LBNL-XXXX

ERNEST ORLANDO LAWRENCE
BERKELEY NATIONAL LABORATORY

Impacts of Wind Turbine Proximity on Property Values in Massachusetts

Carol Atkinson-Palombo
University of Connecticut

Ben Hoen
Lawrence Berkeley National Laboratory

Environmental Energy Technologies Division

August 2013

This work was supported by the U.S. Department of Energy's Wind & Water Power Program, within the Office of Energy Efficiency and Renewable Energy, under Contract No. DE-AC02-05CH1123.

CONTENTS

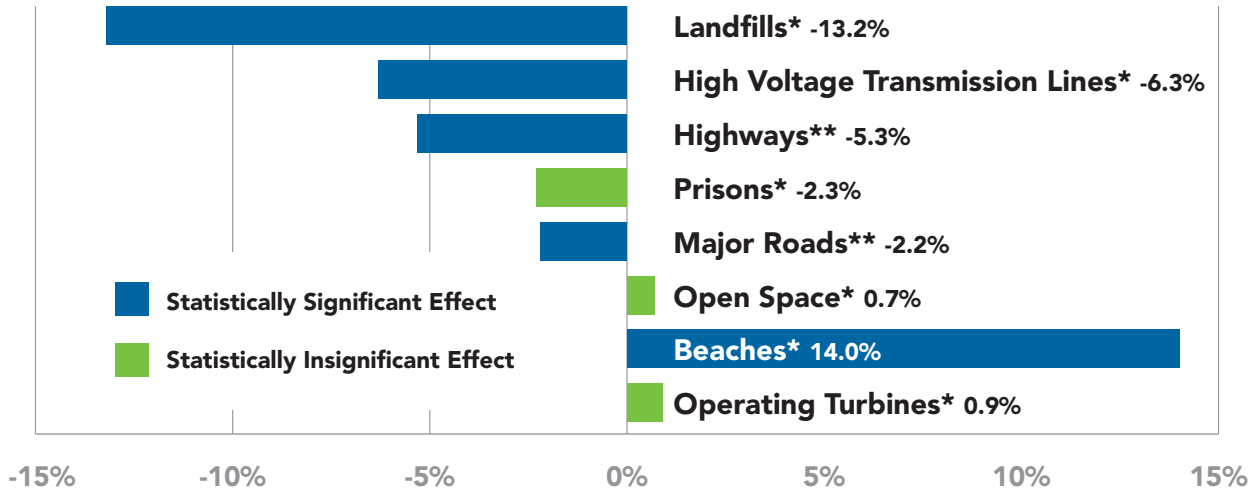
EXECUTIVE SUMMARY **1**
OVERVIEW **2**
1. INTRODUCTION **6**
2. LITERATURE REVIEW **9**
2.1 Public Acceptance of and Opposition to Wind Energy 9
2.2 Hypothetical Stigmas Associated with Wind Turbines 10
2.3 Policies and guidelines which address the siting and operation of wind facilities 11
2.4 Methods to Quantify Whether Wind Turbines are a Disamenity 13
2.5 General Literature on the Effects of Amenities and Disamenities on House Prices 14
2.6 Gaps in the Literature 16
3. EMPIRICAL STUDY **17**
3.1 Hedonic Base Model Specification 17
3.2 Robustness Tests 19
3.2.1 Varying the Distance to Turbine 20
3.2.2 Fixed Effects 20
3.2.3 Screens, Outliers, and Influencers 21
3.2.4 Spatially and Temporally Lagged Nearest-Neighbor Data 21
3.2.5 Inclusion of Additional Explanatory Variables 22
3.3 Data Used For Analysis 22
3.3.1 Wind Turbines 22
3.3.2 Single-Family-Home Sales and Characteristics 22
3.3.3 Distance to Turbine 24
3.3.4 Time of Sale Relative to Announcement and Construction Dates of Nearby Turbines 24
3.3.5 U.S. Census 25
3.3.6 Amenity and Disamenity Variables 25
3.3.7 Spatially and Temporally Lagged Nearest-Neighbor Characteristics 26
3.3.8 Summary Statistics 27
3.4 Results 28
3.4.1 Base Model Results 28
3.4.2 Robustness Test Results 30
4. DISCUSSION AND CONCLUSIONS **32**
4.1 Discussion of Findings in Relation to Research Questions 32
4.2 Conclusion 35
4.3 Suggestions for Future Research 35
LITERATURE CITED **36**
APPENDIX: BASE MODEL FULL RESULTS **43**

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 high-voltage 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 a variety of model and sample specifications detailed further 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 potential nuisance effects of wind facilities on home prices in densely populated Massachusetts.

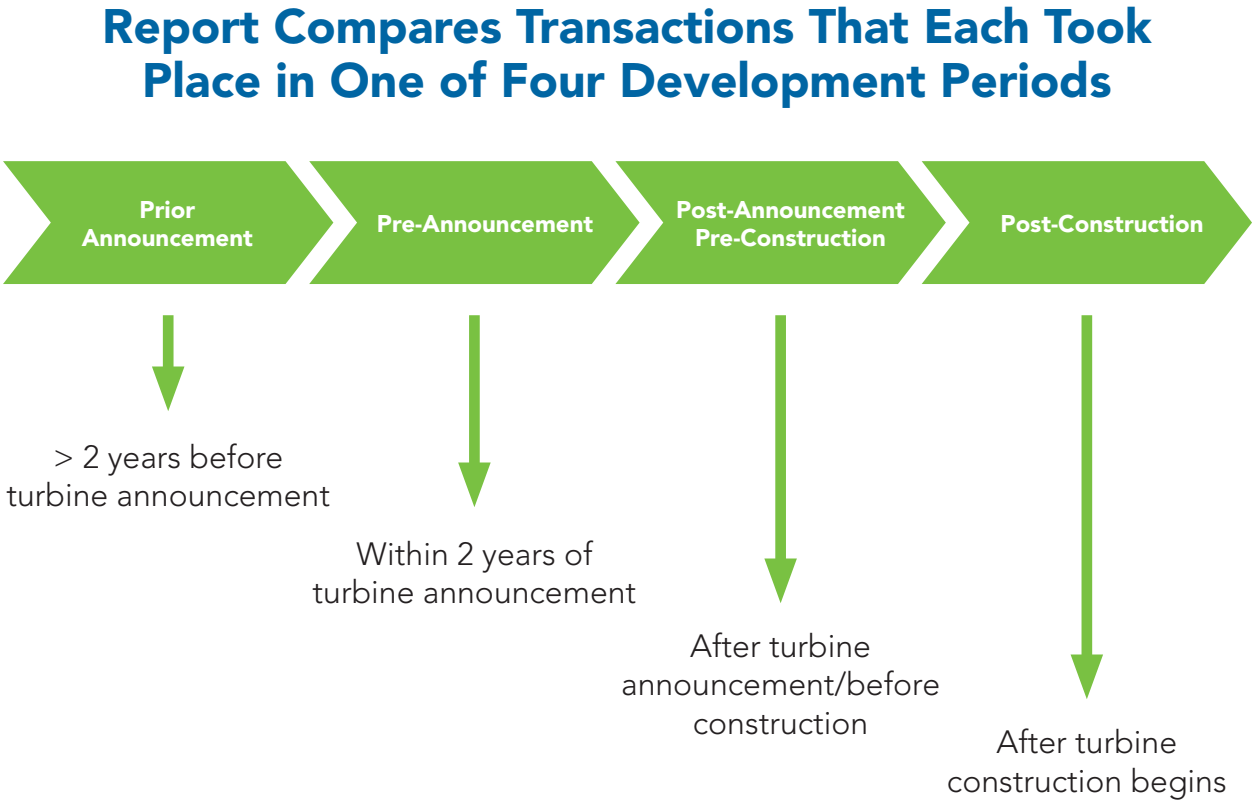
A variety of methods can be used to explore the effects of wind turbines on home prices. Statistical analysis of home sales, using a hedonic model, is the most reliable methodology because it (a) uses actual housing market sales data rather than perceptions of potential impacts; (b) accounts for many 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 122,161 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, high-voltage 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 0.9% higher than they were more than 2 years before the facility was announced (after controlling for market inflation/deflation). This

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 122,161 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 (pronounced "R squared"), indicates how well data points fit a line, curve or, in our case, a regression estimation. An *R* 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.

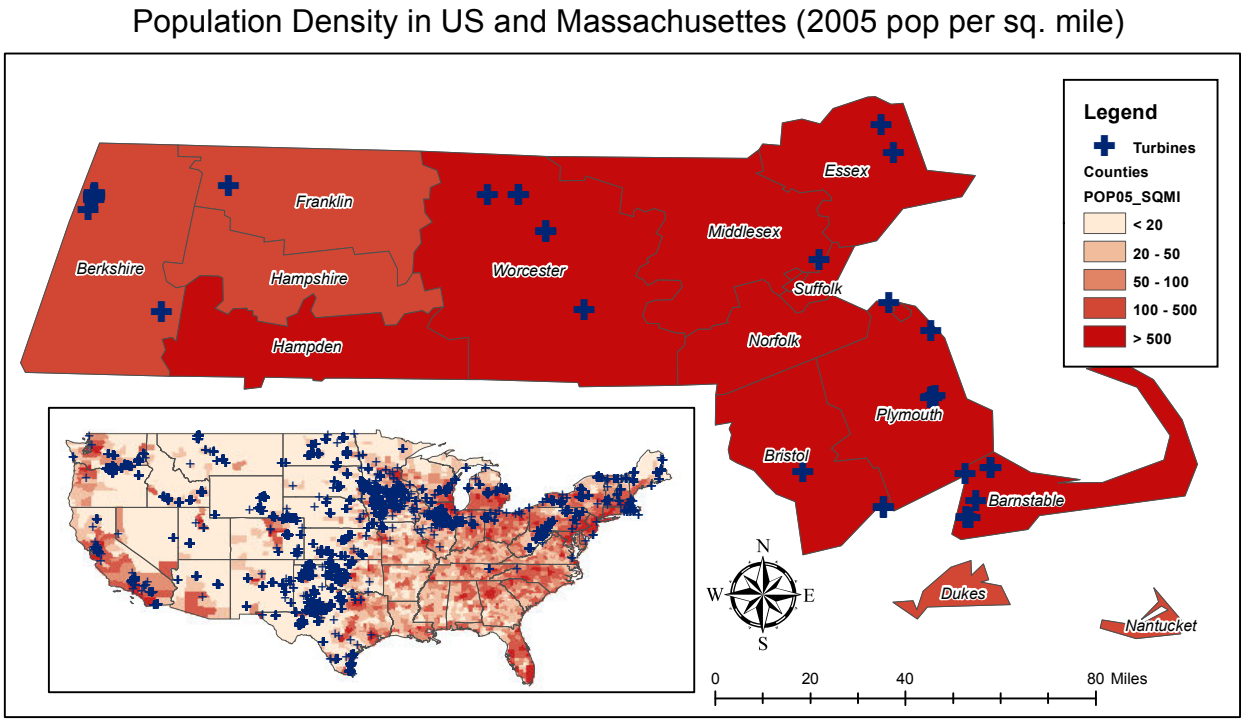
difference is not statistically significant. Post-announcement, pre-construction home prices within a half mile are 2.7% lower than their pre-announcement levels (after controlling for inflation/deflation), which is also a non-significant difference, though two of the robustness models suggest weak evidence 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 4.8% 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 it agrees 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 (through November 2012) and U.S. Wind Turbines through 2011 and population densities



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

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), where geography and/or wind speeds are constrained. 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) or 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.

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 122,161 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), 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 brought jobs and increased property values as well as increased tax

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

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 .)

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 aboard, 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 further than 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 applications, 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 ex-

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: . 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.

perienced as far as 1.4 kilometers (4,590 feet, 0.87 miles) from the turbines (Nissenbaum et al., 2012).

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 can help inform the development of appropriate setback 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 high-voltage 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 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 high-voltage transmission lines, a largely visual disturbance, have ranged from 5% to 20%, fading quickly with distance and disappearing beyond 200 to 300 feet (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 ($n \sim 35$), Hinman ($n \sim 11$), and Carter ($n \sim 41$). 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. 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.

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

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, such as if the home is within a half mile from the amenities open space and beaches; is within a half mile of the disamenities high-voltage transmission line, landfill, and/or prison; and is within 500 feet of the disamenities 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 this period 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.

18 While the coefficients associated with the amenity/disamenity variables and 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.

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 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) 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.[19]

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 <u>and</u> 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 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.[20] 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*),

20 See . 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	3/20/08	5/15/11	12/1/10				
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**

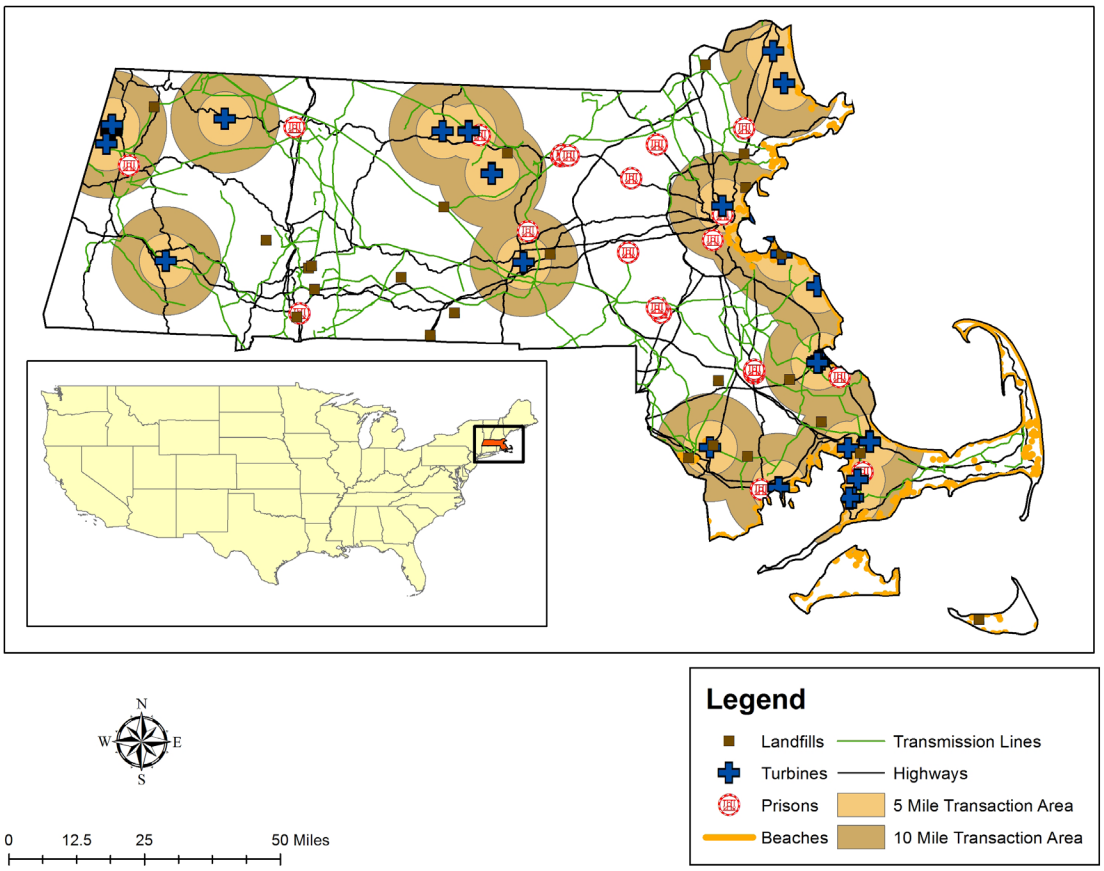
living area in thousands of square feet (*sfla1000*), lot size in acres (*acres*), year the home was built (*yb*), most recent renovation year (*renoyear*), the number of full (*fullbath*) and half (*halfbath*) bathrooms, the style of the home (e.g., colonial, cape, ranch) (*style*), the heat type (e.g., forced air, baseboard, steam) (*heat*), and the x and y coordinates of the home.[21] 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 ($age = sy - (yb\ or\ renoyear)$), age of the home at the time of sale squared ($agesqr = age \times age$), lot size less than 1 acre (*acrelt1*), bathrooms ($bath = fullbath + (halfbath \times 0.5)$).[22]

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

21 The style is used in a robustness test.

22 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 . This was important to ensure that accurate measurements of distance to the nearest turbine were possible.

Figure 4: Locations of Wind Turbines In Massachusetts



screens 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 122,161 transactions within 5 miles of a turbine (and 312,674 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***
0-0.25 mile	60	9	14	38	121
	0.04%	*0.02%*	*0.03%*	*0.06%*	*0.04%*
0.25-0.5 mile	433	149	210	192	984
	0.25%	*0.39%*	*0.47%*	*0.33%*	*0.31%*
0.5-1 mile	3,189	804	813	1,271	6,077
	1.9%	*2.1%*	*1.8%*	*2.2%*	*1.9%*
1-5 mile	62,950	14,652	17,081	20,296	114,979
	37%	*38%*	*38%*	*34%*	*37%*
5-10 mile	104,217	22,475	26,559	37,262	190,513
	61%	*59%*	*59%*	*63%*	*61%*
Total	**170,849**	**38,089**	**44,677**	**59,059**	**312,674**
	100%	*100%*	*100%*	*100%*	*100%*

(*prioranc*),[23] 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 312,674 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,[24] high-voltage transmission lines, prisons, highways, and major roads.[25] 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

23 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.

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

25 Office of Geographic Information (MassGIS), Commonwealth of Massachusetts, Information Technology Division ().

turbines. Based on the data, variables were assigned to each home in the dataset using GIS software. If a home was within a half mile of 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 high-voltage transmission line (*linehalf*), 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 a highway (*highway500*) or otherwise major road (*major500*).[26] Figure 4 shows the location of these amenities and disamenities (except open space) 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 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

Table 3: Summary of Characteristics of Base Model Dataset

Variable	Description	Mean	Std. Dev.	Min	Median	Max
sp	sale price	$322,924	$238,411	$40,200	$265,000	$2,495,000
lsp	log of sale price	12.50	0.60	11	12	15
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)	1.73	0.78	0.41	1.6	9.9
acre*	number of acres	0.51	1.11	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	4664	7517	0	2209	128881
bath**	the number of bathrooms	1.86	0.79	0.5	1.5	11
wtdis	distance to nearest turbine (miles)	3.10	1.20	0.098	3.2	5
fdp	wind facility development period	1.90	1.19	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	30.07	-0.8	52	232
annagesq	average nearest neighbor's agesq	4671	4765	0	3474	68347
annsfla1000	average nearest neighbor's sfla1000	1.73	0.53	0.45	1.6	6.8

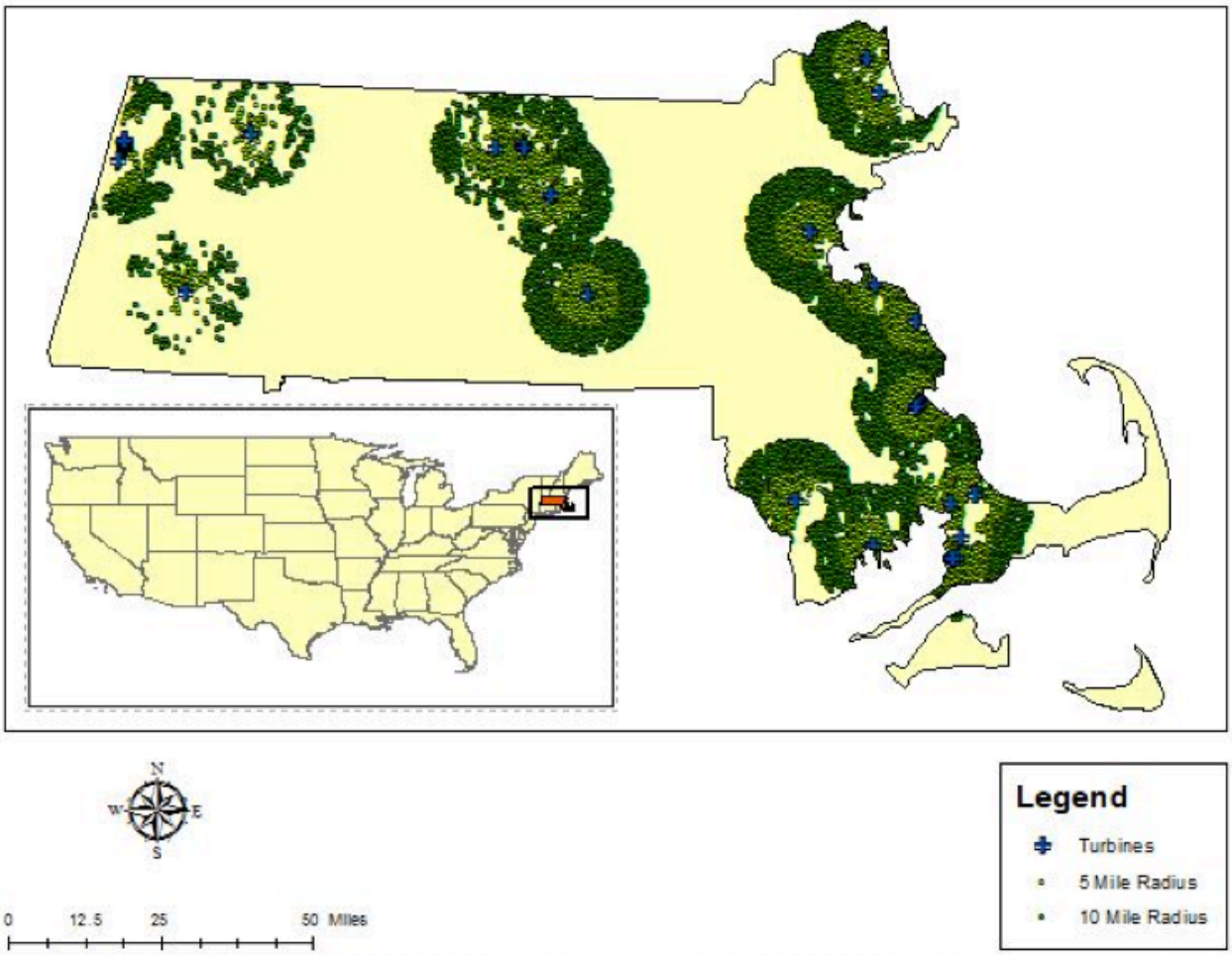
Note: Sample size for the full dataset is 122,161

* 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)

26 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



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 . The average home in the dataset of 122,161 sales from 1998 to 2012 has a sale price of $322,924, sold in 2004, in the 3 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 1.86 bathrooms, and is 3.1 miles from the nearest turbine. As summarized in Table , of the 122,161 sales within 5 miles of a turbine, 7,182 (5.8%) are within 1 mile of a turbine, 1,105 (approximately 0.5%) are within a half mile, and 121 (~ 0.1%) are within a quarter mile. In the post-construction period, 1,501 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 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).[27] 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.[28] 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 27% 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 a half mile of a beach increases a home's value by 6%–14%, being within a half mile of a high-voltage transmission line reduces value by 1%–6%, being within 500 feet of a highway reduces value by 4%–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 13% in only one of the periods, and being within a half mile of open space increases value by 0.6% in one of the periods.

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 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) -4.8%, *preanc* (less than 2 years before announcement) -6.2%, *postancprecon* (after announcement but before the nearest turbine construction commenced) -7.5%, and *postcon* (after construction commenced) -3.9%.[29] Importantly, our model estimates that home values within a half mile of a future turbine were lower than in the

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

28 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.

29 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 estimated and was no different than the post-construction effect presented here.

Table 4. Selected Results from Base Model

		Wind Facility Development Period			
		prioranc	*preanc*	*postanc-precon*	*postcon*
Variables	**Description**	**coefficient**	**coefficient**	**coefficient**	**coefficient**
		p-value	*p*-value	*p*-value	*p*-value
halfmile	halfmile: within a half mile of a wind turbine	**-4.8%*** **	**-6.2%*** **	**-7.5%*** **	**-3.9%*** **
		0.000	*0.008*	*0.000*	*0.144*
Net Difference Compared to *prioranc* Period				**-2.7%**	**0.9%**
				0.199	*0.757*
linehalf	within a half mile of a high voltage transmission line	**-1.3%*** **	**-0.1%**	**-3.5%*** **	**-6.3%*** **
		0.001	*0.904*	*0.000*	*0.000*
fillhalf	within a half mile of a landfill	**1.5%**	**-1.5%**	**0.2%**	**-13.2%*** **
		0.343	*0.647*	*0.952*	*0.001*
beachhalf	within a half mile of a beach	**6.3%*** **	**10.8%*** **	**9.7%*** **	**14%*** **
		0.000	*0.000*	*0.000*	*0.000*
prisonhalf	within a half mile of a prison	**-5.8%*** **	**2.6%**	**2.9%* **	**-2.3%**
		0.001	*0.242*	*0.098*	*0.808*
openhalf	within a half mile of open space	**0.6%** **	**0.1%**	**-0.1%**	**0.7%**
		0.023	*0.790*	*0.873*	*0.148*
hwy500	within 500 feet of a highway	**-7.4%*** **	**-5.4%*** **	**-4.1%*** **	**-5.3%*** **
		0.000	*0.000*	*0.000*	*0.000*
major500	within 500 feet of a major road	**-2.8%*** **	**-2.3%*** **	**-2.6%*** **	**-2.2%*** **
		0.000	*0.000*	*0.000*	*0.000*
sfla1000	living area in thousands of square feet	**23%*** **	**21.5%*** **	**22.5%*** **	**23.6%*** **
		0.000	*0.000*	*0.000*	*0.000*
acre	lot size in acres	**1.1%*** **	**1.8%*** **	**1.3%*** **	**0.0%**
		0.000	*0.000*	*0.000*	*0.954*
acrelt1	lot size less than 1 acre	**21.5%*** **	**17%*** **	**14.4%*** **	**21.9%*** **
		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%*** **	**8.5%*** **	**11.2%*** **
		0.000	*0.000*	*0.000*	*0.000*

Coefficients *represent the percentage change in price for every unit of change in the characteristic. Therefore 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*

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 -2.7% ([-7.5%] - [-4.8%] = -2.7%; *p*-value 0.20). The net *postcon* effect is 0.9% ([-3.9%] - [-4.8%] = 0.9%: *p*-value 0.76).[30] 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.[31] 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 in that distance range, see Table 2), providing no evidence of a large negative effect near the turbines. Further, there are significant net *postancprecon* impacts for style and heat (-3.7%) and relaxing the screens (-5.0%), 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 (-2.2%–3.3%), further reinforcing the non-significant results from the base model.

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

31 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	**coef**	**coef**	**coef**	**coef**	**coef**	**coef**	**coef**	**coef**
				p-value	*p*-value	*p*-value	*p*-value	*p*-value	*p*-value	*p*-value	*p*-value	*p*-value
	Base Model	*122,161*	*0.80*		**-4.8%*** **			**-2.7%**			**0.9%**	
					0.00			*0.20*			*0.76*	
1	Inside 1/4 mile	*122,161*	*0.80*	**-5.8%**			**12.2%**			**5.3%**		
				0.22			*0.14*			*0.94*		
2	Between 1/2 and 1 Mile	*122,161*	*0.80*		**-4.9%*** **	**-0.6%**		**-2.3%**	**1.5%**		**1.3%**	**1.1%**
					0.00	*0.35*		*0.26*	*0.18*		*0.64*	*0.37*
3	All Sales Out to 10 Miles	*312,674*	*0.82*		**-5.6%*** **			**-0.7%**			**1.3%**	
					0.00			*0.74*			*0.65*	
4	Using Outside of 5 Miles as Reference	*312,674*	*0.82*		**-7.4%*** **			**1.2%**			**1.4%**	
					0.00			*0.56*			*0.62*	
5	Including Style & Heat Variables	*120,256*	*0.81*		**-3.5%*** **			**-3.7% * **			**3.3%**	
					0.01			*0.08*			*0.27*	
6	Using Block Group	*122,161*	*0.81*		**-2.7%*** **			**-1.5%**			**-2.2%**	
					0.05			*0.48*			*0.41*	
7	No Screens	*123,518*	*0.73*		**-3.8%*** **			**-5.0%** **			**-0.3%**	
					0.01			*0.05*			*0.92*	
8	Removing Outliers and Influencers	*119,584*	*0.79*		**-4.1%*** **			**-2.9%**			**0.3%**	
					0.00			*0.13*			*0.91*	
9	Including Spatial Variables	*122,161*	*0.80*		**-5.1%*** **			**-1.9%**			**1.8%**	
					0.00			*0.37*			*0.54*	

*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.*

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 effect, we examine the coefficient in the *prioranc* period, in which sales occurred more than 2 years before a nearby wind facility was announced. The -4.8% 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.[32] 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 -4.8% and a *postcon* effect of -3.9%, the "net" effect is 0.9% 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 -2.2% to 3.3%, effectively bound the results from the base model. Therefore, in our sample of more than 122,000 sales, of which more than 21,757 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

32 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

a half mile (and that within 1 mile: n = 1,501) 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).[33] 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 -7.5% minus *prioranc* effect of -4.8%), which is -2.7% and not statistically significant. This base model result is bounded by robustness-model *postancprecon* effects ranging from -5.0% to 1.2%. Two of the robustness models reveal a statistically significant effect: -3.7% (p-value 0.08), when additional characteristics (style and heat type) of the homes are included and -5.0% (p-value 0.05) when the set of data screens is relaxed. It is unclear, however, whether these statistically significant findings result from spurious data or multicollinear parameters, examination of which is outside the scope of this research. Still, it is reasonable to say that these *postancprecon* results, which sporadically find an effect, *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 6% to 14% to price when within a half mile), high-voltage transmission lines (reducing price 1% to 6% when within a half mile), highways (reducing price 4% to 7% 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% to price when within a half mile), prisons (reducing price 6% when within a half mile), and landfills (reducing price 13% when within a half mile) also affected home prices in some models.

Our disamenity findings are in the range of findings in previous studies. For example, Des Rosiers (2002)

33 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.

found price reduction impacts ranging from 5% to 20% near high-voltage transmission lines; although those impacts faded quickly with distance. Given that we measured only the impact within a distinct distance and not how the effect changed over linear distance, our findings are not entirely comparable. However, they do seem to be consistent with the lower end of his range. 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 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, consistently seeing more value where beaches are near and less where highways, major roads, and high-voltage transmission lines are near—with sporadic value distinctions where landfills, prisons, and open spaces 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 0.25% 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 0.47% in the *postancprecon* period and then drops to 0.31% 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.[34]

34 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 from a variety of negative features (such as high-voltage 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 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. Policymakers 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.

LITERATURE CITED

Anderson, S. T. and West, S. E. (2006a) Open Space, Residential Property Values and Spatial Context. *Regional Science and Urban Economics.* 36(6): 773-789.

Anderson, S. T. and West, S. E. (2006b) Open Space, Residential Property Values, and Spatial Context. *Regional Science and Urban Economics.* 36(6): 773-789.

Andersson, H., Jonsson, L. and Ogren, M. (2010) Property Prices and Exposure to Multiple Noise Sources: Hedonic Regression with Road and Railway Noise. *Environmental & Resource Economics.* 45(1): 73-89.

Anselin, L. (2002) Under the Hood - Issues in the Specification and Interpretation of Spatial Regression Models. *Agricultural Economics.* 27(3): 247-267.

Atkinson-Palombo, C. (2010) Comparing the Capitalisation Benefits of Light-Rail Transit and Overlay Zoning for Single-Family Houses and Condos by Neighbourhood Type in Metropolitan Phoenix, Arizona. *Urban Studies.* 47(11): 2409-2426.

Barone, M. (2011) Survey of Techniques for Reduction of Wind Turbine Blade Trailing Edge Noise. Prepared for Sandia National Laboratory. August 2011.

Bateman, I., Day, B. and KLake, I. (2001) The Effect of Road Traffic on Residential Property Values: A Literature Review and Hedonic Pricing Study. Edinburgh, Scotland. 207 pages.

Benson, E. D., Hansen, J. L. and Aurthur L. Schwartz, J. (2000) Water Views and Residential Property Values. *The Appraisal Journal.* 68(3): 260-270.

Berglund, B., Hassmen, P. and Job, R. F. S. (1996) Sources and Effects of Low-Frequency Noise. *Journal of the Acoustical Society of America.* 99(5): 2985-3002.

Blanco, J. C. and Flindell, I. (2011) Property Prices in Urban Areas Affected by Road Traffic Noise. *Applied Acoustics.* 72(4): 133-141.

Bolin, K., Kedhammar, A. and Nilsson, M. E. (2012) The Influence of Background Sounds on Loudness and Annoyance of Wind Turbine Noise. *Acta Acustica United with Acustica.* 98(5): 741-748.

Bond, M. T., Seiler, V. L. and Seiler, M. J. (2002) Residential Real Estate Prices: A Room with a View. *Journal of Real Estate Research.* 23(1/2): 129-137.

Boyle, M. A. and Kiel, K. A. (2001) A Survey of House Price Hedonic Studies of the Impact of Environmental Externalities. *Journal of Real Estate Research.* 9(2): 117-144.

Braden, J. B., Feng, X. and Won, D. (2011) Waste Sites and Property Values: A Meta-Analysis. *Environmental & Resource Economics.* 50(2): 175-201.

Brandt, S. and Maennig, W. (2011) Road Noise Exposure and Residential Property Prices: Evidence from Hamburg. *Transportation Research Part D-Transport and Environment.* 16(1): 23-30.

Brannstrom, C., Jepson, W. and Persons, N. (2011) Social Perspectives on Wind-Power Development in West Texas. *Annals of the Association of American Geographers.* 101(4): 839-851.

Braunholtz, S. and MORI (2003) Public Attitudes to Windfarms: A Survey of Local Residents in Scotland. Prepared for Scottish Executive, Edinburgh, Scotland.

Butler, R. V. (1982) The Specification of Hedonic Indexes for Urban Housing. *Land Economics.* 58(1): 96-108.

Carter, J. (2011) The Effect of Wind Farms on Residential Property Values in Lee County, Illinois. Thesis Prepared for M.A. Illinois State University, Normal, Illinois. Spring 2011. 35 pages.

Clapp, J. M. and Giaccotto, C. (1998) Residential Hedonic Models: A Rational Expectations Approach to Age Effects. *Journal Of Urban Economics.* 44(3): 415-437.

Day, B., Bateman, I. and Lake, I. (2007) Beyond Implicit Prices: Recovering Theoretically Consistent and Transferable Values for Noise Avoidance from a Hedonic Property Price Model. *Environmental & Resource Economics.* 37(1): 211-232.

Dent, P. and Simms, S. (2007) What Is the Impact of Wind Farms on House Prices? Prepared for Royal Institute of Chartered Surveyors/Oxford Brookes University, Oxford, UK. March 2007.

Des Rosiers, F. (2002) Power Lines, Visual Encumbrance and House Values: A Microspatial Approach to Impact Measurement. *Journal of Real Estate Research.* 23(3): 275-301.

Devine-Wright, P. (2005) Beyond Nimbyism: Towards an Integrated Framework for Understanding Public Perceptions of Wind Energy. *Wind Energy.* 8(2): 125-139.

Devine-Wright, P. (2008) Reconsidering Public Acceptance of Renewable Energy Technologies: A Critical Review. Section in Delivering a Low Carbon Electricity System: Technologies, Economics and Policy. Cambridge University Press. Cambridge, UK.

Devine-Wright, P. (2009) Rethinking Nimbyism: The Role of Place Attachment and Place Identity in Explaining Place-Protective Action. *Journal of Community & Applied Social Psychology.* 19(6): 426-441.

Devine-Wright, P. (2011) Public Engagement with Large-Scale Renewable Energy Technologies: Breaking the Cycle of Nimbyism. *Wiley Interdisciplinary Reviews-Climate Change.* 2(1): 19-26.

Devine-Wright, P. (2012) Renewable Energy and the Public: From Nimby to Participation. Earthscan. London, UK. 336 pages. ISBN: 978-1-84407-863-9.

Devine-Wright, P. and Howes, Y. (2010) Disruption to Place Attachment and the Protection of Restorative Environments: A Wind Energy Case Study. *Journal of Environmental Psychology.* 30(3): 271-280.

Ek, K. (2005) Public and Private Attitudes Towards "Green" Electricity: The Case of Swedish Wind Power. *Energy Policy.* 33(13): 1677-1689.

Ekins, P. (2004) Step Changes for Decarbonising the Energy System: Research Needs for Renewables, Energy Efficiency and Nuclear Power. *Energy Policy.* 32(17): 1891-1904.

Eltham, D. C., Harrison, G. P. and Allen, S. J. (2008) Change in Public Attitudes Towards a Cornish Wind Farm: Implications for Planning. *Energy Policy.* 36(1): 23-33.

EU. (2012) European Commission Renewable Energy Targets by 2020.

Firestone, J. and Kempton, W. (2007) Public Opinion About Large Offshore Wind Power: Underlying Factors. *Energy Policy.* 35(3): 1584-1598.

Graham, J. B., Stephenson, J. R. and Smith, I. J. (2009) Public Perceptions of Wind Energy Developments: Case Studies from New Zealand. *Energy Policy.* 37(9): 3348-3357.

Halvorsen, R. and Palmquist, R. (1980) The Interpretation of Dummy Variables in Semilogarithmic Equations. *American Economic Review.* 70(3): 474-475.

Hasselmann, K., Latif, M., Hooss, G., Azar, C., Edenhofer, O., Jaeger, C. C., Johannessen, O. M., Kemfert, C., Welp, M. and Wokaun, A. (2003) The Challenge of Long-Term Climate Change. *Science.* 302(5652): 1923-1925.

Haugen, K. M. B. (2011) International Review of Policies and Recommendations for Wind Turbine Setbacks from Residences: Setbacks, Noise, Shadow Flicker, and Other Concerns. Prepared for Minnesota Department of Commerce: Energy Facility Permitting. October 19th, 2011.

Heintzelman, M. D. and Tuttle, C. (2012) Values in the Wind: A Hedonic Analysis of Wind Power Facilities. *Land Economics.* 88: 571-588.

Hessler, D. (2011) Best Practices Guidelines for Assessing Sound Emissions from Proposed Wind Farms and Measuring the Performance of Completed Projects. Prepared for National Association of Regulatory Utility Commissioners, Minnesota Public Utilities Commission. October 13, 2011.

Hinman, J. L. (2010) Wind Farm Proximity and Property Values: A Pooled Hedonic Regression Analysis of Property Values in Central Illinois. Thesis Prepared for M.A. Illinois State University, Normal, Illinois. May 2010. 143 pages.

Hoen, B. (2006) Impacts of Windfarm Visibility on Property Values in Madison County, New York. Thesis Prepared for Master of Arts. Bard College, Annandale-on-Hudson, NY. April 2006. 73 pages.

Hoen, B. (2012) Population Density Surrounding Wind Turbines in the United States. Lawrence Berkeley National Laboratories. New York.

Hoen, B., Wiser, R., Cappers, P., Thayer, M. and Sethi, G. (2011) Wind Energy Facilities and Residential Properties: The Effect of Proximity and View on Sales Prices. *Journal of Real Estate Research.* 33(3): 279-316.

Hoen, B., Wiser, R., Cappers, P., Thayer, M. A. and Gautam, S. (2009) The Impact of Wind Power Projects on Residential Property Values in the United States: A Multi-Site Hedonic Analysis. Prepared for Lawrence Berkeley National Laboratory, Berekley, CA. December 2009. 146 pages. LBNL-2829E.

Hoen, B., Wiser, R. and Eckholdt, H. (2010) Assessing the Impacts of Reduced Noise Operations of Wind Turbines on Neibour Annoyance: A Preliminary Analysis in Vinalhaven, Maine. Prepared for Office of Energy Efficiency and Renewable Energy Program, Wind and Hydropower Technologies Program, US Department of Energy.

Hubbard, H. H. and Shepherd, K. P. (1991) Aeroacoustics of Large Wind Turbines. *Journal of the Acoustical Society of America.* 89(6): 2495-2508.

Irwin, E. G. (2002) The Effects of Open Space on Residential Property Values. *Land Economics.* 78(4): 465-480.

Jackson, T. O. (2001) The Effects of Environmental Contamination on Real Estate: A Literature Review. *Journal of Real Estate Literature.* 9(2): 91-116.

Jackson, T. O. (2003) Methods and Techniques for Contaminated Property Valuation. *The Appraisal Journal.* 17(4): 311-320.

Jager-Waldau, A. and Ossenbrink, H. (2004) Progress of Electricity from Biomass, Wind and Photovoltaics in the European Union. *Renewable & Sustainable Energy Reviews.* 8(2): 157-182.

Jauregui, A. and Hite, D. (2010) The Impact of Real Estate Agents on House Prices near Environmental Disamenities. *Housing Policy Debate.* 20(2): 295-316.

Jepson, W., Brannstrom, C. and Persons, N. (2012) "We Don't Take the Pledge": Environmentality and Environmental Skepticism at the Epicenter of Us Wind Energy Development. *Geoforum.* 43(4): 851-863.

Jones, C. R. and Eiser, J. R. (2009) Identifying Predictors of Attitudes Towards Local Onshore Wind Development with Reference to an English Case Study. *Energy Policy.* 37(11): 4604-4614.

Jones, C. R. and Eiser, J. R. (2010) Understanding 'Local' Opposition to Wind Development in the Uk: How Big Is a Backyard? *Energy Policy.* 38(6): 3106-3117.

Kahn, M. E. (2013) Local Non-Market Quality of Life Dynamics in New Wind Farm Communities. *Energy Policy*: Available Online May 14, 2013.

Kiel, K. A. and McClain, K. T. (1995) House Price During Siting Decision Stages - the Case of an Incinerator from Rumor through Operation. *Journal of Environmental Economics and Management.* 28(2): 241-255.

Kim, K. S., Park, S. J. and Kweon, Y.-J. (2007) Highway Traffic Noise Effects on Land Price in an Urban Area. *Transportation Research Part D-Transport and Environment.* 12(4): 275-280.

Kuminoff, N. V., Parmeter, C. F. and Pope, J. C. (2010) Which Hedonic Models Can We Trust to Recover the Marginal Willingness to Pay for Environmental Amenities? *Journal of Environmental Economics and Management.* 60(3): 145-160.

Leloudas, G., Zhu, W. J., Sorensen, J. N., Shen, W. Z. and Hjort, S. (2009). Prediction and Reduction of Noise from a 2.3mw Wind Turbine. Presented at Jounral of Physics, Conference Series 75.

Moragues-Faus, A. M. and Ortiz-Miranda, D. (2010) Local Mobilisation against Windfarm Developments in Spanish Rural Areas: New Actors in the Regulation Arena. *Energy Policy.* 38(8): 4232-4240.

Nadai, A. and van der Horst, D. (2010) Wind Power Planning, Landscapes and Publics. *Land Use Policy.* 27(2): 181-184.

NARUC (2012) Wind Energy & Wind Park Siting and Zoning Best Practices and Guidance for States. Prepared for Prepared for Minnesota Public Utilities Commission., Saint Paul, MN. January 2012.

Nissenbaum, M. A., Aramini, J. J. and Hanning, C. D. (2012) Effects of Industrial Wind Turbine Noise on Sleep and Health. *Noise & Health.* 14(60): 237-243.

Oerlemans, S., Sijtsma, P. and Lopez, B. M. (2006) Location and Quantification of Noise Sources on a Wind Turbine. *Journal of Sound and Vibration.* 299(4-5): 869-883.

Pasqualetti, M. J. (2011) Opposing Wind Energy Landscapes: A Search for Common Cause. *Annals of the Association of American Geographers.* 101(4): 907-917.

Pasqualetti, M. J., Gipe, P. and Righter, R. W. (2002) A Landscape of Power. Section in Wind Power in View: Energy Landscapes in a Crowded World. San Diego Academic Press. San Diego, California.

Pedersen, E., Hallberg, L.-M. and Waye, K. P. (2007) Living in the Vicinity of Wind Turbines-a Grounded Theory Study. *Qualitative Research in Psychology.* 4(1-2): 49-63.

Pedersen, E., van den Berg, F., Bakker, R. and Bouma, J. (2010) Can Road Traffic Mask Sound from Wind Turbines? Response to Wind Turbine Sound at Different Levels of Road Traffic Sound. *Energy Policy.* 38(5): 2520-2527.

Pedersen, E. and Waye, K. P. (2007) Wind Turbine Noise, Annoyance and Self-Reported Health and Well-Being in Different Living Environments. *Occupational and Environmental Medicine.* 64(7): 480-486.

Petitjean, B., Drobeitz, R. and Kinzie, K. (2011) Wind Turbine Blade Noise Mitigation Technologies. Rome, Italy. April 12-14, 2011.

Pohl, J., Faul, F. and Mausfeld, R. (1999) Annoyance Caused by Periodic Shadow Casting (or Shadow Flickering) of Wind Turbines. Prepared for Centrum for Vindbruk, Gotland University.

Pohl, J., Faul, F. and Mausfeld, R. (2000) Harassment by Periodic Shadow of Wind Turbines: Laboratory Pilot Study. Prepared for Centrum for Vindbruk, Gotland University.

Ready, R. C. (2010) Do Landfills Always Depress Nearby Property Values? . *Journal of Real Estate Research.* 32(3): 321-339.

Rosen, S. (1974) Hedonic Prices and Implicit Markets - Product Differentiation in Pure Competition. *Journal Of Political Economy.* 82(1): 34-55.

Simons, R. A. and Saginor, J. D. (2006) A Meta-Analysis of the Effect of Environmental Contamination and Positive Amenities on Residential Real Estate Values. *Journal of Real Estate Research.* 28(1): 71-104.

Sims, S., Dent, P. and Oskrochi, G. R. (2008) Modeling the Impact of Wind Farms on House Prices in the Uk. *International Journal of Strategic Property Management.* 12(4): 251-269.

Sirmans, G. S., MacDonald, L., Macpherson, D. A. and Zietz, E. N. (2006) The Value of Housing Characteristics: A Meta Analysis. *Journal of Real Estate Finance and Economics.* 33(3): 215-240.

Slattery, M. C., Johnson, B. L., Swofford, J. A. and Pasqualetti, M. J. (2012) The Predominance of Economic Development in the Support for Large-Scale Wind Farms in the U.S. Great Plains. *Renewable & Sustainable Energy Reviews.* 16(6): 3690-3701.

Studds, T. (2013) Summary of Wind Turbine Setback Distances in Massachusetts. Letter sent to Report Authors. June 25, 2013.

Sunak, Y. and Madlener, R. (2012) The Impact of Wind Farms on Property Values: A Geographically Weighted Hedonic Pricing Model. Prepared for Institute for Future Energy Consumer Needs and Behavior (ACN), RWTH Aachen University. May, 2012 (revised March 2013). 27 pages. FCN Working Paper No. 3/2012.

Sunak, Y. and Madlener, R. (2013) The Impact of Wind Farms on Property Values: A Geographically Weighted Hedonic Pricing Model. Prepared for Institute for Future Energy Consumer Needs and Behavior (ACN), RWTH Aachen University. May, 2012 (revised March 2013). 27 pages. FCN Working Paper No. 3/2012.

Swofford, J. and Slattery, M. (2010) Public Attitudes of Wind Energy in Texas: Local Communities in Close Proximity to Wind Farms and Their Effect on Decision-Making. *Energy Policy.* 38(5): 2508-2519.

Toke, D. (2005) Explaining Wind Power Planning Outcomes: Some Findings from a Study in England and Wales. *Energy Policy.* 33(12): 1527-1539.

Toke, D., Breukers, S. and Wolsink, M. (2008) Wind Power Deployment Outcomes: How Can We Account for the Differences? *Renewable & Sustainable Energy Reviews.* 12(4): 1129-1147.

van den Berg, G. P. (2004) Effects of the Wind Profile at Night on Wind Turbine Sound. *Journal of Sound and Vibration.* 277(4-5): 955-970.

van der Horst, D. and Vermeylen, S. (2011) Local Rights to Landscape in the Global Moral Economy of Carbon. *Landscape Research.* 36(4): 455-470.

Walker, G., Devine-Wright, P., Hunter, S., High, H. and Evans, B. (2010) Trust and Community: Exploring the Meanings, Contexts and Dynamics of Community Renewable Energy. *Energy Policy.* 38(6): 2655-2663.

Warren, C. R., Lumsden, C., O'Dowd, S. and Birnie, R. V. (2005) 'Green on Green': Public Perceptions of Wind Power in Scotland and Ireland. *Journal of Environmental Planning and Management.* 48(6): 853-875.

Warren, C. R. and McFadyen, M. (2010) Does Community Ownership Affect Public Attitudes to Wind Energy? A Case Study from South-West Scotland. *Land Use Policy.* 27(2): 204-213.

Watson, R. T. (2003) Climate Change: The Political Situation. *Science.* 302(5652): 1925-1926.

Wharton, S. and Lundquist, J. K. (2012) Atmospheric Stability Affects Wind Turbine Power Collection. *Environmental Research Letters.* 7(014005).

WHO. (2011). Noise: Facts and Figures.

Wilson, D., Berg, D., Barone, M., Berg, J., Reser, B. and Lobitz, D. (2009) Active Aerodynamic Blade Control Design for Load Reduction on Large Wind Turbines.

Wiser, R. and Bolinger, M. (2012) Wind Technologies Market Report. Prepared for Lawrence Berkeley National Laboratory, Berkeley, California. DOE/GP-102012-3472, LBNL-5559E.

Wolsink, M. (2000) Wind Power and the Nimby-Myth: Institutional Capacity and the Limited Significance of Public Support. *Renewable Energy.* 21(1): 49-64.

Wolsink, M. (2007) Wind Power Implementation: The Nature of Public Attitudes: Equity and Fairness Instead of 'Backyard Motives'. *Renewable & Sustainable Energy Reviews.* 11(6): 1188-1207.

Wolsink, M. (2010) Contested Environmental Policy Infrastructure: Socio-Political Acceptance of Renewable Energy, Water, and Waste Facilities. *Environmental Impact Assessment Review.* 30(5): 302-311.

Zabel, J. E. and Guignet, D. (2012) A Hedonic Analysis of the Impact of Lust Sites on House Prices. *Resource and Energy Economics.* 34(4): 549-564.

APPENDIX: BASE MODEL FULL RESULTS

	Coef	SE	t	p-value
Intercept	12.18	0.01	1410.5	0.000
within a half mile of a wind turbine				
prioranc	-4.8%	0.01	-3.7	0.000
preanc	-6.2%	0.02	-2.66	0.008
postancprecon	-7.5%	0.02	-4.37	0.000
postcon	-3.9%	0.03	-1.46	0.144
within a half mile of a high voltage transmission line				
prioranc	-1.3%	0.00	-3.39	0.001
preanc	-0.1%	0.01	-0.12	0.904
postancprecon	-3.5%	0.01	-5.72	0.000
postcon	-6.3%	0.01	-8.05	0.000
within a half mile of a landfill				
prioranc	1.5%	0.02	0.95	0.343
preanc	-1.5%	0.03	-0.46	0.647
postancprecon	0.2%	0.03	0.06	0.952
postcon	-13.2%	0.04	-3.31	0.001
within a half mile of a beach				
prioranc	6.3%	0.01	11.97	0.000
preanc	10.8%	0.01	12.93	0.000
postancprecon	9.7%	0.01	13.39	0.000
postcon	14.0%	0.01	18.07	0.000
within a half mile of a prison				
prioranc	-5.8%	0.02	-3.35	0.001
preanc	2.6%	0.02	1.17	0.242
postancprecon	2.9%	0.02	1.65	0.098
postcon	-2.3%	0.09	-0.24	0.808
within a half mile of open space				
prioranc	0.6%	0.00	2.28	0.023
preanc	0.1%	0.00	0.27	0.790
postancprecon	-0.1%	0.00	-0.16	0.873
postcon	0.7%	0.00	1.45	0.148

	Coef	SE	t	p-value
within 500 feet of a highway				
prioranc	-7.4%	0.01	-14.32	0.000
preanc	-5.4%	0.01	-4.72	0.000
postancprecon	-4.1%	0.01	-4.5	0.000
postcon	-5.3%	0.01	-4.03	0.000
within 500 feet of a major road				
prioranc	-2.8%	0.00	-11.99	0.000
preanc	-2.3%	0.00	-5.09	0.000
postancprecon	-2.6%	0.00	-5.68	0.000
postcon	-2.2%	0.00	-4.45	0.000
living area in thousands of square feet				
prioranc	23.0%	0.00	86.38	0.000
preanc	21.5%	0.01	41.64	0.000
postancprecon	22.5%	0.00	48.28	0.000
postcon	23.6%	0.01	46.57	0.000
lot size in acres				
prioranc	1.1%	0.00	6.7	0.000
preanc	1.8%	0.00	6.31	0.000
postancprecon	1.3%	0.00	4.44	0.000
postcon	0.0%	0.00	-0.06	0.954
lot size less than 1 acre				
prioranc	21.5%	0.01	34.28	0.000
preanc	17.0%	0.01	18.16	0.000
postancprecon	14.4%	0.01	15.7	0.000
postcon	21.9%	0.01	21.42	0.000
age of the home at time of sale				
prioranc	-0.16%	0.00	-21.81	0.000
preanc	-0.16%	0.00	-11.34	0.000
postancprecon	-0.19%	0.00	-13.86	0.000
postcon	-0.24%	0.00	-16.32	0.000
age of the home at time of sale squared				
	0.00056%	0.00	13.77	0.000
preanc	0.00046%	0.00	5.72	0.000
postancprecon	0.00063%	0.00	8.79	0.000
postcon	0.00082%	0.00	10.3	0.000

	Coef	SE	t	p-value
number of bathrooms				
	6.36%	0.00	29.18	0.000
preanc	7.88%	0.00	17.86	0.000
postancprecon	8.49%	0.00	20.56	0.000
postcon	11.15%	0.00	25.63	0.000
sy				
1998	-0.52	0.01	-73.84	0.000
1999	-0.41	0.01	-58.82	0.000
2000	-0.27	0.01	-38.01	0.000
2001	-0.13	0.01	-18.44	0.000
2002	0.01	0.01	1.81	0.070
2003	0.14	0.01	20.64	0.000
2004	0.24	0.01	36.36	0.000
2005	0.31	0.01	48.66	0.000
2006	0.27	0.01	43.31	0.000
2007	0.23	0.01	37.1	0.000
2008	0.12	0.01	18.23	0.000
2009	0.04	0.01	7.01	0.000
2010	0.04	0.01	5.95	0.000
2011	-0.02	0.01	-3.92	0.000
2012	Omitted			
sq				
1	-0.07	0.00	-28	0.000
2	-0.02	0.00	-9.55	0.000
3	Omitted			
4	-0.01	0.00	-2.88	0.004

n	**122,161**
R^2	**0.80**
Adj R^2	**0.80**
F	**2543**

ACKNOWLEDGEMENTS & DISCLAIMERS

Funding for this study was provided, in part, by the Massachusetts Clean Energy Center (MassCEC). MassCEC is a quasi-public agency dedicated to accelerating the success of clean energy technologies, companies, and projects in Massachusetts while creating responsibly-sited generation projects, high quality jobs, and long-term economic growth for the people of Massachusetts. MassCEC provides seed investments to startup companies and renewable energy rebates for residents and businesses, and it supports the development of a local clean energy workforce. Since its inception in 2009, MassCEC has helped clean energy companies grow, supported municipal clean energy projects, and invested in residential and commercial renewable energy installations, creating a robust marketplace for innovative clean technology companies and service providers. The views and opinions of authors expressed herein do not necessarily state or reflect those of the Massachusetts government, any agency thereof, or the MassCEC.

Additional funding was provided (to support Ben Hoen's contribution) by the U.S. Department of Energy's Wind & Water Power Program, within the Office of Energy Efficiency and Renewable Energy, under Contract No. DE-AC02-05CH1123.

Therefore, this document was prepared, in part, as an account of work sponsored by the United States Government. While this document is believed to contain correct information, neither the United States Government nor any agency thereof, nor The Regents of the University of California, nor any of their employees, makes any warranty, express or implied, or assumes any legal responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by its trade name, trademark, manufacturer, or otherwise, does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof, or The Regents of the University of California. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof, or The Regents of the University of California.

Ernest Orlando Lawrence Berkeley National Laboratory is an equal opportunity employer.

The authors would like to thank the following people for their substantive comments and suggestions on this report and an earlier version: Dr. Thomas Jackson, Texas A&M University; Dr. Corey Lang, University of Rhode Island; Dr. Mark Thayer, San Diego State University; and Dr. Jeffrey Zabel, Tufts University.

DISCLAIMER

This document was prepared as an account of work sponsored by the United States Government. While this document is believed to contain correct information, neither the United States Government nor any agency thereof, nor the Regents of the University of California, nor any of their employees, makes any warranty, express or implied, or assumes any legal responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by its trade name, trademark, manufacturer, or otherwise, does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof, or the Regents of the University of California. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof or the Regents of the University of California.

DE-AC02-05CH11231