially correlated) neighborhood factors in the model.[14]

A common approach for controlling for the unobserved neighborhood factors is to include neighborhood fixed effects (e.g., Bourassa, Cantoni, and Hoesli, 2010; 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), although alternative methods could have been used (Anselin, 2002). Using the data obtained from the 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 are derived for use in a robustness test. For each transaction, the five nearest neighbors were selected that transacted within the preceding six months and were the closest in terms of Euclidian distance. Using those five transactions, average 1,000s 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 (model l).

Results

Base Model Results

The base model results for the turbine, amenity, and disamenity variables are presented in Exhibit 5. 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, Lynn, Macpherson, and Zietz, 2005).[15] In the model, we interact 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.[16] The controlling variables do vary across the periods, although they are relatively stable. For example, each additional 1,000 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 2012 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 the 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

Exhibit 5 | Selected Results from Base Model: Wind Facility Development Period

Variables	Description	*prioranc* Coeff.	*preanc* Coeff.	*postanc-precon* Coeff.	*postcon* Coeff.
halfmile	Within a half mile of a wind turbine	−5.1%*** (0.000)	−7.1%*** (0.002)	−7.4%*** (0.000)	−4.6%* (0.081)
	Net Difference Compared to *prioranc* Period			−2.3% (0.264)	0.5% (0.853)
beach500ft	Within 500 feet of a beach	20.8%*** (0.000)	30.4%*** (0.000)	25.3%*** (0.000)	25.9%*** (0.000)
beachhalf	Within a half mile and outside of 500 feet of a beach	5.3%*** (0.000)	8.8%*** (0.000)	8.7%*** (0.000)	13.5%*** (0.000)
openhalf	Within a half mile of open space	0.6%** (0.021)	0.1% (0.729)	0.1% (0.903)	0.9%* (0.062)
line500ft	Within 500 feet of a electricity transmission line	−3.0%*** (0.001)	−0.9% (0.556)	−0.9% (0.522)	−9.3%*** (0.000)
prisonhalf	Within a half mile of a prison	−5.9%*** (0.001)	2.6% (0.291)	2.8% (0.100)	−2.3% (0.829)
hwy500ft	Within 500 feet of a highway	−7.3%*** (0.000)	−5.2%*** (0.000)	−3.7%*** (0.000)	−5.3%*** (0.000)
major500ft	Within 500 feet of a major road	−2.8%*** (0.000)	−2.3%*** (0.000)	−2.5%*** (0.000)	−2.0%*** (0.000)
fillhalf	Within a half mile of a landfill	1.8% (0.239)	−0.9% (0.780)	1.0% (0.756)	−12.2%*** (0.002)

Exhibit 5 | (continued)

Selected Results from Base Model: Wind Facility Development Period

		prioranc	*preanc*	*postanc-precon*	*postcon*
Variables	Description	Coeff.	Coeff.	Coeff.	Coeff.
sfla1000	Living area in thousands of square feet	22.9%*** (0.000)	21.4%*** (0.000)	22.6%*** (0.000)	23.5%*** (0.000)
acre	Lot size in acres	1.1%*** (0.000)	1.9%*** (0.000)	1.3%*** (0.000)	−0.02% (0.863)
acrelt1	Lot size less than 1 acre	21.7%*** (0.000)	17.2%*** (0.000)	14.7%*** (0.000)	22.1%*** (0.000)
age	Age of the home at time of sale	−0.2%*** (0.000)	−0.2%*** (0.000)	−0.2%*** (0.000)	−0.2%*** (0.000)
agesq†	Age of the home at time of sale squared	0.6%*** (0.000)	0.5%*** (0.000)	0.6%*** (0.000)	0.8%*** (0.000)
bath	Number of bathrooms	6.4%*** (0.001)	7.9%*** (0.556)	8.4%*** (0.522)	11.1%*** (0.000)

Notes: Results from the base model showing consistently statistically significant differences in home prices for those located within a half mile of a turbine's current or eventual location, yet no significance difference in price when comparing across periods. 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. The model adjusted R^2 is 0.80; $f < 0.001$; $n = 122{,}198$. *p*-values are in parentheses.

† Coefficient values are multiplied by 1,000 for reporting purposes only.

* Significant at 0.10.

** Significant at 0.05.

*** Significant at 0.01.

Exhibit 6 | Robustness Results

				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
#	Model Name	*n*	Adj. R^2	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
	Base Model	122,198	0.80		−5.1%*** (0.000)			−2.3% (0.264)			0.5% (0.853)	
a	Inside 1/4 mile	122,198	0.80	−5.3% (0.260)			12.7% (0.118)			0.7% (0.916)		
b	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)
c	All Sales Out to 10 Miles	312,677	0.82		−5.8%*** (0.000)			−3.0% (0.886)			1.0% (0.724)	
d	Using Outside of 5 Miles as Reference	312,677	0.82		−7.6%*** (0.000)			1.6% (0.435)			1.1% (0.695)	
e	Distance Decay	122,198	0.80		−2.0%*** (0.000)			0.5% (0.458)			0.003% (0.997)	
f	Using Block Group	122,198	0.81		−3.1%*** (0.024)			−1.3% (0.554)			−2.6% (0.324)	
g	No Screens	123,555	0.73		−4.0%*** (0.003)			−4.6%* (0.072)			−0.8% (0.800)	
h	Removing Outliers and Influencers	119,623	0.79		−4.3%*** (0.001)			−2.6% (0.205)			0.04% (0.989)	

Exhibit 6 | (continued)

Robustness Results

				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
#	Model Name	*n*	Adj. R^2	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
i	No Homes Near Negative Externalities	121,676	0.80		−2.4%*** (0.000)			−4.6% (0.101)			−1.3% (0.714)	
j	Using Indices of Disamenities	122,198	0.80		−6.4%*** (0.000)			0.3% (0.884)			−0.9% (0.730)	
k	Including Census Variables	122,198	0.80		−3.7%*** (0.000)			−2.8% (0.168)			0.2% (0.945)	
l	Including Spatial Variables	122,198	0.80		−5.3%*** (0.000)			−1.5% (0.467)			1.4% (0.621)	

Notes: An extensive set of robustness tests results in similar findings as the main base model: there is not a statistically significant difference in price of homes near turbines that sold before the turbines were erected as compared to those that sold after the turbines we built and operational. 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. *p*-values are in parentheses.

† Coefficient values are multiplied by 1,000 for reporting purposes only.

* Significant at 0.10.

** Significant at 0.05.

*** Significant at 0.01.

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 related to the amenity/disamenity variables, because they all likely existed well before this sample period—and therefore the turbine's operation—began. 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 show 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 (Exhibit 5). The coefficients for the *halfmile* variable over the four periods are as follows: *prioranc* (sale more than two years before the nearest wind turbine was announced) −5.1%, *preanc* (less than two years before announcement) −7.1%, *postancprecon* (after announcement but before the nearest turbine construction commenced) −7.4%, and *postcon* (after construction commenced) −4.6%.[17] Importantly, we estimate 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 five 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).[18] Therefore, after accounting for the "preexisting price differential" that predates a turbine's development, there is no evidence of an additional impact from a turbine's announcement or eventual construction.

Robustness Test Results

To test and possibly bound the results from the base model, several robustness tests were explored. Exhibit 6 shows the robustness test results and the base model results for comparison. 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 *prioranc* period.[19] Throughout the rest of this section, those effects will be referred to as net *postancprecon* and net *postcon.*

A number of key points 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 in that distance range, see Exhibit 3), providing no evidence of a large negative effect near the turbines (model a). 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 (model g). 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 spans from zero (−2.6% to 1.4%), further reinforcing the non-significant results from the base model. Importantly, using an alternative representation of distance to turbine as a ''distance decay'' function as a robustness test (model e), and the set of three robustness tests used to test the way in which the disamenity variables were specified (models i, j, and k) did not change our results.

Discussion

In this study, we estimate a base hedonic model along with a large set of robustness models to test and bound the results. These results are now applied to our research questions.

Question 1: Have wind facilities in Massachusetts been located in areas where average home prices were lower than prices in surrounding areas (i.e., a preexisting price differential)?

To test for this effect, we examine the coefficient in the *prioranc* period, in which sales occurred more than two 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 five 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 comparable houses 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. Some of these locations (e.g., 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.[20] It is possible that the choice of these locations for wind development was driven, in part, by the preexisting land use. This is echoed by other researchers; Sims and Dent (2007, p. 5), after their examination of three locations in Cornwall, United Kingdom, commented that "wind farm developers are...locating their developments in places where the impact on prices is minimized, carefully choosing their sites to avoid any negative impact on the locality." Regardless of the reason for this preexisting 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—if one is to accurately measure the incremental impact of turbines.

Question 2: 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 preexisting price differential. In the base model, with a *prioranc* effect of −5.0% and a *postcon* effect of −3.7%, the net effect is 1.2% 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 −1.8% to 3.3%, 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 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 = 1,501) is orders of magnitude larger than had been collected in previous North American studies and is large enough to find effects of the magnitude others have claimed to have found (e.g., Heintzelman and Tuttle, 2012; Grieser, Sunak, and Madlener, 2015).[21] 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, Dent, and Oskrochi, 2008; Hoen et al., 2009; Hinman, 2010; Carter, 2011; Hoen et al., 2011). Our study differs from previous analyses because we examine sales near turbines in more urban settings than had been studied previously. Contrary to what one might expect, 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.

Question 3: 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 multicollinearity 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, Dent, and Oskrochi, 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.

Question 4: 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 account for the surrounding environment when establishing home prices. Beaches (adding 20%–30% to price when within 500 feet, and adding 5%–13% to price when within a half mile), highways (reducing price 4%–8% when within 500 feet), and major roads (reducing price 2%–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.

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%–4% for homes near "noisy" roads (Andersson, Jonsson, and Ogre, 2010; Bateman, Day, and Lake, 2001; Blanco and Flindell, 2011). Further, although sporadic, the large price reduction impact we find 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. One potential explanation for the sporadic nature of the coefficients is the small number of observations. 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 (2006) 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 that 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.

Question 5: Is there evidence that houses that sold during the post-announcement and post-construction periods did so at lower relative 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 (see Exhibit 3). Approximately 0.29% of all homes in our sample (i.e., inside of ten miles from a turbine) that sold in the *prioranc* period are 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 ten 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.[22]

Conclusion

In this study, we investigate 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 or relatively small 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 whether wind turbines have a negative impact on property values in urban settings, we analyze 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. Over 1,100 transactions were within a half mile of the turbines, an amount ample enough to gauge relatively small effects.

The results of this study do not support the claim that wind turbines affect nearby home prices. Although we 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, we 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 of a variety of model and sample specifications.

We identify 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, we aggregate 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. One additional characteristic of home sales that may be worth investigating in future research is whether or not the amount of time that a house is on the market (TOM) is affected by the announcement or construction of a wind turbine.

Appendix

Full Set of Results

	Coeff.	SE	*t*-stat.	*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

Appendix (continued)
Full Set of Results

	Coeff.	SE	*t*-stat.	*p*-value
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
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

Appendix (continued)

Full Set of Results

	Coeff.	SE	*t*-stat.	*p*-value
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	−0.002	0.00	−21.87	0.000
preanc	−0.002	0.00	−11.33	0.000
postancprecon	−0.002	0.00	−13.99	0.000
postcon	−0.003	0.00	−16.47	0.000
Age of the home at time of sale squared				
prioranc	0.00001	0.00	28.55	0.000
preanc	0.00001	0.00	17.03	0.000
postancprecon	0.00001	0.00	20.01	0.000
postcon	0.00001	0.00	26.40	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

Appendix (continued)

Full Set of Results

	Coeff.	SE	*t*-stat.	*p*-value
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

Notes: $n = 122{,}198$; $R^2 = 0.80$; Adj. $R^2 = 0.80$; and $F = 2{,}418$.

Endnotes

1 Heintzelman and Tuttle (2012) do not appear convinced that the effect they found is related to the post-announcement period, yet the two counties in which they found an effect (Clinton and Franklin Counties, New York) had transaction data produced almost entirely in that period.

2 Defined as accepting more than 500 tons per day.

3 Any preexisting price differential, by definition, 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. There are some known possible explanations for these possible latent effects, such as being co-located with a wastewater treatment facility or an industrial facility, as is the case for some wind facilities in Massachusetts. Further, there might be unknown effects. We were not able to obtain reliable data on the wastewater and industrial facilities, and any other unknown effects, and therefore estimated the DID model to control for those. We did include seven different amenities and disamenities in our model to account for many of these latent effects.

4 We used this cut-off point because installations smaller than this built on individual properties would theoretically not have spatial spillover effects.

5 We purchased the data for these variables from the Warren Group. Any duplicate observations, cases where key information is missing, or observations where the data appeared to be erroneous are removed from the dataset. Screens are used to remove sales prices lower than $40,000 and over $2,500,000; properties with more than 12 bathrooms or bedrooms; lot size greater than 25 acres; and sale price per square foot less than $30 or more than $1,250. These screens are relaxed for a robustness test, creating no significant change to the results.

[6] Although not shown in the exhibit, homes nearest the turbines are consistently lower in value in all development periods than homes further away, but also have less living area, are on slightly smaller parcels, and are a bit younger in age. Homes outside of a half mile but inside of five miles are relatively similar in terms of price, age, size, and parcel size, but homes outside of five miles are higher in value, larger, younger, and are on slightly larger parcels. Full summary statistics are available from the authors upon request.

[7] An anonymous reviewer suggested we consider not using the spline function but instead the natural log of lot size. Our results are robust to this alternative specification.

[8] A binary variable is used to represent whether a property is located in a particular Census Tract or not.

[9] Each of the amenity/disamenity variables are expressed as a binary variable: 1 if "yes," 0 if "no," giving a total of seven individual binary variables. In addition, we use factor analysis to generate three indices of disamenity based on these individual variables, which are subsequently used in the regression in place of the individual binary variables as a robustness check. We assume that all disamenities existed prior to the wind facilities' development.

[10] We use separate yearly and quarterly binary variables and assume that seasonality is constant over time. We did, however, conduct a robustness test using separate binary variables for each year and quarter, and because the results are unchanged, opted to use the more parsimonious specification.

[11] Our results for the wind turbine variables are robust to alternative specifications without these interactions.

[12] 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 with these subsets of data.

[13] One anonymous reviewer suggested we estimate a two-step Heckman model, but because the form of the model used for this analysis utilized a large set of fixed effect and dummy variables, which are not acceptable when estimating a Heckman model in Stata, we were not able to explore this method.

[14] LeSage and Pace (2009) argue that including an expression of neighboring observations (i.e., a spatial lag, known 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.

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

[16] 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.

[17] 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 is also estimated and is no different than this post-construction effect.

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

[19] The full set of robustness results is available upon request.

[20] 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.

[21] However, as discussed earlier, their findings might be the result of their continuous distance specification and not the result of the data; moreover, although Heintzelman and Tuttle (2012) claim to have found a *postcon* effect, their data primarily occurs prior to construction.

[22] This conclusion is confirmed with Friedman's two-way analysis of variance for related samples using period as the ranking factor, which confirms that the distributions of the frequencies across periods is statistically the same.

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Ben Hoen, Lawrence Berkeley National Laboratory, Berkeley, CA 94720-8136 or bhoen@lbl.gov.

Carol Atkinson-Palombo, University of Connecticut, Storrs, CT 06269-4148 or carol.atkinson-palombo@uconn.edu.