2023

Property value impacts of onshore wind energy in New England: The importance of spatial heterogeneity and temporal dynamics

Luran Dong
University of Rhode Island

Vasundhara Gaur

Corey Lang
University of Rhode Island, clang@uri.edu

Citation/Publisher Attribution
Dong, L., Gaur, V., & Lang, C. (2023). Property value impacts of onshore wind energy in New England: The importance of spatial heterogeneity and temporal dynamics. *Energy Policy*, *179*, 113643. https://doi.org/10.1016/j.enpol.2023.113643
Available at: https://doi.org/10.1016/j.enpol.2023.113643

Forthcoming, Energy Policy

Property Value Impacts of Onshore Wind Energy in New England: The Importance of Spatial Heterogeneity and Temporal Dynamics

Luran Dong, Vasundhara Gaur, and Corey Lang*

Abstract
The purpose of this paper is to update and extend prior studies that examine the impact of onshore wind turbines on property values. Our data come from Massachusetts and Rhode Island, two states that are population dense and rapidly transitioning to renewable energy. We use a difference-in-differences identification strategy with treatment defined by proximity. In contrast to prior research in these states, our results suggest that property values decline when wind turbines are built. These negative impacts are mostly confined to properties within 1 km of a turbine. However, we delve deeper into these aggregate results by examining how treatment effects vary for different regions and how treatment effects vary over time. Importantly, we find that the negative impacts found are almost entirely driven by Cape Cod and Nantucket, Massachusetts. We estimate small and typically insignificant effects for other regions of Massachusetts and Rhode Island. Further, we estimate dynamic models that allow for heterogeneous treatment effects in time since construction. These results suggest that negative impacts abate over time, though in the case of Cape Cod and Nantucket never go to zero. Possible explanations for our complex findings include contagion from opposition to Cape Wind, preference-based sorting, and acclimatization.

Keywords: Onshore wind energy, hedonic model, valuation, property values,
JEL Codes: Q42, Q51

*Corresponding author. Address: 214 Coastal Institute, 1 Greenhouse Rd., Kingston, RI, 02881. Email: clang@uri.edu.
We thank two anonymous reviewers and conference participants at NAREA for valuable feedback. We thank Ben Hoen for help with the Hitachi Velocity Suite. This work was supported by the USDA National Institute of Food and Agriculture, Agricultural and Food Research Initiative Competitive Program, Critical Agricultural Research and Extension, grant number 2019-68008-29826.

1 Introduction

To mitigate climate change and improve air quality, the world is in the midst of a transition to renewable energy. In recent years, the development of wind energy has increased significantly. Cumulative US wind capacity increased 200% between 2010 and 2020 from 40.35 GW to 121.99 GW (Department of Energy 2021). Further, virtually all this increase has been onshore, as opposed to offshore.

Given the growth of wind energy, empirical assessment of externalities is an important area of research. Externalities associated with onshore wind include views, noise, and shadow flicker. One common framework to examine these externalities is the hedonic price method (HPM), which analyzes the prices people are willing to pay for residential housing near wind turbines relative to similar properties further away, and hence reveal preferences. HPM studies in Europe tend to find consistent negative effects of wind turbines on property values (Gibbons 2015, Dröes and Koster 2016, Sunak and Madlener 2016, Jarvis 2021, Dröes and Koster 2021). In contrast, studies focused in the United States and Canada are inconsistent. Several studies find no effect (Lang et al. 2014, Hoen et al. 2015, Hoen and Atkinson-Palombo 2016), but others do find negatives (Heintzelman and Tuttle 2012, Heintzelman et al. 2017). Vyn (2018) finds both negative and null effects when communities are split based on expressed opposition to wind development via municipal resolution. However, the US-Canada literature is lacking because all of it is either dated or is based on samples with few proximate properties.

The purpose of this paper is to provide an updated analysis of property value impacts of onshore wind turbines in the United States and to extend prior analyses by examining spatial and temporal heterogeneity in price effects. We specifically focus on the states of Massachusetts (MA) and Rhode Island (RI) in southern New England. These states were the setting for the studies by Lang et al. (2014) and Hoen and Atkinson-Palombo (2016), and both states are relatively population dense compared to other wind energy areas like the rural areas of the Midwest and Texas. The combination of high population density and rapid wind energy development yields many properties proximate to turbines, which in turn enables precise estimation of externalities. Hoen and Atkinson-Palombo (2016) include transactions through 2012, and Lang et al. (2014) include just a couple more months through February 2013. In the current paper, we observe transactions starting in January 2000 and going through June 2019, which yields substantially more post-construction observations and many more installed wind turbines. We analyze this updated dataset using similar difference-in-differences (DID) methods as Lang et al. (2014) and Hoen and Atkinson-Palombo (2016).

The specific research questions we ask are: 1) Are property values impacted by nearby wind turbine development? 2) Are price impacts heterogeneous for different regions? And 3) How do price impacts evolve as a function of time since construction?

Our analysis focusing on our first research question yields results that suggest that property values decline when wind turbines are built, and the impacts are mostly confined to within 1 km. Our basic DID model suggests that properties within one kilometer (km) of a turbine site decrease in value about 2.5%-4.6% after construction relative to properties three to ten km away, though not all specifications yield statistically significant coefficients. We find no evidence that properties one to two km or two to three km from a turbine site decline in value, indicating the effect is highly localized. There is also suggestive evidence that values begin to decline in the two years leading up to project completion, which we interpret as anticipation effects. For research question 2, we split our sample area into four regions and estimate separate DID models for each. We only estimate consistent negative price impacts for the region consisting of Cape Cod and Nantucket, MA, and the price impacts are much larger, ranging from -7.0% to -10.8%. In contrast, coefficients for the other three regions are much smaller in magnitude and usually statistically insignificant. For research question 3, we estimate models that allow price impacts to vary as a function of years since construction, and this model reveals critical patterns that place nuance on the baseline DID results. For the whole sample combined, as well as our geographic subsets, we find that that price impacts often follow a “U-shaped” pattern, meaning nearby prices start declining in the pre-construction time period, reach a maximum impact shortly after construction completes, and then start rebounding. For areas excluding Cape Cod and Nantucket, price impacts abate to zero relatively quickly. However, for Cape Cod and Nantucket, while price impacts do rebound some, they remain around -9% up to nine years post construction. We posit several theories that could explain the results in the conclusion.

This paper contributes to the literature discussed above by updating US-based HPM onshore wind energy externality estimates and adding nuance to our understanding of where and for how long price impacts occur. We investigate two important avenues for heterogeneity in treatment effects. The first, spatial heterogeneity, is rarely examined; typically, papers estimate a single model for all regions. Prior literature conducted in MA and RI (Lang et al. 2014, Hoen and Atkinson-Palombo 2016) found no evidence of price impacts. These findings are mostly consistent with the current findings because in three of our four regions we also find no consistent negative effects. By disaggregating our sample area, we find that negative impacts do exist, but are contained in just one area. The second avenue of price effect heterogeneity we investigate is by time since construction. This is also rarely examined; to the best of our knowledge, only two papers estimate dynamic effects. Using data from the Netherlands, Dröes and Koster (2016) find negative treatment effects diminish some over time but stabilize at a non-zero level. Jarvis's (2021) estimated dynamics show some evidence of a U-shaped pattern, but his estimates only extend four years post construction.

This paper also contributes to our broader understanding of externalities of renewable energy sources. Recently a series of papers have explored property value impacts of utility-scale solar energy (Abashidze 2019, Dröes and Koster 2021, Jarvis 2021, Elmallah et al. 2023, Gaur and Lang 2023), with several papers finding negative house price effects, in both the US and EU. Intuition regarding which renewable source has stronger negative effects can go both ways. Wind turbines are noisier, more visible, and create shadow flicker for some properties. However, utility-scale solar is more land intensive (Trainor et al. 2016), and development on agricultural and forested lands seem to be key drivers for the negative house price effects and disapproval found (Elmallah et al. 2023, Gaur and Lang 2023, Gaur et al. 2023). While we by no means clear up this debate, our results suggest that the ordering depends on the location. Utility-scale solar tends to be more recently developed than wind turbines, and the dynamic analysis of changing treatment effects is more limited with solar. It will be important to update these studies in some years. Offshore wind brings different concerns than onshore wind, with possible negative effects on property values focused almost exclusively on adulterated ocean views. While nascent, the HPM and HPM-adjacent literature finds offshore wind does not negatively affect property values (Jensen et al. 2018, Dong and Lang 2022), and can even boost the vacation rental market (Carr-Harris and Lang 2019).

The paper proceeds as follows. In Section 2, we provide details on data sources and dataset assembly. Section 3 presents our difference-in-differences methodology and discusses support for the assumptions necessary for causal inference. In Section 4, we present results, starting with all regions combined and then analyzing regions separately to test for heterogeneity.

Section 5 concludes and offers policy implications. The manuscript is also supported by an online appendix, which provides supplementary analysis.

2 Data

2.1 Wind Turbines

We obtain information on wind turbine installations from two sources: the United States Wind Turbine Database (USWTDB), and the Energy Information Administration's (EIA's) report EIA-860M, or the Monthly Update to the Annual Electric Generator Report. We restrict the data to turbines that were constructed between January 2001 and December 2019. The USWTDB includes information on capacity, location (latitude and longitude), and the year of operation of all onshore wind turbines in MA and RI. One drawback of this dataset is that only the year of turbine operation is reported and not month, which is imprecise. We therefore use the EIA-860M dataset which includes information on the month of operation for 89 onshore turbines in MA and RI that have a 1 megawatt (MW) or larger capacity.[1] For the remaining 30 turbines (<1 MW), we assume that the operation month is July.[2] Our combined dataset consists of 119 turbines. Figure 1 represents a map our sample turbine locations. The installations are well dispersed across all regions in both states, which increases confidence that estimates will not be affected by unobserved regional shocks.

An important deficiency of our wind turbine dataset is that it does not include the date the turbine was announced or proposed and the date that construction began or was completed. We rely on Hitachi Velocity Suite[3] that has compiled average lengths of time from announcement to construction and from construction to generation across hundreds of wind energy projects. Based on this information, the construction completion date is defined as 8 months prior to the operation date, and the announcement date is defined as 30 months prior to operation date.[4]

[1] The EIA-860M does not record information on any energy generation plants that have a capacity less than 1 MW.
[2] This assumption is certainly ad hoc, but we test the robustness of results to alternative assumptions about the month of generation. Table A1 in the online appendix presents results, which are near-identical to the main results.
[3] https://www.hitachienergy.com/us/en/products-and-solutions/energy-portfolio-management/market-intelligence-services/velocity-suite
[4] These estimates come from wind energy developments of size 5 MW or less built in the United States. The average number of days between construction complete and generation is 244.8, which we round to 8 months. The average number of days between announcement and construction complete is 645.5, which we round to 22 months, and implying 30 months between announcement and generation. We assess robustness of these timelines in the online appendix.

Figure 2 graphs new and cumulative wind capacity by year. The first installation began operation in June 2001, but that was a bit anomalous as no other capacity was added until 2006. New capacity remained low (<5 MW) through 2008, but then increased substantially in 2009-2011. 2012 was by far the single largest increase in capacity, with 61.78 MW being added, 36.32% of total capacity installed through 2019. New capacity was low again in 2013-2015, but then rebounded to higher levels in 2016 and beyond. As of August 2019, the cumulative wind capacity in MA and RI is 170 MW. Capacity factors for this region are about 25% (Wiser et al. 2021), which means these wind turbines are collectively producing about 372.3 Gigawatt hours (GWh) of electricity per year, which is enough to provide electricity to about 45,342 New England homes.[5]

2.2 Housing transactions

We use ZTRAX housing transaction data from Zillow (http://www.zillow.com/data) for MA and RI. The dataset includes sales prices, street addresses, geographic coordinates, Census divisions, transaction dates, and property characteristics (bedrooms, bathrooms, etc.). We include transactions that occurred between January 2000 and June 2019. Sales prices are adjusted to 2019 levels using the Northeast regional housing Consumer Price Index from Bureau of Labor Statistics. We spatially merge the turbine data with the property dataset by matching every property to the nearest eventual site of turbine development to infer proximity. We limit the geographic scope of the sample to properties within 10 km of the nearest eventual turbine site.

We made the following sample cuts. We include only single-family housing and exclude condominiums. We exclude transactions with missing observations for sales price, bedrooms, and bathrooms. We also drop groups of properties with the same latitudes and longitudes, but different addresses because this indicates incorrect geocoordinates (Nolte et. al. 2021). After dropping transactions with prices of $100 or less, since these are clearly not arms-length transactions, we drop transactions in the bottom and top 5% of the sales price distribution to get rid of outliers. Further, we drop observations that have more than four stories, six bedrooms, five full bathrooms, or three half bathrooms. Houses that underwent major reconstruction are dropped since they may have different attributes in previous transactions. We exclude homes that sell before they were built, as there is evidence these are lot sales without improved property.

[5] EIA (2022) estimates average annual electricity usage of homes in the Northeast United States to be 8,211 kWh.

Properties that transact more than once on the same date are likely to be subdivisions and are therefore excluded. The final dataset used for regression includes 369,260 transactions.

2.3 Summary statistics

Table 1 presents summary statistics for our sample properties. The first column presents sample means for the entire sample. The average sales price is $362,650 (adjusted to 2019 levels). The houses on average have just over three bedrooms and just over 3000 square feet of living area. Only 4% of houses have a pool and about one-third have central air conditioning. We discuss Columns 2-4 in Section 3.1 below.

3 Methods

We develop a difference-in-differences (DID) hedonic valuation model to analyze the causal impact of wind installations on housing prices. This is a standard but powerful model for causal inference of location-based amenities or disamenities in the housing market. Prior research on turbine externalities used DID (Lang et al. 2014, Gibbons 2015, Hoen et al. 2015, Dröes and Koster 2016, Hoen and Atkinson-Palombo 2016, Vyn 2018, Jarvis 2021, Dröes and Koster 2021), as well as hedonic research about fossil fuel power plants and fracking. We begin with a standard hedonic DID setup, in which treatment and control are defined based on proximity. Properties located near turbines are compared to similar properties that are further away from such installations, before and after construction.

Within this framework, we make two important modeling choices. First, we are unsure about the range of treatment effects, so we define distance bins in 1 km increments for properties that are 0 to 3 km from an eventual turbine site, and the evolution of these properties' prices are compared to the control group of properties located 3 to 10 km away. Second, we model an anticipation effect in addition to a post-construction effect. If externalities are present, it is likely that some of those externalities or expectations about future externalities are capitalized into prices before the turbine is fully constructed. To account for this period, we include in our model a time period called PAPC, which stands for "post-announcement, pre-construction". As discussed above, we define this period as between 30 and 8 months prior to generation commencing. We define the period PC ("post-construction") as any time after 8 months prior to generation commencing. The addition of the PAPC time period will account for any capitalization prior to construction completion, which if not accounted for could bias post-construction treatment effects.[6]

Table 2 presents the distribution of transactions across the four distance bands for the three time periods. For identifying the effect of proximity on prices, we need a substantial number of observations in close range. There are 8,153 transactions within 1 km, with nearly half occurring PC, which should be sufficient for identifying an effect if it is there. This table makes clear the benefits of examining wind turbine valuation in population dense states. In addition, Table 2 gives the proportion of transactions occurring in each distance band for each time period, which can give a sense of whether transaction volume is substantially different for treated distance intervals in either PAPC or PC. The proportions appear roughly constant across time suggesting neither announcement nor construction affects transaction volume.

Our baseline DID specification is as follows:

$$\begin{aligned} \ln(price_{icmt}) = \beta_0 &+ \sum_{k=1}^{3} \beta_1^k \left(dist_i^k\right) + \beta_2 PAPC_{imt} + \beta_3 PC_{imt} \\ &+ \sum_{k=1}^{3} \beta_4^k \left(dist_i^k \times PAPC_{imt}\right) + \sum_{k=1}^{3} \beta_5^k \left(dist_i^k \times PC_{imt}\right) \\ &+ \boldsymbol{X_i \beta_6} + \gamma_{mt} + \delta_{ct} + \varepsilon_{icmt} \end{aligned} \tag{1}$$

$\ln(price_{icmt})$ is the natural log of sales price of property i located in county c that transacts in month m and year t. $dist_i^k$ is a dummy variable equal to one if a property i lies within the k^{th} distance band to the nearest turbine site. The distance bands are defined as 0-1 km, 1-2 km, and 2-3 km; the 3-10 km distance band is the omitted, or reference, group. $PAPC_{imt}$ is a binary variable equal to one if the transaction occurs between 30 and 8 months prior to generation commencing. PC_{imt} is a binary variable equal to one if the transaction occurs in the time after wind turbine construction is complete, which we assume is 8 months prior to generation commencing. The omitted, or reference, time period is PA ("pre-announcement"), which is transactions occurring more than 30 months before generation commences. $\boldsymbol{X_i}$ is a set of property-specific, time-invariant control variables, including structural characteristics (e.g., bedrooms and bathrooms) and spatial fixed effects that control for unobserved, spatially

[6] Tables A2 and A3 in the online appendix assess robustness of the main results using alternative lengths of time for the announcement and construction dates. Results are quite similar, though as the construction complete time is closer to the generation time, there is evidence of negative housing price effects in the PAPC time period.

delineated price determinants (e.g., school quality, proximity to other amenities and disamenities, traffic volume, walkability, etc.) that may be correlated with treatment. We estimate models that use Census blocks as the spatial fixed effects, as well as models that use individual properties as the spatial fixed effects, which is a repeat sales model, and will additionally control for unobservable elements of the property that may be correlated with treatment. γ_{mt} are month-year fixed effects to control for common price fluctuations across all areas. We also include county-year fixed effects, δ_{ct}, in some specifications to control for localized price variation. Lastly, ε_{icmt} is the error term. In all models, we cluster standard errors at the census tract level to allow for correlated errors within a larger area. β_4^k and β_5^k are the difference-in-differences coefficients of interest. β_4^k measures price changes between the PA and PAPC time periods for each of the k distance bands relative to properties 3-10 km away. β_5^k measures price changes between the PA and PC time periods for each of the k distance bands relative to properties 3-10 km away.

The second model we estimate is a similar DID model but allows for heterogeneous treatment effects in the post construction time period. We refer to this as our dynamic specification. Results from these models are exclusively presented in the online appendix. In the main text, we rely on event-study style graphs to assess the dynamics of treatment effects.

3.1 Assessing the DID Assumptions

A critical assumption of DID designs is that treatment and control outcome trends would be similar in the absence of treatment occurring. While this cannot be verified, we examine pre-treatment trends to assess the likelihood that this assumption holds. Figure 3 presents a graph of estimated differences between housing prices in the 0-1 km distance bin and the 3-10 km distance bin for one-year increments. Time zero is when generation commences, and we have plotted vertical lines for the approximate times of the beginning of the PAPC period and the beginning of the PC period (and end of the PAPC period). We use the estimates before the beginning of the PAPC period to assess parallel trends. All coefficient estimates for the pre-treatment time are very similar, close to zero, and show no evidence of any trend. Hence, we have strong confidence that the parallel trends assumption holds in this case.

If we look beyond the pre-treatment period, Figure 3 also previews our results. During the PAPC period, prices in the 0-1 km distance bin begin to decline relative to the 3-10 km distance bin. Price differences continue through the beginning of the PC period, but then begin to abate. By eight years after generation commences, differences are back to zero. These results suggest that treatment effects change over time, declining at first, but then rebounding completely. We test this more robustly using our dynamic model (Equation 2).

Returning to Table 1, we can also bolster the parallel trends assumption by comparing the statistical overlap between treatment and control properties. Columns 2 and 3 of Table 1 present sample means between properties within 1 km of an eventual turbine site (those most treated) and properties 3 to 10 km of an eventual turbine site (control), before treatment occurs. The last column statistically compares the means by presenting the normalized difference (Imbens and Wooldridge 2009). On average, control properties are worth more and are larger in terms of square feet, bedrooms and bathrooms. However, only the difference in fireplaces is statistically significant, as the normalized difference in means exceeds the 0.25 threshold. Overall, these comparisons suggest that our treatment and control properties are similar, which makes sense given the spatial proximity, and the control properties will provide a high-quality counterfactual for the treatment group.

The second necessary assumption of DID is the stable unit treatment value assumption (or SUTVA), which posits that control observations are not impacted by treatment. In our case, we are assuming properties 3-10 km from an eventual turbine site are not impacted by the turbines. In our regression models, we estimate effects for distance bins out to three km. Empirically, we find no impact of turbines in the final bin (2-3 km), so we believe this supports the assumption that no impacts would be felt by properties even further away.

4 Results

Table 3 presents baseline results from estimating Equation (1). We present four specifications to assess robustness of the results to modeling choices. The first two columns use Census block fixed effects and the third and fourth column include property fixed effects instead. Columns 2 and 4 additionally include county-year fixed effects.

The first set of coefficients are the conditional differences in prices between the three treatment bins and the control properties in the PA time period (β_1^k in Equation (1)). These are only identified in Columns 1 and 2 as they are collinear with property fixed effects in Columns 3 and 4. The results suggest no statistical differences between the treatment properties and control properties.

The second set of coefficients are the conditional differences in prices between the PA and PAPC periods and the PA and PC periods for the control properties (β_2 and β_3 in Equation (1)). Columns 1 and 3 show evidence of price declines, though Columns 2 and 4 show no such changes. Keep in mind all columns include year-month fixed effects, so these results do not indicate prices are actually declining over this time. Neither the first nor the second set of coefficients are causally identified, so we do not place tremendous weight on their interpretation, but they are presented for completeness.

The third set of coefficients are those of most interest, the DID treatment effects. These provide the estimated changes in prices for the treatment bins relative to the control group from the PA period to the PAPC period or the PC period (β_4^k and β_5^k, respectively, in Equation (1)). In the PAPC time period, none of the coefficients are statistically significantly different than zero, suggesting no evidence of anticipation effects. However, the coefficients for the 0-1 km bin are all negative, ranging from -0.010 to -0.023. Further, these coefficients are all more negative than the 1-2 km bin estimates, which in turn are all more negative than the 2-3 km bin estimates. All together, these results provide some evidence that there are weak anticipatory effects that are monotonically decreasing with distance from the turbine. Anticipation effects are also observed in Figure 3, and those estimates suggest that they become more negative as time goes on. Because the estimates in Table 3 are an average of the effect for the whole time period, they may miss some of the effect.

In the PC time period, the coefficients for the 0-1 km bin range from -0.025 to -0.046, but only two of them are statistically significant. Given the average house price for the 0-1 km bin in the PA time period was \$354,242, the point estimates imply property value losses ranging from \$8,856 to \$16,295. There is no evidence of price changes in either the 1-2 km bin or the 2-3 km bin, indicating that wind turbine externalities are limited to a 1 km radius.[7]

Our third research question focuses on heterogeneity of price impacts in the post construction time period. We see some evidence of how valuation evolves over time in Figure 3, which suggests a "U-shaped" pattern, meaning that price impacts grow in anticipation of wind turbine construction, reach their largest level in the first full year following construction, and then begin to rebound eventually reaching zero impact. To investigate this further, we develop

[7] Table A4 in the online appendix assesses robustness of results to changing the control group definition. DID results are very similar using different distances.

and estimate a version of Equation (1) that allows treatment effects to vary in three years bins (see Equation (A1)). Table A6 presents results. We find that the results are largely consistent with our main findings and confirm the trend we observe in Figure 3. Specifically, we find that prices decline on average 7.7% in the first three years following construction, but this effect abates to only 5.7% in the next three years. Beyond six years, none of the coefficients are statistically significant and all are much smaller in magnitude than the first six years.

4.1 Heterogeneity by region

We now turn to our second research question about whether price impacts vary across regions. We divided our study area into four regions, three for Massachusetts and then one for Rhode Island.[8] The split for Massachusetts is somewhat ad hoc, but is based on similarities in geography and housing markets. It is essentially one for Western MA, which is primarily rural, one for Eastern MA, which is more urban and suburban, and then one for Cape Cod and Nantucket Island, which are coastal and high income. No turbines exist in our sample on Martha's Vineyard, otherwise it would be included in the last region too.

Table 4 presents results for the heterogeneity analysis. Each panel presents coefficients obtained by estimating Equation (1) on the different geographic subsets of our data. Columns 1 – 4 are as described in Table 3. We only present estimated values of β_5^1 (i.e., the coefficients associated with the 0 – 1 km bin in the PC period) because that is where price impacts are most likely to show up.

All coefficients in Panel A (Western Massachusetts) are negative and range between -0.037 and -0.056. The coefficient in Column (1) is the only one that is significant (at the 5% level), which provides weak evidence of housing price declines in Western Massachusetts as a result of proximity to wind turbines. However, given the lack of significance in all other columns, we do not have much confidence in these effects.

In Panel B we present coefficients estimated for the subset of properties located in Eastern Massachusetts (excluding Cape Cod and Nantucket). The coefficients range

[8] This is similar to prior research that has estimated separate models for cities or states in order to assess heterogeneity or estimate a demand function (e.g., Zabel and Kiel 2000, Blanchette et al. 2021, Elmallah et al. 2023).

between -0.020 and 0.012, and none are significant. This suggests that wind turbines have no statistical impact on housing prices in this region.

In Panel C we present coefficients estimated for the regions of Cape Cod and Nantucket. We find that all coefficients are highly significant (at the 1% level) and range between -0.070 and -0.108. This implies that properties lying within 1 km of wind turbines experience large decreases in prices, ranging from -7.0% to -10.8%, following turbine construction. Given that the average pre-turbine construction housing price in these areas is $373,422, these estimates translate to a loss between $26,140 and $40,330.

Panel D presents coefficients estimated using the sample of observations from Rhode Island. We find that the coefficients vary in sign, magnitude, and significance across columns, ranging between -0.058 and 0.006. The coefficient in Column 4 is the only one that is significant (at the 1% level), suggesting a 5.8% decline in housing prices for properties within 1 km of wind turbines in Rhode Island, post construction. Similar to Panel A, since the effect is not robust across specifications in either magnitude or significance, we do not have much confidence in this estimate.

In sum, Table 4 suggests that substantial heterogeneity exists in the property value impacts of onshore wind turbines. In only one of four regions are consistent, negative, statistically significant results found. In turn, this implies that the negative estimates shown in Table 3 were driven almost entirely by a single region, and that those results do not generalize.

Given this spatial heterogeneity, we return to our third research question about heterogeneity across time since construction. For this analysis, we combine the three regions that showed no consistent price impacts and compare those price trends to Cape Cod and Nantucket. Figures 4a and 4b present event study trends using exactly the same method as used to create Figure 3, except we now subset the data.

Figure 4a presents estimated price dynamics for the study area excluding Cape Cod and Nantucket. We find that prices are statistically indistinguishable from zero in the PA and PAPC time periods. In the PC period, there is a statistically significant (at the 5% level) decline in housing prices in the year immediately after construction. However, the market quickly adjusts, and we see a general upward trend in coefficients following the initial decline. Coefficients return and even exceed zero by five years post construction, though none of those coefficients are significant. Table A7 in the online appendix provides regression evidence that supplements

Figure 4a. The post construction period is split into bins of three years each. Results indicate that prices decline 4.6% in the first three years following construction, and then return to pre-construction levels in year four and beyond.

Figure 4b presents estimated price dynamics for Cape Cod and Nantucket. We find a sharp and statistically significant decline in prices starting 2-3 years pre-construction, and this effect continues to remain negative and statistically significant throughout the PAPC and PC time periods. Prices bottom out in the second year post construction and then start to rebound. However, in contrast to 4a, the coefficients remain highly negative, and only reach about -8% in the eighth year post construction. Table A8 in the online appendix provides regression evidence that supplements Figure 4b, again estimating separate coefficients for each three-year bin. We find large, negative effects for all time period bins, with the magnitude of the effect abating only slightly over time. Prices are significantly lower (by 9.2%) even nine years post construction compared to pre-treatment levels, suggesting that properties in Cape Cod and Nantucket experience larger and more persistent price declines post turbine construction, compared to other regions in MA and RI.

5 Conclusion and Policy Implications

This paper estimates externalities associated with onshore wind turbines using hedonic valuation. We examine the same regions as previous research, Lang et al. (2014) and Hoen and Atkinson-Palombo (2016), but use more than six years of additional transactions and turbine developments. The additional data allow us to explore heterogeneity in price effects for different regions and as a function of time since construction, which lead to new insights and different conclusions. In terms of spatial heterogeneity, we only estimate consistent, negative price impacts in one of the four regions in our study, Cape Cod and Nantucket. But these impacts are large relative to estimates in the literature, ranging from -7.0% to -10.8%. In terms of temporal heterogeneity, we generally find that that price impacts often follow a “U-shaped” pattern, meaning nearby prices start declining in the pre-construction time period, reach a maximum impact shortly after construction completes, and then start rebounding. For areas excluding Cape Cod and Nantucket, price impacts abate to zero relatively quickly. However, for Cape Cod and Nantucket, while price impacts do rebound some, they remain around -9% up to nine years post construction. Dröes and Koster (2016) find a similar pattern that negative impacts dissipate as time since construction increases, but never disappear completely.

What is the explanation for our results? We begin by thinking about the disparities between Cape Cod/Nantucket and the rest of the study area. One possible explanation is contagion from opposition to Cape Wind. Cape Wind was a proposed offshore wind farm sited in between Cape Cod and Nantucket Island. It was proposed in 2001 and faced immediate, well-funded opposition, including from high profile politicians such as Senator Ted Kennedy (Haughton et al. 2003). Firestone and Kempton (2007) conducted a survey of Cape Cod, Nantucket, and Martha's Vineyard residents and found strong opposition to the project. Haughton et al. (2003) surveyed Cape Cod homeowners and found that they expected property values to decline an average of 4% if Cape Wind would be built; that number rose to 10.9% for coastal homeowners. Despite the project receiving several state approvals, the project was ultimately scrapped about a decade after being proposed. We theorize that the opposition to Cape Wind spilled over into dislike of onshore wind in that region, and that led home buyers and sellers to negatively value proximity to turbines. We cannot test this hypothesis, but Vyn (2018) offers some corroborating evidence. He finds that municipalities that pass a symbolic resolution against wind energy experience negative housing market impacts of wind turbine proximity, whereas no such disamenity valuation exists in municipalities that do not pass such a resolution. Preferences could be different across regions, or preferences could be impacted by events and leaders.

For the U-shaped dynamic effects, we posit two, non-mutually exclusive, possible explanations for our results, with both receiving support from qualitative research. Devine-Wright (2005) argues that renewable energy acceptance may be U-shaped, with initially high levels of approval before a project, low levels of approval during construction and maybe the first few years after construction, and finally high levels of approval as people get used to it. Our results, particularly those excluding Cape Cod and Nantucket (Figure 4a), fit this story well because prices begin to dip pre-construction, reach a nadir in the first couple years following construction, and then begin to rebound. Wilson and Dyke (2016) conduct a "before-after" study on a panel of respondents near a wind installation in England. They find that on average attitudes became more favorable to the project several years after construction was complete compared to the planning stages. A second explanation involves preference-based residential sorting (Tiebout

1956). Existing residents may not like new turbines being built in places they hold dear and may be willing to sell at a discount. But new residents may move in who either are indifferent or admire the turbines, and prices return to parity with properties further away from the turbines. Hoen et al. (2019) conduct a cross sectional survey of household living near wind turbines. They find evidence of sorting because people who moved in after construction had more favorable views of turbines than those who lived there before construction. In addition, they find slight evidence that opinions are more favorable the longer the turbine has been there.

The heterogeneous nature of our findings makes policy implications difficult. Our results suggest that negative externalities of onshore turbines do exist, but not everywhere. Barring an objective measure of a priori preferences, it may be difficult or impossible to predict in which areas property values will be impacted. The dynamic price patterns observed may suggest that as the amount of wind energy increases and more people experience them, then price impacts may lessen. However, if preference-based sorting is the cause of the dynamic pattern, then as more turbines are built, there may be fewer people who have positive or ambivalent opinions about turbines to live in proximate houses, which may result in less of a price rebound.

A second important means of assessing policy implications is through a lens of energy justice and equity. Carley and Konisky (2020) detail potential concerns about the renewable transition, arguing that, while there a clear global benefits for carbon mitigation, the distribution of local benefits and burdens may be unevenly spread across different populations. When it comes to wind energy, the primary local benefit is new jobs or economic growth, and the main burdens are increase electricity prices, noise, and shadow flicker. Brunner and Schwegman (2022) find increases in wind energy in US counties are associated with increases in per capita GDP, and the relationship is stronger in rural areas. Mueller and Brooks (2020) are focused on the burdens and examine whether there is differential exposure, meaning injustice, to wind energy using census county- and tract-level data. They do find some evidence of disproportionate exposure for younger, rural, and less-educated populations, but not along the lines of race, ethnicity, or income. Our results can add to the debate about equity concerns by examining the distribution of financial losses due to the expansion of onshore wind energy. If property values are diminished by a new disamenity, then the impacted homeowners suffer a financial loss due to a loss of home equity (Lang et al. 2023). Our results suggest that this loss of equity is predominantly experienced by homeowners on Cape Cod and Nantucket. Table A9 in the online appendix presents basic socioeconomic data for our four regions of analysis. Cape Cod and Nantucket residents are on average wealthier and much less likely to be Black or Hispanic relative to the other regions. This in turn would suggest that the burden of home equity loss is being shouldered by relatively advantaged populations, which is positive from an environmental justice perspective.

Our research suggests several directions for future research. First, whenever there is sufficient data, examining heterogeneity in both of the dimensions we investigate would be beneficial. Additional research could 1) help determine if the U-shaped findings are generalizable and 2) begin to assess patterns for where negative impacts occur. Second, research that investigates the sorting explanation of the U-shaped price impacts would be valuable. Residential sorting models could be conducted to see if certain types of households are more likely to locate near turbines post-construction and to study heterogeneous preferences for turbine proximity. In addition, more qualitative work to complement hedonic studies is needed. Panel studies over a longer time horizon would be of particular value to assess changing attitudes. Lastly, yet another source of heterogeneity that is important in hedonic onshore wind studies is views of the turbines. Some studies have taken views into account (e.g., Lang et al. 2014, Gibbons 2015, Sunak and Madlener 2016), but methods for assessing viewshed are inconsistent across studies. Refining and standardizing the methods and assessing valuation of turbine views would contribute greatly to this literature.

References

Abashidze, N. (2019). *Essays on Economic and Health Effects of Land Use Externalities*. [North Carolina State University]. https://repository.lib.ncsu.edu/handle/1840.20/38420

Blanchette, A., Lang, C., & VanCeylon, J. (2021). Variation in Valuation: Open Space and Geography. *Land Economics*, *97*(4), 768-780.

Brunner, E. J., & Schwegman, D. J. (2022). Commercial wind energy installations and local economic development: Evidence from US counties. *Energy Policy*, *165*, 112993.

Carley, S., & Konisky, D. M. (2020). The justice and equity implications of the clean energy transition. *Nature Energy*, *5*(8), 569-577.

Carr-Harris, A., & Lang, C. (2019). Sustainability and tourism: The effect of the United States' first offshore wind farm on the vacation rental market. *Resource and Energy Economics*, *57*, 51–67.

Devine-Wright, P. (2005). Beyond NIMBYism: towards an integrated framework for understanding public perceptions of wind energy. *Wind Energy: An International Journal for Progress and Applications in Wind Power Conversion Technology*, *8*(2), 125-139.

DOE. Land-Based Wind Market Report: 2021 Edition Data. https://www.energy.gov/eere/wind/articles/land-based-wind-market-report-2021-edition-released. Accessed November 8, 2021.

Dong, L., & Lang, C. (2022). Do Views of Offshore Wind Energy Detract? A Hedonic Price Analysis of the Block Island Wind Farm in Rhode Island. *Energy Policy*, *167*, 113060.

Dröes, M. I., & Koster, H. R. (2016). Renewable energy and negative externalities: The effect of wind turbines on house prices. *Journal of Urban Economics*, *96*, 121-141.

Dröes, M. I., & Koster, H. R. (2021). Wind turbines, solar farms, and house prices. *Energy Policy*, *155*, 112327.

EIA (2022) *Use of energy explained*. https://www.eia.gov/energyexplained/use-of-energy/electricity-use-in-homes.php. Accessed September 21, 2022.

Elmallah, S., Hoen, B., Fujita, K. S., Robson, D., & Brunner, E. (2023). Shedding light on large-scale solar impacts: An analysis of property values and proximity to photovoltaics across six US states. *Energy Policy*, *175*, 113425.

Firestone, J., & Kempton, W. (2007). Public opinion about large offshore wind power: Underlying factors. *Energy policy*, *35*(3), 1584-1598.

Gaur, V., Lang, C., Howard, G., & Quainoo, R. (2023). When Energy Issues are Land Use Issues: Estimating Preferences for Utility-Scale Solar Energy Siting. *Land Economics*, *99,* 3.

Gaur, V., & Lang, C. (2023). House of the Rising Sun: The Effect of Utility-scale Solar Arrays on Housing Prices. *Energy Economics*, *122*, 106699.

Gibbons, S. (2015). Gone with the wind: Valuing the visual impacts of wind turbines through house prices. *Journal of Environmental Economics and Management*, *72*, 177–196.

Haughton, J. H., Giuffre, D., & Barrett, J. (2003). *Blowing in the wind: Offshore wind and the Cape Cod economy*. Boston, MA: Beacon Hill Institute at Suffolk University.

Heintzelman, M. D., & Tuttle, C. M. (2012). Values in the wind: a hedonic analysis of wind power facilities. *Land Economics*, 88(3), 571-588.

Heintzelman, M. D., Vyn, R. J., & Guth, S. (2017). Understanding the amenity impacts of wind development on an international border. *Ecological Economics*, *137*, 195-206.

Hoen, B., & Atkinson-Palombo, C. (2016). Wind Turbines, Amenities and Disamenitites: A study of Home Value Impacts in Densely Populated Massachusetts. *Journal of Real Estate Research*, *38*(4), 473–504.

Hoen, B., Brown, J. P., Jackson, T., Thayer, M. A., Wiser, R., & Cappers, P. (2015). Spatial hedonic analysis of the effects of US wind energy facilities on surrounding property values. *The Journal of Real Estate Finance and Economics*, *51*(1), 22-51.

Hoen, B., Firestone, J., Rand, J., Elliot, D., Hübner, G., Pohl, J., ... & Kaliski, K. (2019). Attitudes of US wind turbine neighbors: analysis of a nationwide survey. *Energy Policy*, *134*, 110981.

Imbens, G. W., and Wooldridge, J. M. (2009). Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature*, *47*(1), 5–86. https://doi.org/10.1257/jel.47.1.5

Jarvis, S. (2021). *The economic costs of NIMBYism: Evidence from renewable energy projects*. 2. Working paper.

Jensen, C. U., Panduro, T. E., Lundhede, T. H., Nielsen, A. S. E., Dalsgaard, M., & Thorsen, B. J. (2018). The impact of on-shore and off-shore wind turbine farms on property prices. *Energy Policy*, *116*, 50–59.

Lang, C., Opaluch, J. J., & Sfinarolakis, G. (2014). The windy city: Property value impacts of wind turbines in an urban setting. *Energy Economics*, *44*, 413–421.

Lang, C., VanCeylon, J., & Ando, A. W. (2023). Distribution of capitalized benefits from land conservation. *Proceedings of the National Academy of Sciences*, *120*(18), e2215262120.

Mueller, J. T., & Brooks, M. M. (2020). Burdened by renewable energy? A multi-scalar analysis of distributional justice and wind energy in the United States. *Energy Research & Social Science*, *63*, 101406.

Nolte, C., Boyle, K. J., Chaudhry, A. M., Clapp, C. M., Guignet, D., Hennighausen, H., Kushner, I., Liao, Y., Mamun, S., Pollack, A., Richardson, J., Sundquist, S., Swedberg, K., and Uhl, J. H. (2021). *Studying the Impacts of Environmental Amenities and Hazards with Nationwide Property Data: Best Data Practices for Interpretable and Reproducible Analyses* (SSRN Scholarly Paper No. 3900806). https://doi.org/10.2139/ssrn.3900806

Sunak, Y., & Madlener, R. (2016). The impact of wind farm visibility on property values: A spatial difference-in-differences analysis. *Energy Economics*, *55*, 79–91.

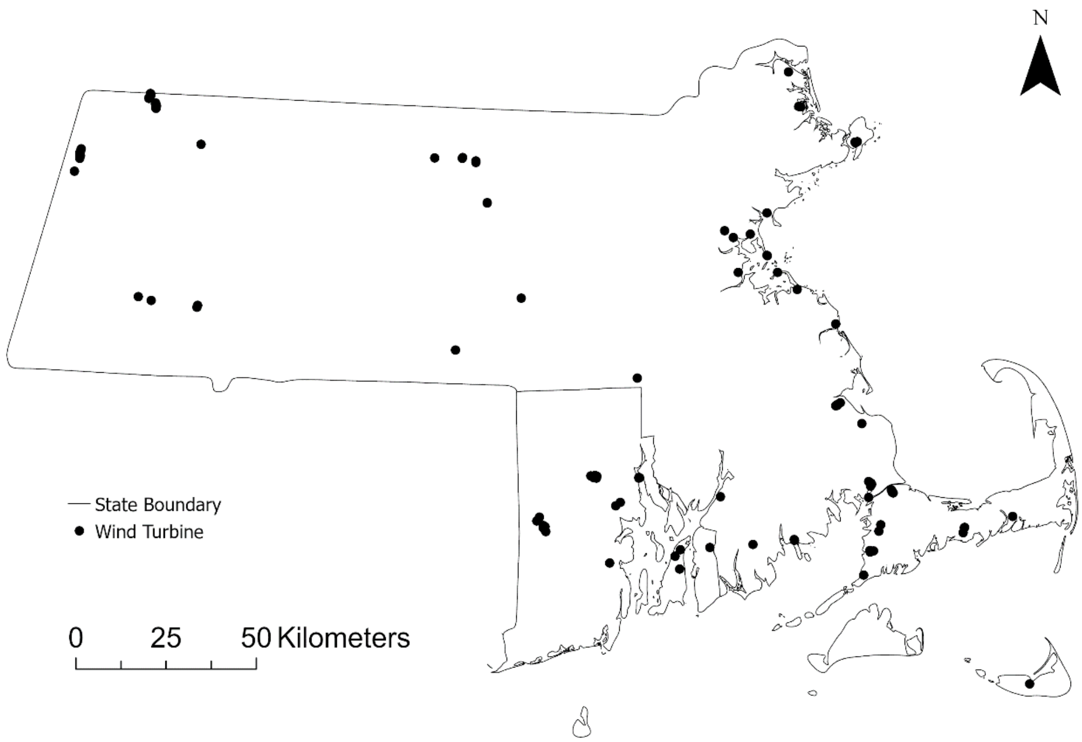
Tiebout, C. M. (1956). A pure theory of local expenditures. *Journal of political economy*, *64*(5), 416-424.

Trainor, A. M., McDonald, R. I., and Fargione, J. (2016). Energy Sprawl Is the Largest Driver of Land Use Change in United States. *PLOS ONE*, *11*(9), e0162269. https://doi.org/10.1371/journal.pone.0162269

Vyn, R. J. (2018). Property Value Impacts of Wind Turbines and the Influence of Attitudes toward Wind Energy. *Land Economics*, *94*(4), 496–516.
Wilson, G. A., & Dyke, S. L. (2016). Pre-and post-installation community perceptions of wind farm projects: the case of Roskrow Barton (Cornwall, UK). *Land use policy*, *52*, 287-296.
Wiser, R., Bolinger, M., Hoen, B., Millstein, D., Rand, J., Barbose, G., Darghouth, N., Gorman, W., Jeong, S., Mills, A., & Paulos, B. (2021). Land-Based Wind Market Report: 2021 Edition (p. 87). US Department of Energy. https://www.energy.gov/sites/default/files/2021-08/Land-Based%20Wind%20Market%20Report%202021%20Edition_Full%20Report_FINAL.pdf
Zabel, J. E., & Kiel, K. A. (2000). Estimating the demand for air quality in four US cities. *Land Economics*, 174-194.

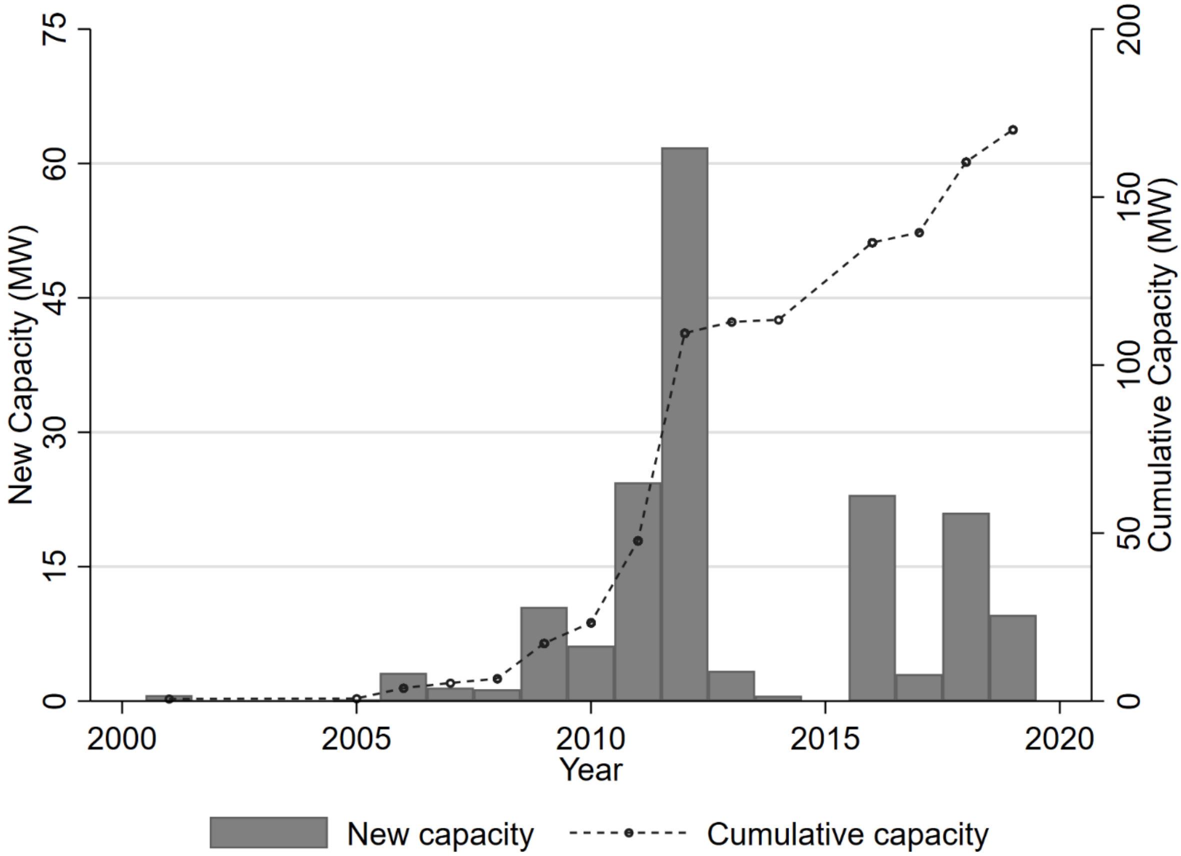
Figures and Tables

Figure 1. Map of wind turbines across Massachusetts and Rhode Island



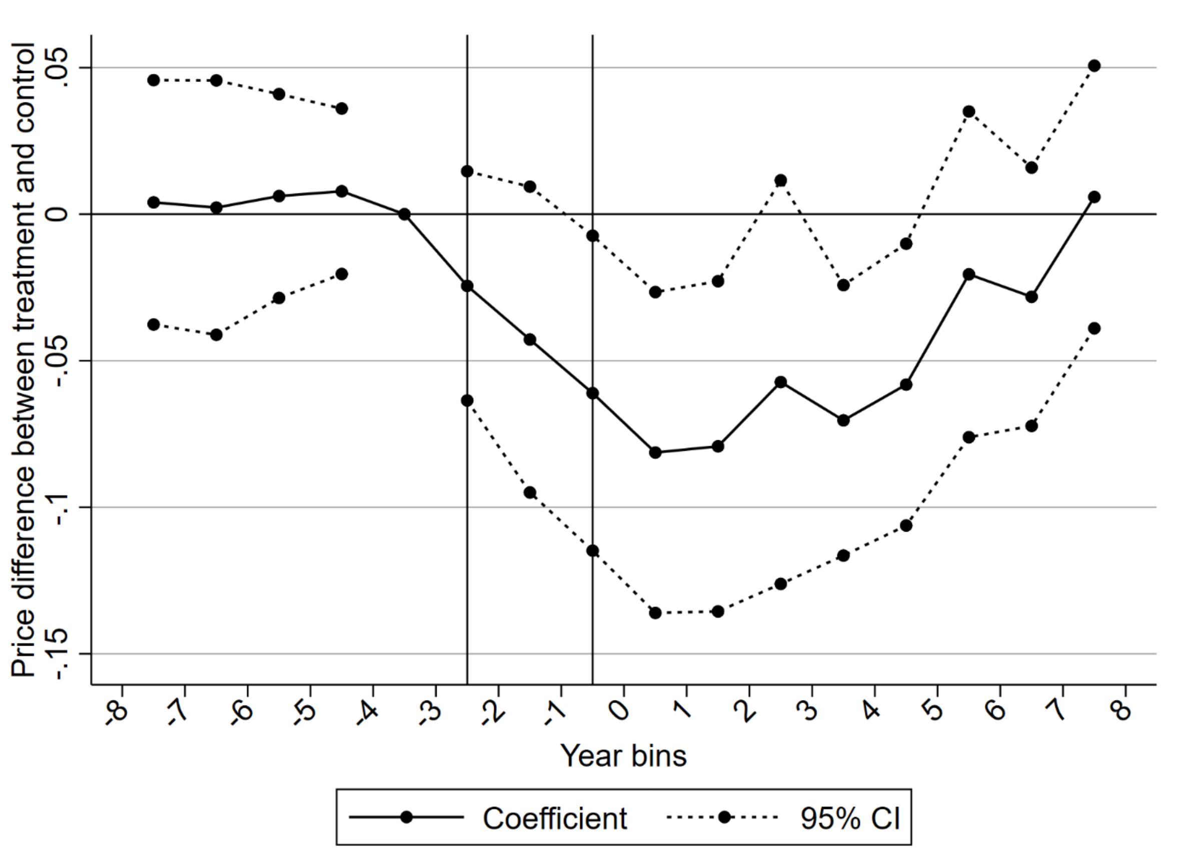
Notes: Data are from USWTDB and EIA for years 2000-2019. N=119.

Figure 2. New and cumulative wind capacity by year



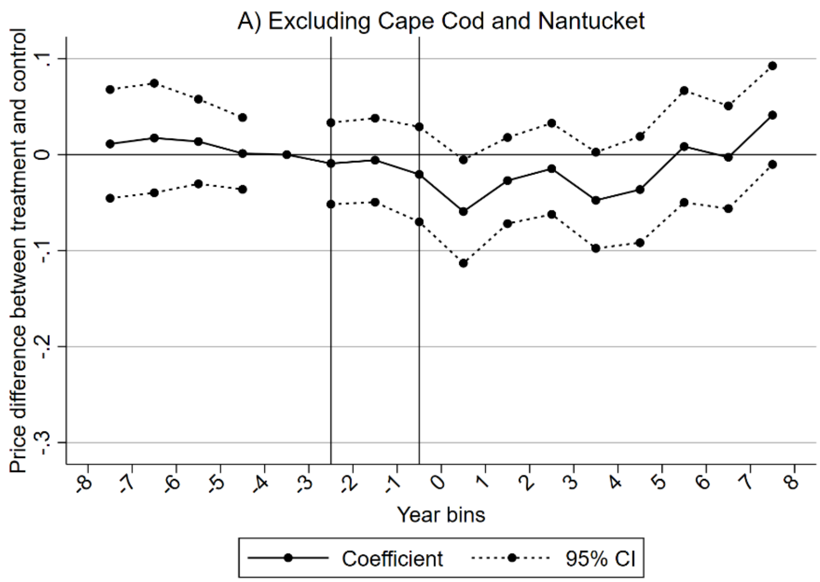
Notes: Data are from USWTDB and EIA for years 2000-2019. N=119.

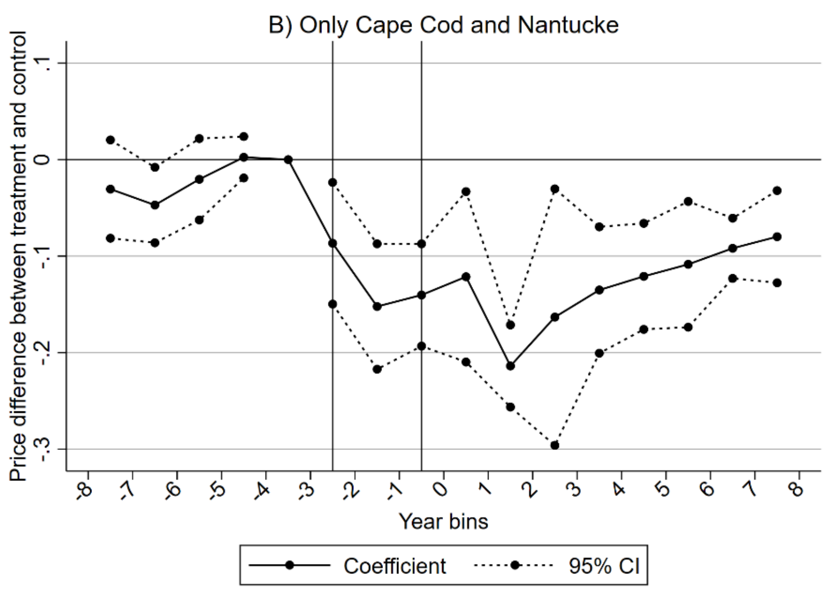
Figure 3. Event study of prices differences before and after wind turbine operation



Notes: The treatment group is houses within 1km from the closest wind turbine; the control group is houses between 3km and 10km of the closest wind turbine. Year bins represent the number of years before (negative) or after (positive) the operation date of the wind turbine. The reference time period is 3.5 years prior to the operation date of the wind turbine. The first vertical line represents the approximate start of the construction of the wind turbine; the second vertical line represents the approximate completion of the construction of the wind turbine. The coefficients are obtained by estimating a DID model similar to Equation 1 that regresses log sales price on the interaction between the treatment and the time period variables, along with month-year, county-year, and block fixed effects. The observations where the distance to the closest turbine is between 1km and 3km are dropped. Data are from ZTRAX, USWTDB, and EIA for years 2000-2019. N=312,308. Standard errors are clustered at the tract level. Resulting coefficients and 95% confidence intervals are graphed.

Figure 4. Event study of prices before and after wind turbine operation, separating Cape Cod and Nantucket from the rest of the study area





Notes: The treatment group is houses within 1km from the closest wind turbine; the control group is houses between 3km and 10km of the closest wind turbine. Year bins represent the number of years before (negative) or after (positive) the operation date of the wind turbine. The reference time period is 3.5 years prior to the operation date of the wind turbine. The first vertical line represents the approximate start of the construction of the wind turbine; the second vertical line represents the approximate completion of the construction of the wind turbine. The coefficients are obtained by estimating a DID model similar to Equation 1 that regresses log sales price on the interaction between the treatment and the time period variables, along with month-year, county-year, and block fixed effects. The observations where the distance to the closest turbine is between 1km and 3km are dropped. Data are from ZTRAX, USWTDB, and EIA for years 2000-2019. N4a=291,495; N4b=20,806. Standard errors are clustered at the tract level. Resulting coefficients and 95% confidence intervals are graphed.

Table 1: Housing attributes means by treatment status.

Variable	Full sample	Pre-treatment means [0, 1) km	Pre-treatment means [3, 10) km	Normalized difference in means
Sales price ($1000)	362.65	353.12	374.27	-0.029
Lot size (acres)	0.34	0.30	0.35	-0.077
Full bathrooms	1.54	1.51	1.54	-0.010
Half bathrooms	0.50	0.39	0.49	-0.114
Bedrooms	3.04	2.97	3.03	-0.010
Fireplace number	0.42	0.20	0.44	-0.375
Living area (sq. ft.)	3069.99	2894.61	3072.00	-0.030
Age of home (years)	57.35	46.09	50.95	-0.050
Pool (1 = yes)	0.04	0.03	0.04	-0.143
Air conditioner (1 = yes)	0.32	0.25	0.32	-0.123
Observations	369,260	3,606	135,321	

Notes: Sales prices are adjusted to 2019 levels using the CPI. The pre-announcement period is defined as 30 or more months prior to a turbine commencing operation. Normalized difference in means is calculated according to Imbens and Wooldridge (2009). Normalized differences exceeding 0.25 in absolute value are considered statistically different. Data are from ZTRAX for years 2000-2019.

Table 2: Transaction counts by distance and time period

Distance interval (km)	PA	PAPC	PC	Total
[0, 1)	3,606	715	3,832	8,153
	2.19%	2.24%	2.22%	2.21%
[1, 2)	10,882	2,043	11,625	24,550
	6.62%	6.41%	6.72%	6.65%
[2, 3)	14,575	2,757	14,962	32,294
	8.87%	8.64%	8.65%	8.75%
[3, 10)	135,321	26,377	142,565	304,263
	82.32%	82.71%	82.42%	82.40%
Total	164,384	31,892	172,984	369,260
	100%	100%	100%	100%

Notes: 'PA' stands for pre-announcement, 'PAPC' for post-announcement/pre-construction, and 'PC' for post-construction. The percentages are the proportion of all transactions for a given time period occurring in that distance band. Data are from ZTRAX for years 2000-2019.

Table 3: Difference-in-differences estimates of the impact of wind turbine proximity on housing prices

Variables		(1)	(2)	(3)	(4)
Distance (relative to 3–10 km)					
0–1 km		0.007	0.013		
		(0.016)	(0.017)		
1–2 km		-0.005	0.003		
		(0.014)	(0.013)		
2–3 km		0.006	0.010		
		(0.008)	(0.007)		
Timeline (relative to PA)					
PAPC		-0.030	-0.000	-0.036	-0.005
		(0.005)***	(0.005)	(0.006)***	(0.006)
PC		-0.040	0.006	-0.043	0.005
		(0.008)***	(0.006)	(0.010)***	(0.008)
Difference-in-differences					
PAPC ×	[0, 1) km	-0.010	-0.017	-0.022	-0.023
		(0.015)	(0.014)	(0.022)	(0.018)
	[1, 2) km	-0.005	-0.007	0.001	-0.001
		(0.011)	(0.010)	(0.015)	(0.014)
	[2, 3) km	0.004	0.007	0.005	0.006
		(0.008)	(0.007)	(0.011)	(0.010)
PC ×	[0, 1) km	-0.025	-0.041	-0.035	-0.046
		(0.017)	(0.013)***	(0.024)	(0.017)***
	[1, 2) km	0.009	-0.008	0.014	-0.005
		(0.013)	(0.009)	(0.018)	(0.013)
	[2, 3) km	0.004	-0.006	0.015	0.002
		(0.010)	(0.006)	(0.012)	(0.009)
Year by month FEs		Y	Y	Y	Y
Block FEs		Y	Y	N	N
Property FEs		N	N	Y	Y
County by year FEs		N	Y	N	Y
Observations		369,260	369,260	223,870	223,870
R-squared		0.794	0.805	0.876	0.885

Notes: 'PA' stands for pre-announcement, 'PAPC' for post-announcement/pre-construction, and 'PC' for post-construction. Columns 1 and 2 include the following housing characteristics as controls: lot size, lot size squared, living area, living area squared, number of bedrooms, full bathrooms, half bathrooms, house age, house age squared, house age cubed, indicator variables for the presence of a fireplace, pool, air conditioning, and a set of dummy variables for the subjective condition of the house. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Data are from ZTRAX, USWTDB, and EIA for years 2000-2019.

Table 4: Heterogeneity of treatment effect by regions

	(1)	(2)	(3)	(4)
Panel A: Western Massachusetts				
PC × [0, 1) km	-0.049	-0.037	-0.056	-0.044
	(0.022)**	(0.023)	(0.043)	(0.045)
Observations	54,840	54,840	34,547	34,543
R-squared	0.754	0.759	0.848	0.852
Panel B: Eastern Massachusetts (Excluding Cape Cod and Nantucket)				
PC × [0, 1) km	-0.023	-0.013	0.005	0.014
	(0.023)	(0.016)	(0.030)	(0.024)
Observations	172,010	172,010	99,825	99,815
R-squared	0.753	0.763	0.858	0.866
Panel C: Cape Cod and Nantucket Massachusetts				
PC × [0, 1) km	-0.070	-0.092	-0.093	-0.108
	(0.025)***	(0.017)***	(0.026)***	(0.020)***
Observations	25,716	25,716	15,157	15,157
R-squared	0.713	0.717	0.852	0.854
Panel D: Rhode Island				
PC × [0, 1) km	0.006	-0.018	-0.028	-0.058
	(0.029)	(0.022)	(0.021)	(0.017)***
Observations	116,693	116,693	74,341	74,341
R-squared	0.777	0.779	0.861	0.862
Year by month FEs	Y	Y	Y	Y
Block FEs	Y	Y	N	N
Property FEs	N	N	Y	Y
County by year FEs	N	Y	N	Y

Notes: 'PC' stands for post-construction. Columns 1and 2 include the following housing characteristics as controls: lot size, lot size squared, living area, living area squared, number of bedrooms, full bathrooms, half bathrooms, house age, house age squared, house age cubed, indicator variables for the presence of a fireplace, pool, air conditioning, and a set of dummy variables for the subjective condition of the house. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Data are from ZTRAX, USWTDB, and EIA for years 2000-2019.