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VALUING THE IMPACT OF WIND TURBINES ON HOUSING PRICES

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ABSTRACT

In Chapter 1, I evaluate the impact of offshore wind turbines on housing prices using the Block Island Wind Farm (BIWF) as an example. Using properties from the mainland, I estimate difference-in-differences hedonic valuation models with treatment defined by views of BIWF. Across many specifications and samples, I find no evidence of negative impacts to property values. Coefficient estimates are both negative and positive, but none are statistically distinguishable from zero. I additionally estimate hedonic models using properties on Block Island, which is only 4.8 km from the BIWF, meaning the BIWF is more of a visually dominant feature there as compared to the mainland. These models similarly find insignificant effects of views. In sum, my findings suggest that the viewshed impacts of the BIWF were minimal.

In Chapter 2, I update and extend prior studies that examine the impact of onshore wind turbines on property values. My data come from Massachusetts and Rhode Island, two states that are population dense and rapidly transitioning to renewable energy. I use a difference-in-differences identification strategy with treatment defined by proximity. In contrast to prior research in these states, my 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, I delve deeper into these aggregate results by examining how treatment effects vary for different regions and how treatment effects vary over time. Importantly, I find that the negative impacts found are almost entirely driven by Cape Cod and Nantucket, Massachusetts. I estimate small and typically insignificant effects for other regions of Massachusetts and Rhode Island. Further, I 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 my complex findings include contagion from opposition to Cape Wind, preference-based sorting, and acclimatization.

In Chapter 3, I improve methods of assessing viewshed impacts of onshore wind turbines. The preferred viewshed metrics are calculated using LiDAR Digital Surface Model GIS data, which account for trees and buildings, which obstruct distant turbines. I additionally measure views from not only a particular house, but also the surrounding roads. For comparison, I measure views using elevation data of bare earth only, which has been used in other studies. Using data from New England, USA, I use a difference-in-differences identification strategy with treatment defined by the visibility of a wind turbine, while also controlling for proximity-based treatment effects. The results suggest that property values decline when a wind turbine is visible. Previous viewshed methods underestimate the level of disamenity and reduce the significance level.

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PREFACE

This dissertation is written in three-manuscript form. The first manuscript is coauthored with Corey Lang. The article has been published in *Energy Policy*. The second manuscript is co-authored with Vasundhara Gaur and Corey Lang. The article has been published in *Energy Policy*. The third manuscript is also co-authored with Jason Parent and Corey Lang. The article is being prepared for submission.

Manuscript 1: Do views of offshore wind energy detract? A hedonic price analysis of the Block Island wind farm in Rhode Island

Manuscript 2: Property value impacts of onshore wind energy in New England: The importance of spatial heterogeneity and temporal dynamics

Manuscript 3: Focusing the View: Improved Methods for Assessing Viewshed Impacts of Onshore Wind Turbines

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Do views of offshore wind energy detract? A hedonic price analysis of the Block Island wind farm in Rhode Island

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Abstract

Social concern and disapproval of offshore wind by coastal communities causes delays and costs to offshore wind development. One concern is property value impacts stemming from a loss of pristine ocean views. We evaluate this concern using the Block Island Wind Farm (BIWF), the first of its kind in the United States. While the BIWF has fewer turbines than currently proposed offshore wind developments, it is situated about 26 kilometers [16 miles] from the Rhode Island mainland, which is a policy relevant distance, given that proposed US developments tend to be 21 to 32 kilometers from coastlines. Using properties from the mainland, we estimate difference-in-differences hedonic valuation models with treatment defined by views of BIWF. Across many specifications and samples, we find no evidence of negative impacts to property values. Coefficient estimates are both negative and positive, but none are statistically distinguishable from zero. We additionally estimate hedonic models using properties on Block Island, which is only 4.8 kilometers from the BIWF, meaning the BIWF is more of a visually dominant feature there as compared to the mainland. These models similarly find insignificant effects of views. In sum, our findings suggest that the viewshed impacts of the BIWF were minimal.

Keywords: Offshore wind energy, hedonic model, valuation, property values, Block Island, LiDAR, Digital Surface Model
JEL Codes: Q42, Q51

1 Introduction

Fossil fuels are still the dominant source of energy production. In 2020, fossil fuel consumption represented approximately 80% of energy use in the US (EIA). Burning fossil fuels generates pollution, both criteria pollutants that lead to adverse health impacts and carbon emissions that cause climate change. To address this issue, the US has increased the use of renewables, which are clean and sustainable. Recently, the development of wind energy has increased significantly. According to the Department of Energy (DOE), cumulative US wind capacity increased from 40.35 GW in 2010 to 121.99 GW in 2020. While virtually all this increase has been onshore, in the future offshore wind farms (OSWFs) will likely be a large component of the portfolio (NREL).

However, concerns persist about OSWFs that can inhibit development. There are ecological concerns related to whales, birds, and marine habitats, and anthropocentric concerns about spoiled ocean views and impacts to tourism. In a 2021 hearing before the Maryland Public Service Commission regarding awarding offshore renewable energy certificates for proposed OSWFs (docket 9666), the mayor of Ocean City, Maryland, Richard Meehan, submitted written testimony that

> "Ocean City's concern is that if the wind turbines are built within Ocean City's viewshed, this will have a significantly damaging effect on Ocean City's tourism and economy… Ocean City prides itself on its pristine views, which will no longer be pristine if the turbines are visible from shore… If there are more turbines, some as close as 13 miles from shore, this will have a negative effect on property value. If the appraised value of properties decrease, this will

adversely affect the tax revenue collected by Ocean City."[1]

While the claims about property values were unsubstantiated in the testimony, they are very real concerns for Ocean City and many other coastal communities.

The objective of this article is to evaluate concerns regarding property value impacts of OSWFs using the Block Island Wind Farm (BIWF), the first OSWF in the United States. Completed in August 2016, the BIWF consists of five six-megawatt turbines, each with a hub height of 100 m and a blade length of 75 m.[2] The BIWF is located about 4.8 km [3 miles] off the southeast coast of Block Island, Rhode Island, and the turbines are arrayed perpendicular to the angle of viewing from Block Island and spaced about 835 m apart (see Figure 1). The BIWF is about 26 km [16 miles] from the Rhode Island mainland. While currently proposed OSWF developments will have more turbines than BIWF, they tend to be sited 21 to 32 km from coastlines (BOEM), which makes the effect of BIWF on mainland housing prices a valuable data point to understand impacts of future developments.

We apply the hedonic valuation method and focus on property-specific turbine view as the key feature of BIWF that could impact property values. Any change in property value reflects people's preferences for turbine views improving or contaminating their ocean views. We construct a dataset that contains 11,058 mainland transactions over the years of 2005 to 2020 for properties that are within 3 km of the coast. We use LiDAR Digital Surface Model data to assess views of the turbines as well as views of water. We estimate cross-sectional and repeat sales difference-in-differences models using turbine

[1] https://webapp.psc.state.md.us/newIntranet/casenum/CaseAction_new.cfm?CaseNumber=9666

[2] The below water foundations and above water platforms were completed during September and October 2015 (Shuman 2015). The platforms heights were 21 m above the water, and thus would not be visible from the mainland.

view as treatment. In addition to water views, we also control for proximity to the coast and property characteristics and include a rich set of temporal and spatial fixed effects. Identification is buoyed by micro-variation in viewshed. Due to the presence of trees and buildings, a house with a view of the turbines could be next door to a house without views.

The results suggest that property values are not impacted by turbine views. The treatment effect coefficients from the primary difference-in-differences models range from -0.4% to 12.4% change in value for properties with a turbine view relative to those without. However, all coefficients are not statistically different from zero, implying no statistical impact. We perform many robustness checks that limit the distance from the coast needed to be in the sample and even include only properties that have a water view, as well as including only transactions 2010-2020. In all, the results are qualitatively identical to the main findings with both positive and negative point estimates, none of which are statistically distinguishable from zero. These findings suggests that the BIWF has had no adverse impact on mainland housing prices. As for water view and proximity to the coast, most models display positive and significant estimates, confirming intuition that houses that have a water view or that are adjacent to a waterbody tend to have higher value.

We also explore whether views of the BIWF affect property values on Block Island itself. These models are not our main focus both because data are limited and the results are less relevant for future OSWFs due to the close proximity. Despite this, they are still a useful complement. Intuitively, if there are negative impacts of turbine views, they would be stronger on Block Island than on the mainland. However, similar to our main results, we find no statistical impact of the BIWF viewshed on Block Island property values.

Our study contributes to two literatures. First, we expand the hedonic valuation of renewable energy literature. To date, there is only one article examining the property value impacts of OSWFs. Jensen et al. (2018) examine price effects of two, large OSWFs on both primary and secondary residences in Denmark. They similarly find that views of the turbines do not have a statistical impact on either type of property. Many articles have examined property value impacts of onshore wind turbines with mixed results, with some focusing on proximity and others incorporating viewshed (see Parsons and Heintzelman (2022) for a review). Within the United States, while Heintzelman and Tuttle (2012) find some evidence of negative impacts, studies with larger numbers of observations close to turbines find no significant impact on property prices (Lang et al. 2014, Hoen et al. 2015, Hoen and Atkinson-Palombo 2016). In contrast, studies in European countries consistently find that wind turbines have a significant negative impact on nearby properties, though the magnitude of the effect differs by region (Gibbons 2015, Sunak and Madlener 2016, Dröes and Koster 2021, Jarvis 2021). Using Canadian data, Vyn (2018) finds heterogeneous impacts that are dependent on community acceptance. More recently, several papers have applied hedonic valuation to assess disamenities associated with proximity to utility-scale solar arrays. Abashidze (2019) and Gaur and Lang (2020) find negative impacts working in North Carolina and New England, USA, respectively. However, Jarvis (2021) finds no statistical impact in England.

This paper also contributes to the literature that examines offshore wind acceptance. Firestone et al. (2018) study perceptions of permanent residents on Block

Island and mainland Rhode Island both before and after construction and find average support increases for both groups following construction. Other research tends to focus on tourists and their stated willingness to visit a location with turbines in view, often varying distance from shore. In general, results suggest large disamenities when OSWFs are near shore, but the effects decrease with distance, eventually becoming zero or even positive (Landry et al. 2012, Lutzeyer et al. 2018, Parsons et al. 2020). Trandafir et al. (2020) examine stated recreation preferences of Block Island tourists. On average, respondents are indifferent to activities with and without turbines in view, but those who know about or have seen the BIWF are more likely to choose the with turbine option. The sole revealed preference research in this vein is Carr-Harris and Lang (2019), who analyze the short-term vacation rental market and find increases in bookings and revenue for Block Island properties following the construction of the BIWF relative to other New England tourist destinations. We contribute to this area of research by offering another revealed preference study and focusing on property owners instead of tourists.

2 Data

2.1 Housing transactions

We use ZTRAX housing transaction data from Zillow (http://www.zillow.com/data). The dataset includes sales prices, street addresses, geographic coordinates, Census divisions, transaction dates, and property characteristics (bedrooms, bathrooms, etc.). Prices are adjusted for inflation and brought to quarter 3, 2020 levels using RI quarterly HPI (Federal Housing Finance Agency). Figure 1 displays the study area: the southern coastal area (Westerly, Charlestown, South Kingstown, and Narragansett) of Rhode Island.

We excluded transactions with sales prices below $100,000, excluded condo transactions, limited the geographic scope to properties within 3km of the coast, and limited the temporal scope to transactions from 2005 to 2020. We also exclude transactions that occur before a renovation was done.[3] The final dataset used for regression includes 11,058 transactions.

2.2 GIS

All GIS analyses were conducted using ArcGIS Pro 2.8 including the creation of the Digital Surface Model (DSM) raster, the calculation of the distances to the coast and the nearest turbine, and viewshed analyses including turbine view and water view.

The geospatial data, including RI boundary, LAS data, and coastal water area were acquired from State Boundary (1997), 2011 Statewide LiDAR - UTM (LAS), and Coastal Waters in the Rhode Island Geographic Information System (RIGIS). We observed Zillow geographic coordinates to be inaccurate based on overlay with satellite imagery. Instead, we geocoded properties using Google Sheets to create point features for all sample properties, and confirmed that these were accurate. BIWF turbine coordinates were obtained from Waterway Guide, and we used these to create a second point feature shapefile. We calculated distance to the coast and distance to the nearest turbine for all sample properties.

2.3 LiDAR Digital Surface Model

LiDAR (light detection and ranging) is a popular remote sensing method used for measuring the exact height of an object. A LiDAR system measures the time it takes for emitted light to travel to an object and back. That time is used to calculate distance

[3] The data include whether a renovation was done and, if so, in which year. Because the property characteristics are for the current time only, including transactions pre-renovation would assign incorrect property characteristics to a sale and possibly bias results.

traveled, and then convert the distance to elevation. LiDAR can be used to create both Digital Elevation Models (DEM) and Digital Surface Models (DSM). DEM only measure topography of the Earth's surface, and viewshed analysis using DEM will account for hills, valleys, and curvature of the Earth. In contrast, DSM additionally measures objects like trees and buildings, and thus will better model actual visibility by accounting for these obstructions.

The LiDAR data (RIGIS) were collected in 2011 during leaf-off conditions at a 1-meter or better nominal point spacing (1m GSD) for approximately 1,074 square miles of Rhode Island. We used the LAS files, which contain Lidar point clouds to create the (Digital Surface Model) DSM raster for view analysis. The DSM was created by using the first returned pulses (first returns), which are associated with the highest feature in the landscape, like a treetop or the top of a building. The DSM represents the elevations of the tops of features. We used the linear interpolation method to fill data gaps, and the pixel size was 1 meter. We used a geodesic viewshed tool to conduct viewshed analysis. This tool generates the raster surface locations visible to a set of observer features. For the turbine view analysis, we used turbine points as the observers, and the houses are the points being observed because line-of-sight views are symmetric.[4] The turbine height we used is 100 meters, which is the hub height (General Electric 2021). To assess properties' views of the water, we created many observer points in the ocean, bay, and coastal salt ponds, and similarly determined whether individual properties were visible from any of the water points.[5] In our hedonic model, we distinguish between ocean views and pond

[4] If the viewshed analysis was done the opposite, more intuitive way, the results would be identical, but the processing time would take much longer.
[5] The ocean view points are 2 km from the coast and spaced about 3 km apart. See Figure A1 in the appendix for a map of all water view points.

views.

We set turbine view and water view output raster to have a pixel size of two meters. This improves processing efficiency and is sufficient for property analysis. As we did not have a GIS layer of house footprint, instead only a single point, we created 5-meter buffers around all housing points, and then overlaid those buffers with the viewshed rasters to determine property specific views of turbines and water.[6] For turbine views, we create a dummy variable equal to one if any pixel in the 5-meter buffer can see any of the turbines (specifically, the hubs). For ocean view and pond view, we create count variables that equal the number of ocean and pond points that can be seen in the 5-meter buffer. This count approach distinguishes between properties with a lot of water view versus just a little.

Figure 2 illustrates our findings for turbine viewshed for a small area and communicates an important aspect of our identification strategy. Due to micro-variations in tree cover, buildings, and elevation, houses in close proximity can still have different views of the BIWF. Hence, we can control for spatial unobservable variables without capturing all of the variation in turbine views.

Our LiDAR DSM approach to viewshed is an improvement over other ways to get objective measurement over a large area. In previous studies, some researchers simply used distance as the measurement of the impact of wind turbines and conducted no viewshed analysis (Heintzelman and Tuttle 2012, Hoen et al. 2015, Hoen and Atkinson-Palombo 2016, Vyn 2018, Dröes and Koster 2021). In studies including turbine view as a measurement of the impact, viewshed calculation can be classified into three main

[6] A 5-meter buffer was chosen because these would likely cover most of a typical house without including surrounding trees.

categories: field visits for subjective assessment (e.g., Hoen et al. 2011, Lang et al., 2014), Digital Elevation Model (DEM) (e.g., Gibbons 2015, Jarvis 2021), and DSM (e.g., Sunak and Madlener 2016).[7] Field visits are only feasible with a small sample size and could be constrained by inaccessible properties. DEM only measures the elevation of bare earth without above-ground features, like trees and buildings, and hence is less accurate.

2.4 Summary statistics

Table 1 presents summary statistics for our sample properties. The average sales price for the sample is $560,160 in 2020 dollars. Average structural characteristics are 3,590 square feet of living space, 3.11 bedrooms, and 2.37 bathrooms. The average distance to a coastal waterbody is 0.81 km. The average number of visible ocean points is 0.41 (with a 95th percentile of 3) and the average number of visible pond points is 0.06. The average distance to a wind turbine is 34 km (21 miles). The range of distances to the nearest turbine is 27 to 44 km (17 to 27 miles). Proposed offshore wind developments are typically in the range of 21 to 32 km offshore. For example, Revolution Wind is proposed to be 24 km (15 miles) offshore of Massachusetts, Skipjack is proposed to be 31 km (19 miles) offshore of Deleware, and South Fork Wind is proposed to be 56 km (35 miles) offshore of Long Island (though closer to Rhode Island and Massachusetts).

Our key treatment assignment variable is Turbinview. Our analysis indicates that about 15% of properties have a turbine view. Treatment occurs in August 2016, when the above water construction occurs, and 30% of transactions occur after that time. About 5% of properties transact in August 2016 or later and have turbine views. This set of

[7] Jensen et al. (2018) focus on view as their key independent variable, but do not discuss how they calculated it.

properties will provide key identifying variation in our difference-in-differences model that we discuss next.

3 Methods

We develop a difference-in-differences (DD) hedonic model to examine the impact of turbine view on property values. The basic identification strategy is to compare properties with an eventual view of the turbine to those without from before the view was realized to after. The DD model identifies the treatment effect from differences in trends instead of differences in levels, which mitigates several concerns stemming from differences between properties with turbine views and those without. However, we develop a rich set of control variables to account for those potential differences. Importantly, we include ocean view, pond view, and coastal proximity in our model because these variable are extremely likely to be correlated with both turbine view and price. Our model is specified as follows:

$$\text{(1)} \quad ln(\text{price}_{\text{imt}}) = \beta_1 \text{turbineview}_\text{i} + \beta_2 \text{post}_{\text{mt}} + \beta_3 \text{post\_turbineview}_{\text{imt}} + \beta_4 \text{oceanview}_\text{i} + \beta_5 \text{pondview}_\text{i} + \mathbf{X_i \beta_6} + \pi_\text{m} + \gamma_\text{t} + \varepsilon_{\text{it}}$$

$\ln(price_{imt})$ is the natural log of sales price of property i that transacts in month m and year t. $turbineview_i$ is a dummy variable equal to one if the property has a turbine view once the turbines are built. $post_{mt}$ is a dummy variable equal to one if the transaction occurs in August 2016 or after. $post\_turbineview_{imt}$ is the interaction of $turbineview_i$ and $post_{mt}$ and hence equals one if the property has a turbine view and the transaction occurs in August 2016 or after. β_3 is the key DD coefficient of interest. If $\beta_3 < 0$, this would imply that views of the BIWF reduce property value. $oceanview_i$ and $pondview_i$ are integer values equal to the number of ocean and pond points that can be seen from a property. $\boldsymbol{X}_i$ is a set of property-specific, time-invariant control variables, including structural characteristics (e.g., bedrooms and bathrooms), and a set of dummy variables defined by distance to the coast (0-0.1 km, 0.1-0.25 km, 0.25-0.5 km, and 0.5-1 km), Lastly, π_m are month fixed effects and γ_t are year fixed effects to control for common price fluctuations in the housing market.

We estimate three versions of this model. First, as it is described above. Second, we additionally include block group fixed effects to control for unobserved, spatially delineated price determinants. Third, we estimate a repeat sales model that includes property fixed effects, which captures all observed and unobserved property and location characteristics. The second and third model are our preferred specifications due to their ability to deal with unobservables.

3.1 Assumptions

The key assumption for DD models is the parallel trends assumption, which means that the trends between treatment and control properties would be the same in the absence of treatment. This is of course untestable because treatment does occur. However, we can examine price trends in the pre-treatment period (pre-August 2016) to assess if trends are similar. Figure 3 plots average price trends for properties that eventually have a view of the turbines and properties that never have a view of the turbines. Price trends are quite similar before construction of the BIWF suggesting that the parallel trends assumption is reasonable and properties without a view do serve as a good counterfactual for properties with a view. The figure also indicates that price trends are similar after construction too, suggesting that views of BIWF had little impact on prices. We explore price impacts more rigorously in the next section.

A second assumption we make is that expectations of views of BIWF are not anticipated and are not capitalized into housing prices prior to August 2016. Prior research has shown that expectations of future events do affect housing prices (e.g., Boslett et al. 2016), and some hedonic studies of wind turbines do model a post-siting-decision pre-construction time period to assess if there is an anticipation effect (Lang et al. 2014, Hoen and Atkinson-Palombo 2016). While the BIWF was known about well in advance, and as mentioned in the introduction the platforms were completed in October 2015, our intuition is that the specific viewshed on the mainland was not known until the towers and blades were constructed. Our LiDAR DSM analysis reveals substantial within-block group heterogeneity in views. Thus, we are assuming that no household forms expectations about the specific views of the turbines that they will or will not have. Importantly, however, as we observe in Figure 3, at no time pre-treatment is there a discernable difference in the trends, which suggests no anticipatory treatment effect.

Lastly, we assume that property attributes are time invariant. In terms of structural changes to houses, we mitigate this concern by excluding transactions that predate renovations. Water view is a key independent variable, which could change over time as trees grow or are cut down or new houses are built. However, we have no reason to believe that any time variation in property attributes would be correlated with turbine views.

4 Results

Table 2 presents the main results of the impact of offshore wind turbine views on housing prices. Column 1 is the most basic model and includes only property characteristics (including structural attributes, water views, and proximity to the coast dummies), and year and month fixed effects. Column 2 adds Census block group fixed effects. Column 3 adds property fixed effects and removes all time-invariant property control variables.

The top three rows present the DD coefficients, with the third row being the key coefficient of interest, which is the impact of turbine view on housing prices. The coefficient on Post turbineview is small and negative in Columns 1 and 2, but becomes large and positive in the repeat sales model (Column 3). Because log sale price is the dependent variable, we can interpret the coefficients approximately as percent change due to treatment. Thus, the results suggest that views of the BIWF changed housing prices by -0.4% to 12.4%. However, all of these coefficients are statistically insignificant, meaning we cannot reject views having no effect on prices. Large decreases in property values are statistically inconsistent with the observed data. The coefficients on Turbineview are positive but statistically insignificant. In part, we interpret this to mean our other control variables (particularly water view and coastal proximity) are capturing differences between properties with and without eventual turbine views.[8] The coefficient on Post is also insignificant, which makes sense given the inclusion of month and year fixed effects.

Other coastal amenity variable coefficients have expected signs and magnitudes, which bolsters confidence in our modeling strategy. In Columns 1 and 2, the coefficient on Ocean view is positive and statistically significant. In Column 1, the coefficient of 0.084 means that for every ocean point visible from a property, the price increases 8.4% on average. As we said in the introduction, the 95th percentile for Ocean View is three, meaning that property derives a price bump of over 25% relative to a similar property

[8] If we estimate a version of the DD model without water views and coastal proximity dummies, the coefficient on Turbineview is positive and highly statistically significant.

with no ocean view. The Pond view coefficients are smaller in magnitude and statistically insignificant. Our results indicate that proximity to the coast is highly valued. In Column 1, the results suggest that, on average, properties within 0.1 km of the water sell for over 96.6% more than houses 1-3 km from the water, all else equal.[9] The other distance dummies imply that properties located 0.1-0.25 km from the coast sell for 44.2% more than properties 1-3 km away, properties located 0.25-0.5 km away sell for 30.3% more, and properties located 0.5-1.0 km away sell for 14.6% more. Similar to Ocean view, the magnitude of these premiums decline substantially as block group fixed effects are added, which makes sense given the spatial correlation between these variables. In contrast, the coefficient on Post turbineview varies little when block group fixed effects are added. We hypothesize this to be the case because of the micro-variation in turbine viewshed, which is much less spatially correlated than water view or distance. This is a clear benefit of using LiDAR DSM data to determine viewshed, as opposed to a simpler metric.

4.1 Robustness checks

We now test the robustness of our results along two dimensions: distance from the coast restrictions and temporal restrictions. We want the comparison group of properties without a turbine view to be as similar as possible to those with a turbine view. Even with our extensive set of control variables in Table 2, it is possible that properties further from the coast are not a good control group. To assess this concern, we estimate our models using only properties that are within successively smaller distance bands from the coast. Our main models in Table 2 have a distance restriction of 3 km; we additionally test

[9] As noted earlier, when the dependent variable is log transformed, coefficients can be interpreted approximately as percent change. However, this is less accurate the larger coefficients become, in which case a formal transformation should be used. In this case, the coefficient of 0.676 is translated into percentage terms by exponentiating, $e^{0.676} - 1 = 0.966$, implying a 96.6% increase in property value.

distance restrictions of 2 km and 1 km. Finally, we include only properties that have a view of the water (either ocean or coastal salt pond). In this very restrictive sample, we are comparing properties with a view of the turbines and a view of the water to those properties that just have a view of the water. In terms of temporal restrictions, we additionally estimate our models using only transactions from the time period 2010-2020, whereas the main results use transactions 2005-2020. Two concerns exist with the longer time window. First, 2005-2009 contains the peak and crash of the housing market, which could have affected properties with and without ocean views differently. Second, the long time period increases the chance that the hedonic function changes over the course of the sample (Kuminoff and Pope 2014).

Table 3 presents the results of robustness checks for these two extensions. In all, the table presents results from 16 regression models. Panel A uses the cross-sectional model (same as Column 2 of Table 2) and Panel B uses the repeat sales model (same as Column 3 of Table 2). The first set of four columns uses the sample period 2005-2020 and the second set of four columns uses 2010-2020. The distance and water view restrictions are listed at the top of each column with sample restrictions increasing with successive columns in each set. Across all models, we find that these sample restrictions have little impact on results. The estimated coefficients range from -0.016 to 0.168, but none are statistically different from zero, similar to the results in Table 2. In both panels, standard errors grow as restrictions are imposed, which makes sense because the sample size is decreasing. For instance, less than 10% of transactions included in the main sample are included in the repeat sales sample of properties with an ocean view.

Additional robustness checks are presented in the online appendix. Tables A1 and

A2 examine results when the sample is restricted to areas of the mainland that have views of BIWF unobstructed by Block Island itself. Table A3 excludes all properties within 1000 m from the east boundary of Narragansett but not the south boundary. The idea being that those houses are more likely to have peripheral views of the turbines instead of direct. Table A4 allows for heterogeneous treatment effects as a function of distance to the turbines. Table A5 changes the post treatment date to October 2015 in case platform construction is the correct treatment date. Tables A6 and A7 replace the binary variable Turbineview with a variable Turbineview count that equals the number of turbines visible from a property.[10] Across all of these tables, treatment effect coefficients similarly range from negative to positive and are never statistically significantly different than zero.

Taken together, these results suggest that the ability to see offshore turbines that are at least 27 km (17 miles) away have no impact on property value.

4.2 Turbine view from Block Island

In this section, we examine the impact of turbine view on sales prices using only properties from Block Island. Because the turbines are only 4.8 km from shore at the nearest point, this is unlikely to be a relevant distance for future offshore wind developments. However, for the sake of completeness, we still feel it is worthwhile to present the results.

There are far fewer observations and as a result we modify our model. After the same sample cuts as the mainland sample, there are only 307 transactions during 2005-2020. We move away from DD and instead estimate a simpler cross sectional model, as follows:

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[10] Alternatively, one could examine heterogeneity in views based on which portions of turbines are visible, such as hub, blades, or platform. We leave this for future work.

$$\text{(2)} \qquad ln(\text{price}_{\text{imt}}) = \beta_1 \text{Post\_turbineview}_{\text{imt}} + \beta_2 \text{oceanview}_{\text{i}} + \mathbf{X_i \beta_3} + \gamma_t + \varepsilon_{it}$$

All variables are as defined in Equation 2, except $\boldsymbol{X_i}$, which is a stripped down set of controls.[11]

Summary statistics for this sample are presented in Table A8 of the online appendix. Compared to houses on the mainland, houses on Block Island have similar structural characteristics, but there are other important differences. The average sales price on Block Island is $1,294,090 in 2020 dollars, which is considerably more than double average prices on the mainland. Also, the average distance to a coastal waterbody is 0.52 km with a maximum distance of 1.7 km, and 94% of transactions have a water view (Ocean view + Pond view >0). The average distance to a wind turbine is 7.7 km (4.8 miles) and 20% of transactions have a turbine view. The range of distances to the nearest turbine is 5 to 12 km (3.1 to 7.5 miles).

Table 4 presents the results of the Block Island analysis. We present two columns that only differ by included years: 2005-2020 in Column 1 and 2010-2020 in Column 2. The turbine view coefficients are negative but statistically insignificant in both columns. This implies that views of the BIWF similarly have no statistical impact on housing prices on Block Island.[12] Similar to the results from on the mainland, ocean view is highly valued and statistically significant. In terms of distance to the coast, the results

[11] If we estimate a DD model for the Block Island sample, the resulting coefficients suggest overfitting or insufficient degrees of freedom. Across many different specifications, the coefficients on $Post\_turbineview$ and $Turbineview$ are near-equal in magnitude and opposite in sign. Thus, we do not trust these results. In Equation 2, the matrix $\boldsymbol{X}$ includes lot size, lot size squared, number of bedrooms, number of bathrooms, a quadratic polynomial of construction year, and dummy variables for coastal proximity. Given the evidence of overfitting, we opted for a slightly more parsimonious model. Also, given the relatively small number of observations in this analysis, estimating a repeat sales model is untenable.

[12] Residents on Block Island could actually see the turbine platforms starting in October 2015, though to be clear the viewshed would be considerably smaller than after the full tower is complete. Given this, it is possible that the post treatment period should be defined as starting in October 2015. Appendix Table A9 examines results with this altered post definition and results are similar. We present an additional robustness check in Appendix Table A10 that uses island region fixed effects for the three regions (North, Southeast, Southwest) instead of block groups. Results are qualitatively identical.

suggest large premiums for proximity. Houses within 0.1 km are about 74% more expensive than those greater than 0.5 km away, and houses between 0.1 and 0.25 km are 28% – 31% more expensive.

Another possibility to consider is that there is an island-wide treatment effect of BIWF, meaning that all house values are similarly negatively (or positively) impacted resulting in no differential impact to those properties with turbine views. Carr-Harris and Lang (2019) took this approach arguing that the island is small enough and the turbines prominent enough that any tourist visiting the island would have a hard time avoiding them. They estimate a difference-in-differences model comparing trends in the short-term rental market on Block Island to other New England tourist destinations. As a first step toward undertaking this type of analysis with property transactions, we compared time trends in average Block Island prices to those of Martha's Vineyard and Nantucket Island. We present this graph in the appendix as Figure A3. The trends are far from parallel pre-treatment: the trend for Block Island is much flatter than the other two locations. We are unsure why this is the case, but the disparity in trends far predates construction of BIWF. Thus, we conclude that this type of analysis is inappropriate for these data and would likely lead to biased results.

5 Conclusion and Policy Implications

In the coming decades, offshore wind energy capacity is expected to greatly increase in the United States. This shift will be unambiguously good for greenhouse gas emissions reductions, but many coastal communities are concerned about local impacts to their livelihood. This article examines one concern related to property value declines due to a loss of pristine ocean views. In the tradition of non-market valuation and applying the tool of hedonic valuation, we are estimating the valuation of turbine views by property owners. Much of the literature to date focuses on tourist perceptions or valuation, so we offer a complementary and much needed perspective.

We examine the price impacts of mainland, coastal Rhode Island properties, which range in distance from 27 to 44 km (17 to 27 miles) to the BIWF, a five-turbine, 30 MW installation located in state waters. A critical aspect of our analysis is the use of LiDAR DSM data to comprehensively assess property-specific turbine views. Not only is this an improvement over other methods of determining viewshed, but it yields micro-variation in viewshed that improves estimation of impacts. Using a variety of specifications and samples, we find no evidence of adverse impacts due to views of BIWF. Our results consistently indicate point estimates that range from small and negative to large and positive, but all are not statistically different than zero. We conclude that property owners in coastal areas do not value ocean views with turbines any differently than ocean views without turbines.

Future OSWFs will be comprised of larger turbines and more turbines spaced further apart. It is an open question whether valuation of these types of OSWFs will be the same as we find for the BIWF. Our secondary finding that turbine views also do not significantly impact property values on Block Island is useful in this regard. Larger turbines of future OSWFs will be slightly larger on the horizon than BIWF is from the mainland, but will never be as visually prominent as the BIWF is from Block Island. Thus, we would expect similarly negligible effects. Regardless, future research should examine property value impacts of these larger OSFWs. In addition, with many OSFWs, greater potential for analysis of heterogeneity will exist – related to size of turbines, number of turbines, distance from the coast, and direct vs. peripheral views.

Figures and Tables

Figure 1: Study area

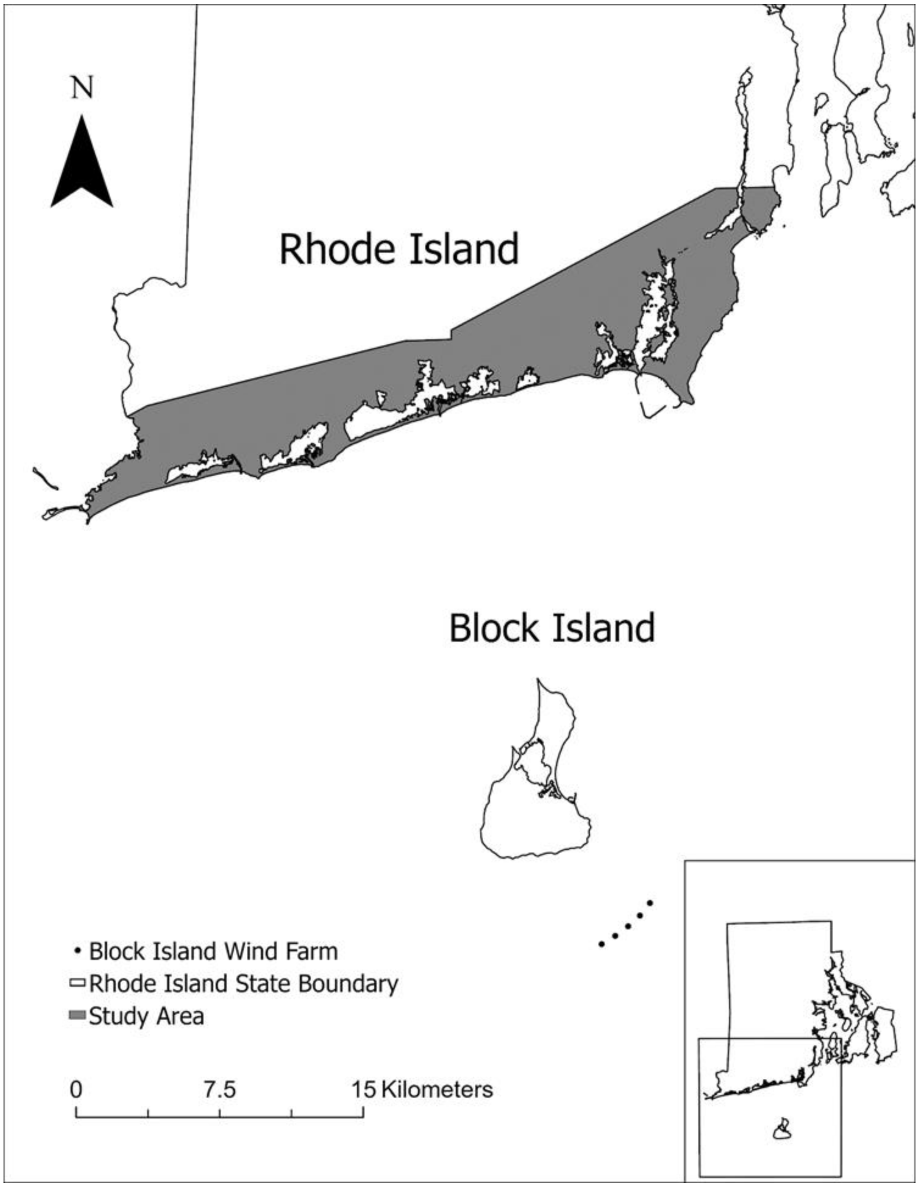


Figure 2: Turbine viewshed for small area on mainland of Rhode Island

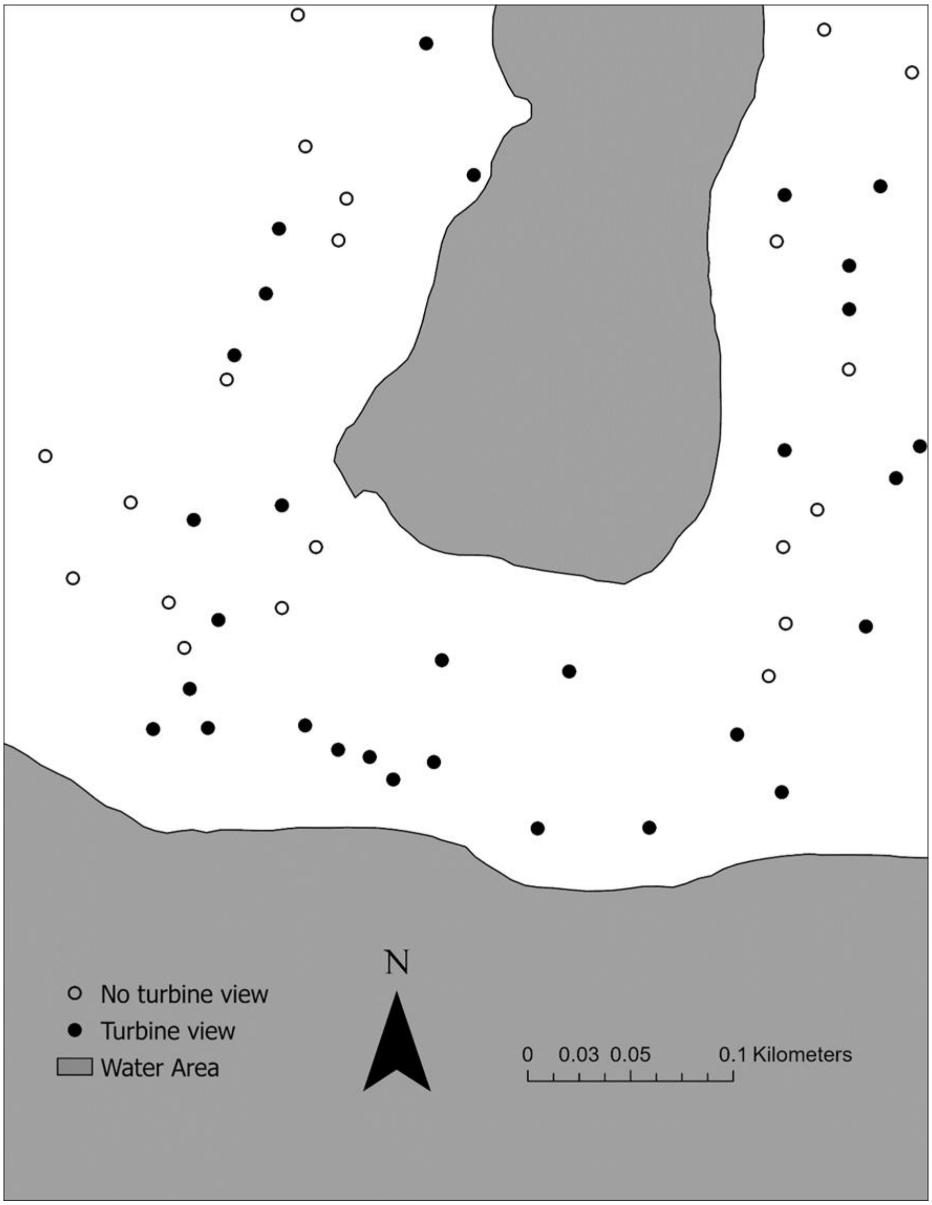
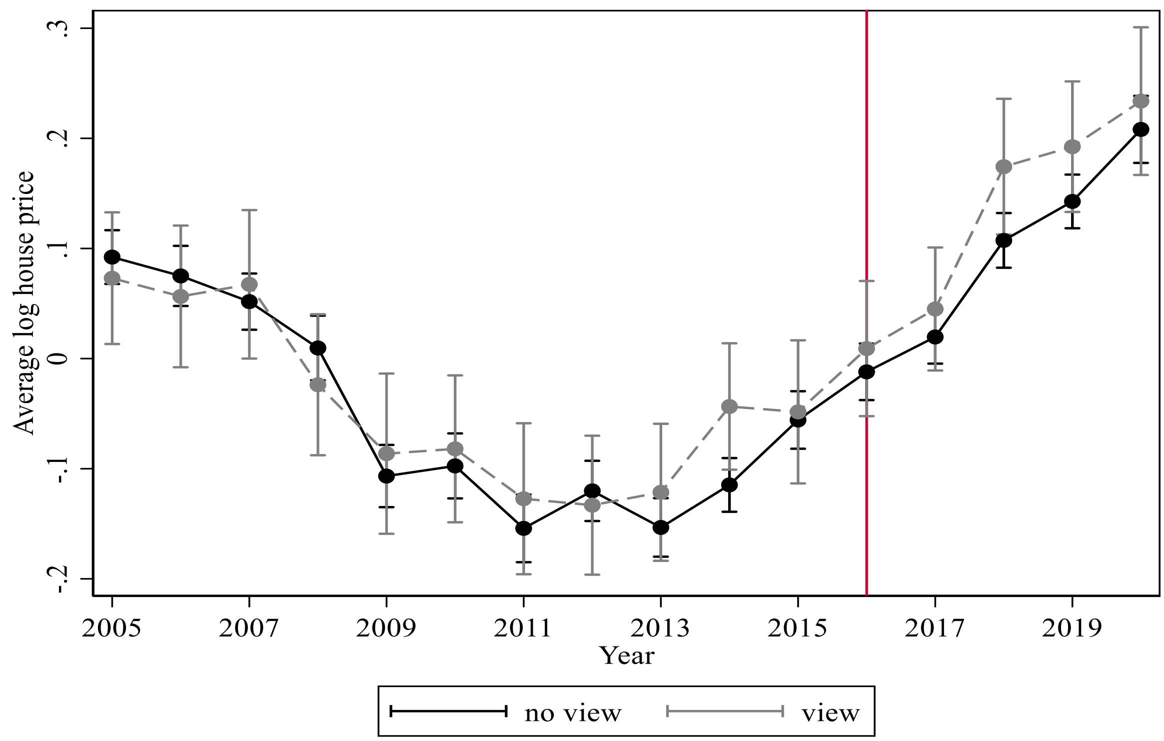


Figure 3: Housing price trends for properties with and without turbine views



Notes: A version of Equation 1 that excludes *turbineview* is estimated and residuals are calculated. The figure plots the mean residuals for properties that have a turbine view post construction and those that do not by year. The vertical line indicates the date of the BIWF construction.

Table1: Housing summary statistics

Variables	Mean	Standard Deviation
Sales price ($1000)	560.16	777.16
Turbineview (1 = yes)	0.15	0.36
Post turbineview (1 = yes)	0.05	0.21
Post (1 = yes)	0.30	0.46
Ocean view	0.41	1.10
Pond view	0.06	0.29
Bedrooms	3.11	0.91
Bathrooms	2.37	1.10
Living area (1000sq. ft.)	3.59	1.78
Lot size (1000sq. ft.)	27.24	49.23
Air conditioner (1 = yes)	0.40	0.49
Building year	1971.41	31.67
Distance to waterbody (km)	0.81	0.73
Distance to nearest turbine (km)	33.99	3.89
Observations	11058	

Notes: Bathrooms is full plus half baths. Ocean view is the number of visible points on the ocean from a house. Pond view is the number of visible points on coastal ponds from a house.

Table 2: Impact of offshore wind turbine views on housing prices

Variables	Dependent variable: Log sale price		
	(1)	(2)	(3)
Turbineview	0.054	0.016	
	(0.035)	(0.021)	
Post	-0.016	0.003	0.007
	(0.023)	(0.021)	(0.087)
Post turbineview	-0.004	-0.001	0.124
	(0.018)	(0.020)	(0.089)
Ocean view	0.084	0.065	
	(0.011)***	(0.012)***	
Pond view	0.023	0.020	
	(0.021)	(0.016)	
Distance to water dummies			
0-0.1 km	0.676	0.479	
	(0.075)***	(0.037)***	
0.1-0.25 km	0.366	0.168	
	(0.066)***	(0.030)***	
0.25-0.5 km	0.265	0.078	
	(0.050)***	(0.018)***	
0.5-1.0 km	0.136	0.040	
	(0.046)***	(0.017)**	
Property controls	Yes	Yes	No
Year FEs	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes
Census Block Group FEs	No	Yes	No
Property FEs	No	No	Yes
Observations	11,058	11,058	6,665
R-squared	0.531	0.617	0.883

Notes: Table presents results from three separate regressions. Sample includes properties in Washington County, Rhode Island that are within 3 km of the coast and transact in the years 2005-2020. Property control variables are lot size, lot size squared, living area, living area squared, number of bedrooms, number of bathrooms, a cubic polynomial of construction year, and an indicator for air conditioning. Standard errors are shown in parentheses and are clustered at the tract level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 3: Robustness checks

Sample period	2005-2020				2010-2020			
Distance from coast restrictions	< 3 km	< 2 km	< 1 km	Water view only	< 3 km	< 2 km	< 1 km	Water view only
Panel A: Cross Sectional								
Post turbineview	-0.001	-0.005	-0.009	0.040	-0.012	-0.012	-0.016	0.043
	(0.020)	(0.020)	(0.023)	(0.040)	(0.021)	(0.022)	(0.028)	(0.043)
Observations	11,058	9,981	7,788	2,072	7,752	6,998	5,493	1,486
R-squared	0.617	0.620	0.601	0.563	0.640	0.641	0.625	0.607
Panel B: Repeat Sales								
Post turbineview	0.124	0.129	0.122	0.130	0.109	0.112	0.101	0.168
	(0.089)	(0.096)	(0.104)	(0.266)	(0.070)	(0.079)	(0.091)	(0.348)
Observations	6,665	5,909	4,415	994	4,567	4,054	3,023	696
R-squared	0.883	0.886	0.886	0.884	0.911	0.915	0.917	0.922

Notes: Table presents results from 16 regressions; each column of each panel is a different regression. Sample includes properties in Washington County, Rhode Island with sample cuts based on year of transaction, distance to the coast, and water view (ocean + pond view >0). The dependent variable is log sales price. For Panel A, the regression specification includes property characteristics (as defined in Table 2), distance to water dummies, year fixed effects, month fixed effects, and census block group fixed effects. For Panel B, the regression specification includes year fixed effects, month fixed effects, and property fixed effects. Standard errors are shown in parentheses and are clustered at the tract level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 4: Estimates of the impact of offshore wind turbine view on Block Island housing prices

Variables	Sample period	
	2005-2020	2010-2020
Post turbineview	-0.048	-0.035
	(0.115)	(0.120)
Ocean view	0.053	0.083
	(0.023)**	(0.027)***
Pond view	-0.022	-0.135
	(0.072)	(0.089)
Distance to water dummies		
0-0.1 km	0.552	0.556
	(0.128)***	(0.159)***
0.1-0.25 km	0.246	0.273
	(0.088)***	(0.106)**
0.25-0.5 km	-0.081	-0.061
	(0.081)	(0.100)
Year FEs	Yes	Yes
Property controls	Yes	Yes
Census Block Group FEs	Yes	Yes
Observations	307	217
R-squared	0.406	0.394

Notes: Table presents two different regression models. The dependent variable is log sales price. Sample includes properties on Block Island, Rhode Island, with sample cuts based on year of transaction defined differently in each column. Property control variables are lot size, lot size squared, number of bedrooms, number of bathrooms, and a quadratic polynomial of construction year. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Appendix

Online Appendix for

DO VIEWS OF OFFSHORE WIND ENERGY DETRACT?
A HEDONIC PRICE ANALYSIS OF THE BLOCK ISLAND WIND FARM IN RHODE ISLAND

(not for publication)

This Appendix provides information that is supplementary to the analyses included in the main paper.

Figure A1 maps the ocean and pond view points used to determine ocean and pond views from properties. The ocean points are placed 2 km from the coast and about 3 km apart. The pond points are placed in the middle of ponds on the smaller side and multiple points are placed in larger ponds.

Figure A2 maps the sample region for the analysis used in Table A1. These are the regions of the mainland that, if they have a view of at least one turbine from BIWF, that view is unobstructed by Block Island.

Figure A3 presents price trends for Block Island, RI, Nantucket, MA, and Martha's Vineyard, MA.

Table A1 presents dif-in-dif regression results using the same specifications as Table 2 but restricting the sample to sample to properties with at least one BIWF turbine unobstructed by Block Island. This sample cut is illustrated by Figure A2.

Table A2 presents dif-in-dif regression results using the same specifications as Table 2 but restricting the sample to sample to properties with all five BIWF turbines unobstructed by Block Island.

Table A3 presents results from a triple difference model that examines heterogeneity in treatment effects by distance to the turbines. The specification estimated is

$$\begin{aligned}\ln(price_{imt}) = {} & \beta_1 turbineview_i + \beta_2 post_{mt} + \beta_3 distance_i + \beta_4 post\_turbineview_{imt} \\ & + \beta_5 post_{mt} \cdot distance_i + \beta_6 turbineview_i \cdot distance_i \\ & + \beta_7 post\_turbineview_{imt} \cdot distance_i + \beta_8 oceanview_i + \beta_9 pondview_i \\ & + \boldsymbol{X_i \beta_{10}} + \pi_m + \gamma_t + \varepsilon_{it}\end{aligned}$$

where distance is the distance between a property and the BIWF in kilometers. We de-mean distance so that β_4 can be interpreted as the treatment effect at the average distance. β_4 and β_7 are the coefficients of interest. Neither are statistically significant.

Table A4 presents dif-in-dif regression results using similar specifications as Table 2, except that Turbineview is replaced with Turbineview count, which is an integer valued variable equal to the number of turbines visible from a property. Similar to the main results, the key treatment effect coefficient ranges from positive to negative and is never statistically different from zero.

Table A5 presents robustness checks similar to Table 3 for the model used in Table A4.

Table A6 present summary statistics for the properties in the Block Island analysis presented in Table 4.

Table A7 presents a robustness check for the Block Island analysis of Table 4. Table 4 uses Census block group fixed effects to control for spatial unobservables, and Table A7 instead uses region fixed effects based on our own knowledge of the different parts of the island.

Appendix Figure and Tables

Figure A1: Ocean view and Pond view points used in LiDAR DSM analysis

Notes: Ocean points are 2 km from the coast and are 3 km apart.

Figure A2: Sample of mainland properties with at least one turbine unobstructed by Block Island

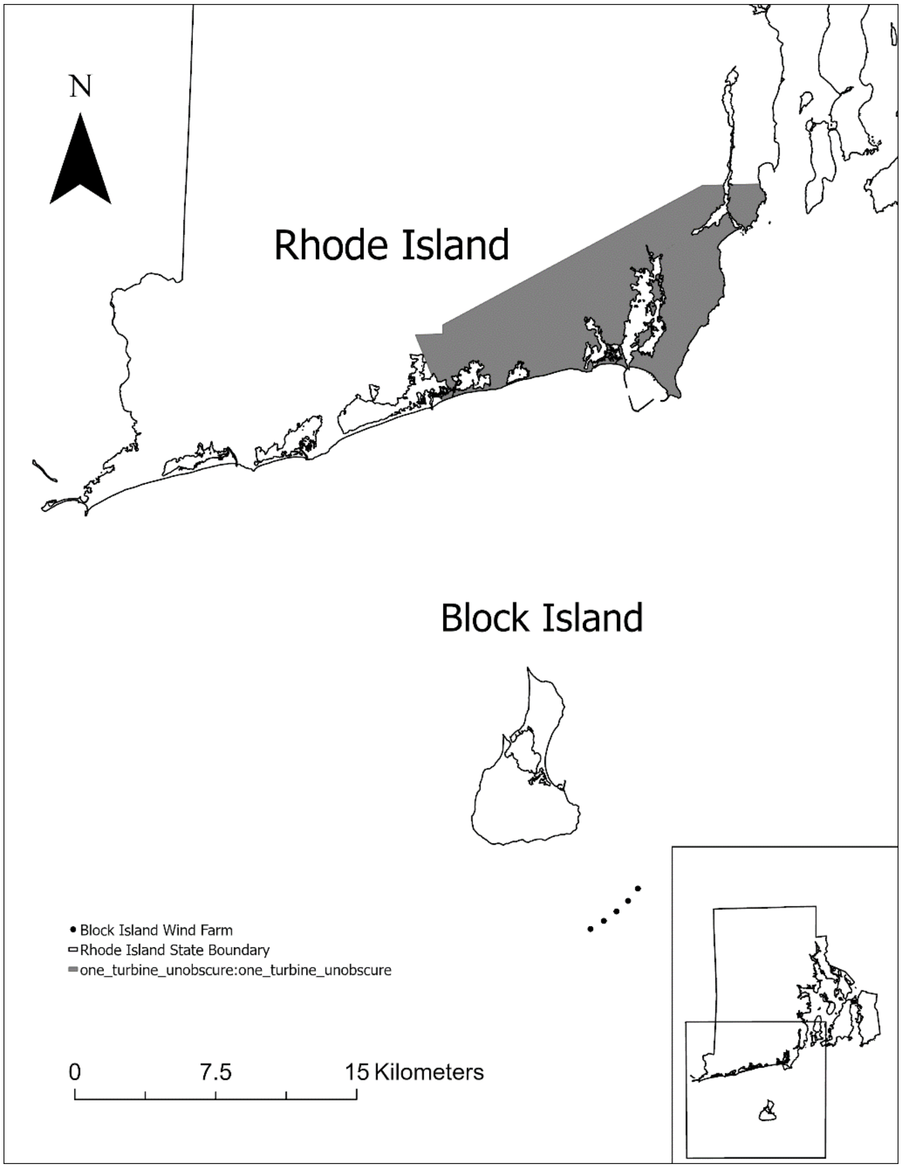
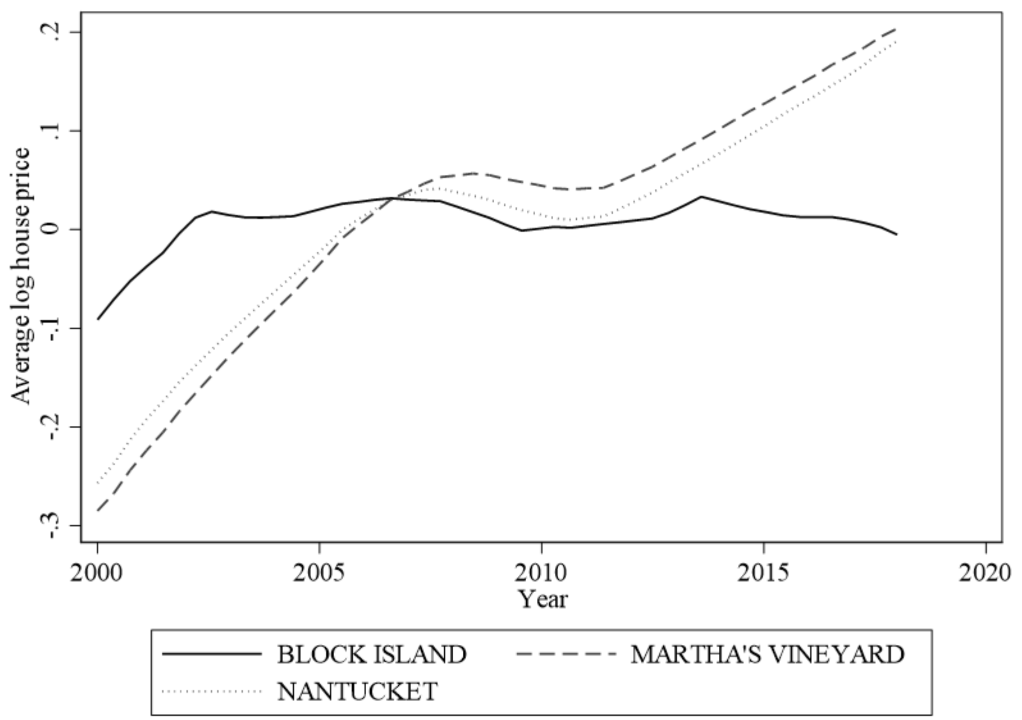


Figure A3: Housing price trends for properties on Block Island and other New England island tourist destinations



Notes: This figure displays a kernel-weighted local polynomial regression of demeaned log price on year for three different places. The bandwidth is 2.5. The solid line is Block Island, the dash line is Martha's Vineyard, and the dot line is Nantucket.

Table A1: Impact of offshore wind turbine views on housing prices, restricting sample to properties with at least one turbine unobstructed by Block Island

Variables	Dependent variable: Log sale price		
	(1)	(2)	(3)
Turbineview	0.032	0.014	
	(0.022)	(0.031)	
Post	-0.016	-0.004	0.067
	(0.023)	(0.024)	(0.062)
Post turbineview	-0.028	-0.023	0.024
	(0.021)	(0.025)	(0.043)
Ocean view	0.079	0.057	
	(0.007)***	(0.014)***	
Pond view	0.019	0.029	
	(0.023)	(0.018)	
Distance to water dummies			
0-0.1 km	0.549	0.481	
	(0.067)***	(0.052)***	
0.1-0.25 km	0.229	0.162	
	(0.048)***	(0.038)***	
0.25-0.5 km	0.176	0.089	
	(0.029)***	(0.024)***	
0.5-1.0 km	0.118	0.046	
	(0.035)***	(0.027)	
Property controls	Yes	Yes	No
Year FEs	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes
Census Block Group FEs	No	Yes	No
Property FEs	No	No	Yes
Observations	7,143	7,143	4,256
R-squared	0.537	0.586	0.875

Notes: Table presents results from three separate regressions. The specifications are the same as those in Table 2. The sample is restricted to areas of mainland Rhode Island that, if a turbine can be seen from the property, the turbine would be unobstructed by Block Island. Standard errors are shown in parentheses and are clustered at the tract level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A2: Impact of offshore wind turbine views on housing prices, restricting sample to properties with all five turbines unobstructed by Block Island

Variables	Dependent variable: Log sale price		
	(1)	(2)	(3)
Turbineview	0.044	0.023	
	(0.025)	(0.032)	
Post	-0.019	-0.001	0.067
	(0.026)	(0.025)	(0.082)
Post turbineview	0.012	0.016	0.043
	(0.027)	(0.022)	(0.088)
Ocean view	0.071	0.034	
	(0.008)***	(0.007)***	
Pond view	0.024	0.026	
	(0.041)	(0.016)	
Distance to water dummies			
0-0.1 km	0.515	0.406	
	(0.083)***	(0.058)***	
0.1-0.25 km	0.204	0.109	
	(0.054)***	(0.041)**	
0.25-0.5 km	0.161	0.042	
	(0.036)***	(0.030)	
0.5-1.0 km	0.113	0.004	
	(0.042)**	(0.028)	
Property controls	Yes	Yes	No
Year FEs	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes
Census Block Group FEs	No	Yes	No
Property FEs	No	No	Yes
Observations	5,677	5,677	3,394
R-squared	0.534	0.593	0.870

Notes: Table presents results from three separate regressions. The specifications are the same as those in Table 2. The sample is restricted to areas of mainland Rhode Island that, if turbines can be seen from the property, all five turbines would be unobstructed by Block Island. Standard errors are shown in parentheses and are clustered at the tract level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A3: Heterogeneity in property value impact as a function of distance to turbine

Variables	Dependent variable: Log sale price		
	(1)	(2)	(3)
Turbineview	0.016	-0.010	
	(0.049)	(0.045)	
Post	-0.008	0.007	0.013
	(0.025)	(0.023)	(0.087)
Post turbineview	-0.029	-0.015	0.167
	(0.050)	(0.050)	(0.205)
Distance to nearest turbine	-0.018	-0.028	
	(0.007)**	(0.014)*	
Distance to nearest turbine*Turbineview	0.004	-0.006	
	(0.016)	(0.013)	
Distance to nearest turbine*Post	-0.002	-0.002	-0.005
	(0.004)	(0.003)	(0.007)
Distance to nearest turbine*Turbineview*Post	-0.005	-0.001	0.018
	(0.013)	(0.014)	(0.040)
Property controls	Yes	Yes	No
Year FEs	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes
Census Block Group FEs	No	Yes	No
Property FEs	No	No	Yes
Observations	11,058	11,058	6,665
R-squared	0.542	0.619	0.883

Notes: Table presents results from three separate regressions. The control variables are identical to those used in Table 2, including ocean and pond view and coastal proximity dummies. Standard errors are shown in parentheses and are clustered at the tract level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A4: Impact of offshore wind turbine views on housing prices, using turbine count as view metric

Variables	Dependent variable: Log sale price		
	(1)	(2)	(3)
Turbineview count	0.008	0.004	
	(0.008)	(0.006)	
Post	-0.018	0.001	0.009
	(0.023)	(0.021)	(0.084)
Post turbineview count	0.002	0.003	0.031
	(0.006)	(0.006)	(0.022)
Ocean view	0.087	0.063	
	(0.011)***	(0.012)***	
Pond view	0.024	0.019	
	(0.021)	(0.016)	
Distance to water dummies			
0-0.1 km	0.678	0.480	
	(0.075)***	(0.037)***	
0.1-0.25 km	0.368	0.168	
	(0.066)***	(0.030)***	
0.25-0.5 km	0.267	0.078	
	(0.050)***	(0.018)***	
0.5-1.0 km	0.138	0.040	
	(0.046)***	(0.017)**	
Property controls	Yes	Yes	No
Year FEs	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes
Census Block Group FEs	No	Yes	No
Property FEs	No	No	Yes
Observations	11,058	11,058	6,665
R-squared	0.531	0.617	0.883

Notes: Table presents results from three separate regressions. The specifications are the same as those in table 2. Standard errors are shown in parentheses and are clustered at the tract level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A5: Robustness checks, using turbine count as view metric

Sample period	2005-2020				2010-2020			
Distance from coast restrictions	< 3 km	< 2 km	< 1 km	Water view only	< 3 km	< 2 km	< 1 km	Water view only
Panel A: Cross Sectional								
Post turbineview count	0.003	0.003	0.002	0.012	0.001	0.001	0.000	0.014
	(0.006)	(0.006)	(0.007)	(0.011)	(0.006)	(0.007)	(0.008)	(0.012)
Observations	11,058	9,981	7,788	2,072	7,752	6,998	5,493	1,486
R-squared	0.617	0.620	0.601	0.563	0.640	0.641	0.625	0.608
Panel B: Repeat Sales								
Post turbineview count	0.031	0.033	0.032	0.032	0.029	0.030	0.028	0.054
	(0.022)	(0.023)	(0.025)	(0.055)	(0.017)	(0.019)	(0.023)	(0.069)
Observations	6,665	5,909	4,415	994	4,567	4,054	3,023	696
R-squared	0.883	0.886	0.886	0.885	0.911	0.915	0.917	0.923

Notes: Table presents results from 16 regressions; each column of each panel is a different regression. Sample includes properties in Washington County, Rhode Island with sample cuts based on year of transaction, distance to the coast, and water view (ocean + pond view >0). The dependent variable is log sales price. For Panel A, the regression specification includes property characteristics (as defined in Table 2), distance to water dummies, year fixed effects, month fixed effects, and census block group fixed effects. For Panel B, the regression specification includes year fixed effects, month fixed effects, and property fixed effects. Standard errors are shown in parentheses and are clustered at the tract level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A6: Housing summary statistics for Block Island

Variables	Mean	Standard Deviation
Sales price ($1000)	1294.09	849.96
Post turbineview (1 = yes)	0.20	0.40
Ocean view	2.54	1.53
Pond view	0.28	0.45
Bedrooms	3.43	0.98
Bathrooms	2.68	1.07
Lot size (1000sq. ft.)	71.09	54.26
Building year	1965.98	47.34
Distance to waterbody (km)	0.52	0.34
Distance to nearest turbine (km)	7.70	1.63
Observations	307	

Notes: Bathrooms is full plus half baths. Ocean view is the number of visible points on the ocean from a house. Pond view is the number of visible points on coastal ponds from a house.

Table A7: Estimates of the impact of offshore wind turbine view on Block Island housing prices, using three regional fixed effects instead of Census block group fixed effects

Variables	Sample period	
	2005-2020	2010-2020
Post turbineview	-0.034	-0.025
	(0.115)	(0.119)
Ocean view	0.055	0.084
	(0.023)**	(0.027)***
Pond view	-0.025	-0.119
	(0.073)	(0.089)
Distance to water dummies		
0-0.1 km	0.573	0.568
	(0.122)***	(0.153)***
0.1-0.25 km	0.267	0.313
	(0.089)***	(0.102)***
0.25-0.5 km	-0.072	-0.033
	(0.085)	(0.104)
Year FEs	Yes	Yes
Property controls	Yes	Yes
Block Island Region FEs	Yes	Yes
Observations	307	217
R-squared	0.411	0.401

Notes: Table presents results from two separate regressions. The specifications are the same as those in Table 4, except that we replace Census block group fixed effects with three regional fixed effects that segment the island into natural parts (North, Southwest, and Southeast). Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Chapter – 2

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

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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

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.[13] For the remaining 30 turbines (<1 MW), we

[13] The EIA-860M does not record information on any energy generation plants that have a capacity less than 1 MW.

assume that the operation month is July.[14] 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[15] 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.[16]

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

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[14] 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.

[15] https://www.hitachienergy.com/us/en/products-and-solutions/energy-portfolio-management/market-intelligence-services/velocity-suite

[16] 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.

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.[17]

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

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

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. 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.[18]

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

[18] 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.

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:

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

$\ln(price_{icmt})$ 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 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.[19]

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

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 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.[20] 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.

[20] 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).

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 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.

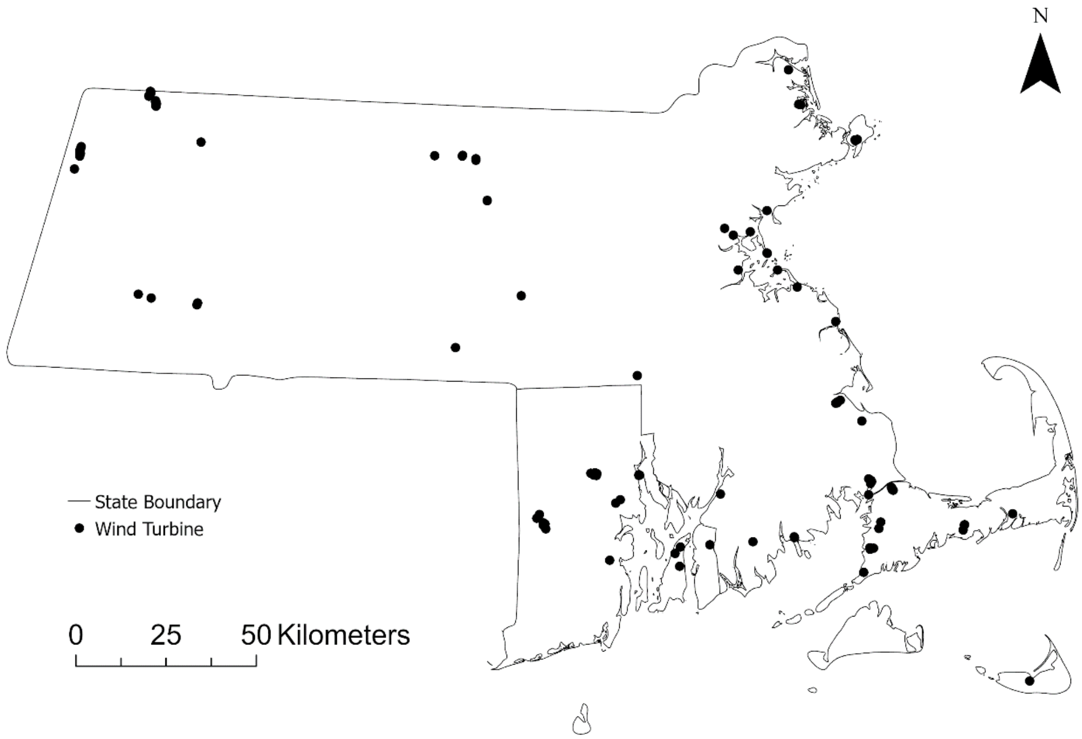
The heterogeneous nature of our findings makes policy implications difficult. Our results suggest that negative externalities of onshore turbines do exist, but not everywhere. Barring an objective measure of a priori preferences, it may be difficult or impossible to predict in which areas property values 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.

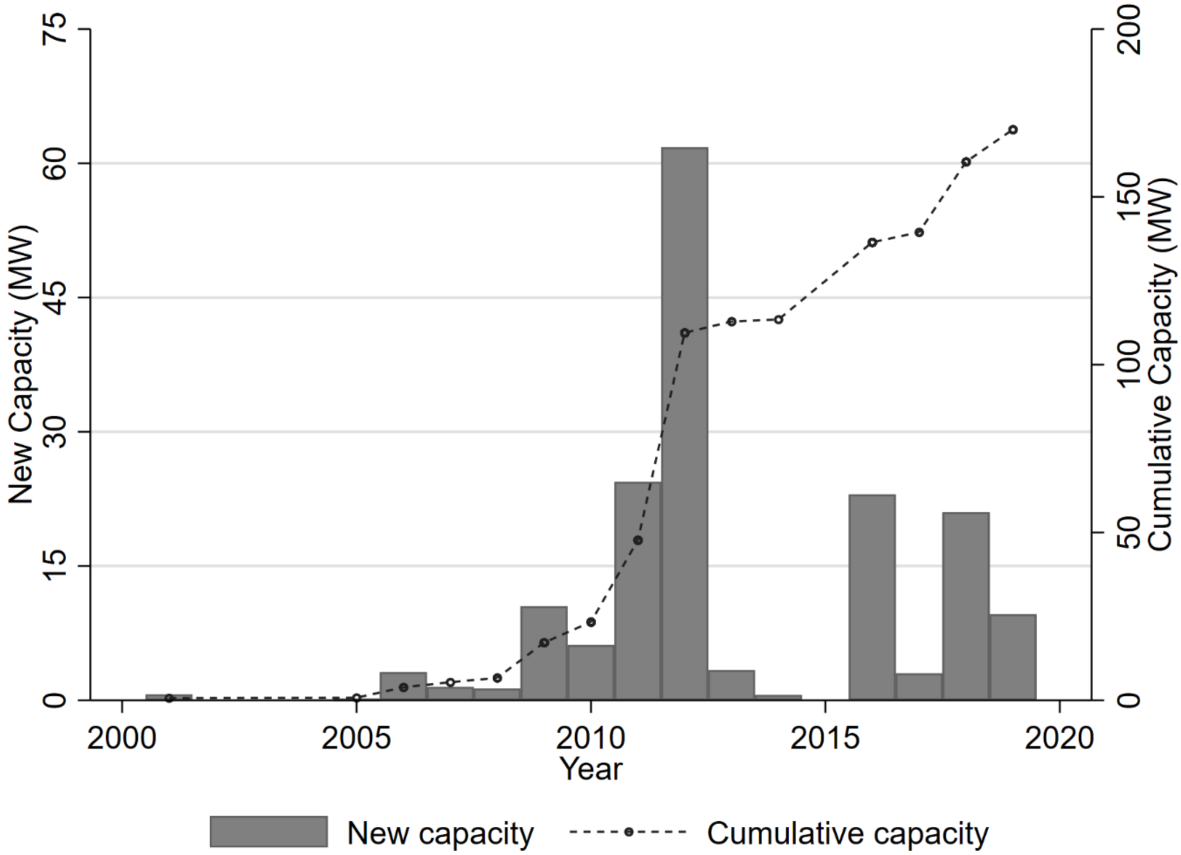
Figures and Tables

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



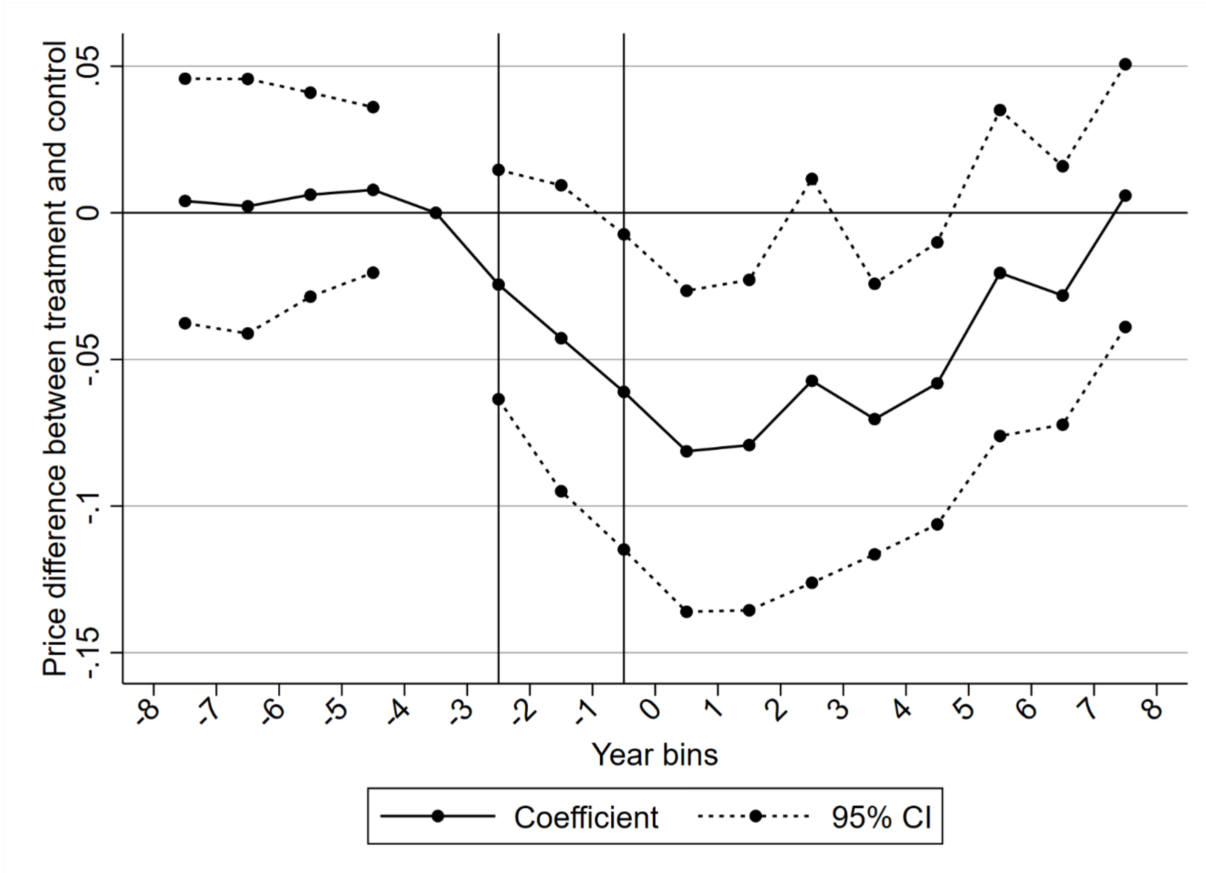
Notes: Data are from USWTDB and EIA for years 2000-2019. N=119.

Figure 2. New and cumulative wind capacity by year



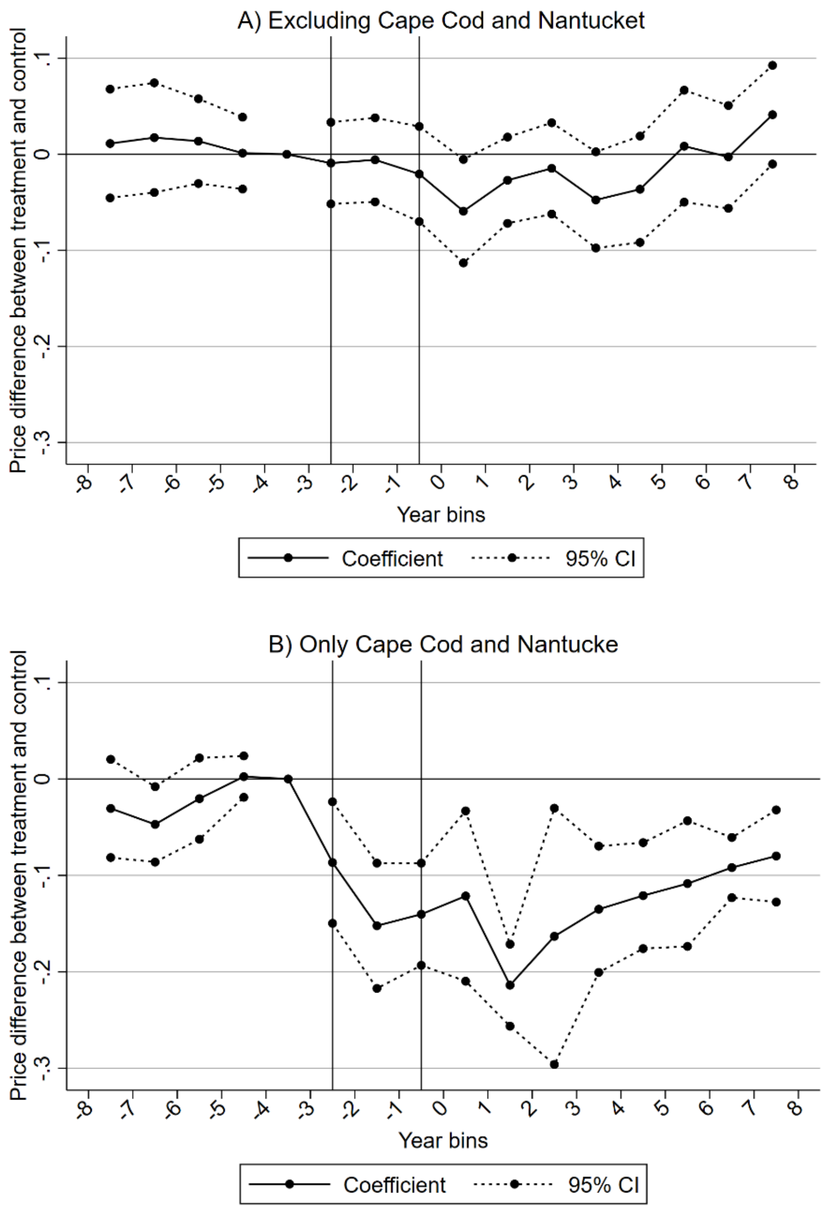
Notes: Data are from USWTDB and EIA for years 2000-2019. N=119.

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		Normalized
		[0, 1) km	[3, 10) km	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	172,001	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.

Appendix

Online Appendix

PROPERTY VALUE IMPACTS OF ONSHORE WIND ENERGY IN NEW ENGLAND: THE IMPORTANCE OF SPATIAL HETEROGENEITY AND TEMPORAL DYNAMICS

May 1, 2023

This appendix provides supplemental equations and tables to our main results.

Table A1 tests the robustness of results to alternative assumptions about the month of generation for 29 turbines with a capacity less than 1 MW. Column 1 assumes that the operating month is January, Column 2 assumes it is July (identical to the post-construction difference-in-difference estimates of Column 4, Table 3 in the main manuscript), and Column 3 assumes December as the operating month. We find that the coefficients are identical in sign and significance, and near identical in magnitude across all columns.

Table A2 assesses robustness of the main results using alternative lengths of time for the construction dates. The construction dates for Column 1 to 4 are defined as 12 months, 8 months, 4 months, and 0 months prior to the operation date, respectively. We present difference-in-difference estimates for the [0, 1) km distance bin in the PAPC and PA time periods, using the same regression model as Column 4 in Table 3 that includes month-year, county-year, and property fixed effects. The coefficients for the PAPC period range between -0.009 and -0.036, becoming larger in magnitude and improving in statistical significance as we move across columns. This suggests that the negative impact of turbines on housing prices becomes larger as the construction completion date gets closer to the generation date. The results for the PC time period are robust across all specifications, with the magnitude ranging between -0.044 and -0.046, and being significant at the 5% level.

Table A3 assesses the robustness of our main results using alternative lengths of time for the announcement dates. The announcement dates for Column 1 to 3 are defined as 40 months, 30 months, and 20 months prior to the operation date, respectively. We present difference-in-difference estimates for the [0, 1) km distance bin in the PAPC and PA time periods, using the same regression model as Column 4 in Table 3 that includes month-year, county-year, and property fixed effects. The coefficients for the PAPC period increase in magnitude as the assumed announcement date gets closer to the generation date: from -0.014 in Column 1, to -0.023 in Column 2, to -0.032 in Column 3. However, as none of those coefficients are statistically significant, we do not lay too much emphasis on their interpretation. The coefficients for the PC time period are near identical across columns, ranging between -0.045 and -0.046 and being significant at the 1% level throughout. This implies that our results are robust to alternative assumptions about the constructing date.

Table A4 assesses the robustness of our main results to changing the control group definition. We define the control group as properties lying in the 3-5 km bin in Column 1, those lying in the 3-6 km bin in Column 2, and those lying in the 3-7 km bin in Column 3. We find that the treatment effect is similar to our main results in both magnitude and significance across all columns, implying that our results are robust to different control group boundary definitions.

We also explore the heterogeneity of the treatment effects in the post construction time period. We obtain these results by estimating a DID model that is similar to our base specification, Equation (1), but which also allows for heterogeneous treatment effects in the post construction time period. We refer to this as our dynamic specification:

$$\begin{aligned}\ln(price_{icmt}) = \beta_0 &+ \sum_{k=1}^{3} \beta_1^k \left(dist_i^k\right) + \beta_2 PAPC_{imt} + \sum_{j=1}^{\tau} \beta_3^j \left(years\_post_{imt}^j\right) \\ &+ \sum_{k=1}^{3} \beta_4^k \left(dist_i^k \times PAPC_{imt}\right) + \sum_{k=1}^{3}\sum_{j=1}^{\tau} \beta_5^{kj} \left(dist_i^k \times years\_post_{imt}^j\right) + \boldsymbol{X_i \beta_6} \\ &+ \gamma_{mt} + \delta_{ct} + \varepsilon_{icmt}\end{aligned} \tag{A1}$$

We have replaced PC_{imt} in Equation (1) with a series of time dummies, $years\_post_{imt}^j$. For the primary specification of Equation (A1), we create bins of three year increments and corresponding dummy variables for each three year bin. Specifically, the bins are [0, 3) years, [3, 6) years, [6, 9) years, [9, 12) years, and more than 12 years, all measured in time since construction is complete, which we still assume occurs 8 months prior to generation commencing. While we could certainly estimate a version of this model with one year bins, we choose to aggregate multiple years to improve statistical precision (see Table A5 for the number of transactions occurring in each time period bin). In this specification, we estimate a separate treatment effect for each three year bin. β_5^{kj} are the difference-in-differences coefficients of interest, and give the change in housing prices from the pre-construction period to each of three year bins for each of the three distance bins relative to the control distance bin.

Table A6 provides estimation results for the β_5^{kj} coefficients in our dynamic equation, with four different fixed effects specifications that are analogous to the four columns in Table 3 in the main manuscript. For the 0-1 km bin, negative impacts are large and statistically significant for 0-3 years and 3-6 years post construction. The results suggest prices decline on average 7.7% in the first three years following construction, but abates to only 5.7% in the next three years. However, beyond six years, none of the coefficients are statistically significant and all are much smaller in magnitude than the first six years. The dynamic model also reveals an interesting pattern for the 1-2 km bin. While no effects were observed in Table 3, Table 5 suggests that prices do decline in the 1-2 km bin by about 2.5% in the first three years following construction. However, beyond those three years, there is no evidence of statistically significant negative effects. Lastly, there is no evidence of any negative impacts in the 2-3 km bin. The coefficients for 1-2 km and 2-3 km for years [9, 12) are statistically significant and positive. Because these are inconsistent with all other results, we view these as anomalous and not a causal impact of nearby turbines. In all, these results suggest that negative impacts are substantial for houses in close proximity to turbines, but these negative results are relatively short-lived.

Table A7 estimates Equation (A1) using a subsample of observations that excludes transactions in Cape Cod and Nantucket. In the 0-1 km bin, the coefficients for years [0, 3) and [3,6) are negative, though only the first one is significant (at the 1% level). This implies that housing prices decline by 4.6% within the first 3 years post construction. All remaining coefficients are positive and statistically indistinguishable from zero, which confirms that prices adjust to pre-treatment levels in later years. For the 1-2km and 2-3 km distance bins, we find that the coefficients for almost all year intervals are insignificant, confirming that negative effects are confined within 1 km of the turbines. The coefficients in years [9, 12) is statistically significant for both distance bins, but we view these as anomalous and not true impact of the wind turbine.

Table A8 estimates Equation (A1) using a subsample including only properties in Cape Cod and Nantucket. We find that all coefficients in the 0-1 km distance bin are significant, with the magnitude of the effect declining only slightly over time. The impact is strongest in years [0, 3), implying a housing price decline of 14% ($37,008) for properties in Cape Cod and Nantucket in the first three years post turbine construction. The magnitude of the impact declines slightly nine years after construction, but prices are still significantly lower (by 9.2%, or $24,319) compared to pre-treatment levels. All coefficients in the 1-2 km distance bin are negative, though only one is significant at the 5% level and two at the 10% level. The magnitude of the effect ranges between -12.9% in years [0, 3) and -5.8% in years 9 and above. This provides suggestive evidence of negative impacts from turbines persisting for larger distances (up to 2 km) in Cape Cod and Nantucket, thought the magnitude of the effect decreases over time. All coefficients in the 2-3 km bin are positive and none are significant, implying that the effects die out beyond 2 km.

Table A9 presents socioeconomic characteristics of the four regions used in Table 4.

Table A1: Robustness to different assumptions about unknown month of beginning generation

Distance interval	January	July	December
	(1)	(2)	(3)
PC × [0, 1) km	-0.048	-0.046	-0.048
	(0.018)***	(0.017)***	(0.017)***
PC × [1, 2) km	-0.004	-0.005	-0.005
	(0.013)	(0.013)	(0.013)
PC × [2, 3) km	0.002	0.002	-0.000
	(0.009)	(0.009)	(0.009)

Notes: All estimates are obtained from the same regression model as Table 3 that includes month-year, county-year, and property fixed effects. All estimates are post-construction difference-in-difference estimates. The online month for turbines less than 1 MW are defined as January, July, and December for Column 1 to 3, respectively. The number of observations is 223,866. R-square is 0.885. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A2: Robustness to different assumptions about construction dates

	12 months	8 months	4 months	0 months
	(1)	(2)	(3)	(4)
PAPC × [0,1) km	-0.009	-0.023	-0.036	-0.036
	(0.018)	(0.018)	(0.016)**	(0.015)**
PC × [0,1) km	-0.048	-0.046	-0.044	-0.044
	(0.017)***	(0.017)***	(0.017)**	(0.018)**

Notes: 'PAPC' stands for post-announcement/pre-construction and 'PC' for post-construction. All estimates are obtained from the same regression model as Table 3 that includes month-year, county-year, and property fixed effects. All estimates are difference-in-difference estimates. The construction dates for Column 1 to 4 are defined as 12 months, 8 months, 4 months, and 0 months prior to the operating date, respectively. The number of observations is 223,866. R-square is 0.885. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A3: Robustness to different assumptions about announcement dates

	40 months	30 months	20 months
	(1)	(2)	(3)
PAPC × [0,1) km	-0.014	-0.023	-0.032
	(0.014)	(0.018)	(0.024)
PC × [0,1) km	-0.046	-0.046	-0.045
	(0.017)***	(0.017)***	(0.017)***

Notes: 'PAPC' stands for post-announcement/pre-construction and 'PC' for post-construction. All estimates are obtained from the same regression model as Table 3 that includes month-year, county-year, and property fixed effects. All estimates are difference-in-difference estimates. The announcement dates for Column 1 to 3 are defined as 40 months, 30 months, and 20 months prior to the generation date, respectively. The number of observations is 223,866. R-square is 0.885. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A4: Robustness to different control group definitions

Distance interval	3-5 km	3-6 km	3-7 km
	(1)	(2)	(3)
PC × [0, 1) km	-0.035	-0.038	-0.042
	(0.015)**	(0.016)**	(0.017)**
PC × [1, 2) km	-0.002	-0.002	-0.003
	(0.012)	(0.012)	(0.013)
PC × [2, 3) km	0.002	0.002	0.001
	(0.009)	(0.009)	(0.009)
Observations	93,163	124,545	152,860
R-squared	0.872	0.878	0.881

Notes: All estimates are obtained from the same regression model as Table 3 that includes month-year, county-year, and property fixed effects. All estimates are post-construction difference-in-difference estimates. The control groups are defined as 3-5 km, 3-6 km, and 3-7 km from the closest wind turbine for Column 1 to 3, respectively. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A5: Number of transactions by distance bin and post-construction time interval

Post-construction time interval	0-1 km	1-2 km	2-3 km
years [0, 3)	1,179	3,449	4,401
years [3, 6)	1,106	3,297	4,606
years [6, 9)	1,035	3,256	4,175
years [9, 12)	492	1,604	1,840
years [12, 15)	56	209	239
years [15, 18)	26	20	13
years [18, 21)	0	5	1

Table A6: Heterogeneity of treatment effect by time using three-year bins

Time interval, post construction	Distance bins			Distance bins			Distance bins			Distance bins		
	0-1 km	1-2 km	2-3 km	0-1 km	1-2 km	2-3 km	0-1 km	1-2 km	2-3 km	0-1 km	1-2 km	2-3 km
years [0, 3)	-0.053	-0.027	-0.007	-0.077	-0.024	0.004	-0.063	-0.029	-0.006	-0.077	-0.025	0.003
	(0.018)***	(0.013)**	(0.008)	(0.024)***	(0.017)	(0.011)	(0.016)***	(0.010)***	(0.007)	(0.017)***	(0.014)*	(0.009)
years [3, 6)	-0.042	0.003	-0.002	-0.047	0.015	0.001	-0.060	-0.011	-0.009	-0.057	-0.003	-0.007
	(0.020)**	(0.015)	(0.011)	(0.027)*	(0.021)	(0.013)	(0.016)***	(0.011)	(0.008)	(0.023)**	(0.015)	(0.010)
years [6, 9)	0.013	0.032	0.016	0.023	0.031	0.032	-0.008	0.006	-0.005	-0.002	0.003	0.007
	(0.021)	(0.017)*	(0.015)	(0.030)	(0.023)	(0.018)*	(0.014)	(0.010)	(0.008)	(0.020)	(0.014)	(0.010)
years [9, 12)	0.013	0.060	0.036	-0.006	0.066	0.063	-0.006	0.026	0.004	-0.020	0.032	0.023
	(0.025)	(0.021)***	(0.020)*	(0.033)	(0.027)**	(0.024)***	(0.015)	(0.012)**	(0.009)	(0.022)	(0.016)**	(0.012)**
years 12 plus	-0.017	0.006	0.011	-0.033	-0.002	-0.028	-0.005	-0.001	0.003	-0.024	-0.022	-0.036
	(0.077)	(0.040)	(0.034)	(0.057)	(0.046)	(0.041)	(0.060)	(0.030)	(0.020)	(0.039)	(0.032)	(0.029)
Year by month FEs		Y			Y			Y			Y	
County by year FEs		N			Y			N			Y	
Block FEs		Y			Y			N			N	
Property FEs		N			N			Y			Y	
Observations		369,260			223,870			369,260			223,866	
R-squared		0.794			0.877			0.805			0.885	

Notes: Distance bins indicate the distance of a property from the nearest turbine. Time interval refers to the time elapsed post turbine construction, for the nearest wind turbine. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A7: Heterogeneity of treatment effect by time excluding Cape Cod and Nantucket

Time interval, post construction	Distance bins		
	0-1 km	1-2 km	2-3 km
years [0, 3)	-0.046	-0.011	0.002
	(0.016)***	(0.012)	(0.010)
years [3, 6)	-0.023	0.005	-0.008
	(0.021)	(0.015)	(0.011)
years [6, 9)	0.025	0.012	0.007
	(0.023)	(0.015)	(0.011)
years [9, 12)	0.011	0.046	0.023
	(0.025)	(0.017)***	(0.012)*
years 12 plus	0.004	-0.011	-0.036
	(0.039)	(0.032)	(0.028)

Notes: All estimates are obtained from a single regression that includes month-year, county-year, and property fixed effects. Distance bins indicate the distance of a property from the nearest turbine. Time interval refers to the time elapsed post turbine construction, for the nearest wind turbine. The number of observations is 209,113. R-square is 0.887. Standard errors are clustered at the tract level and shown in parentheses. ***, **, and ** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A8: Heterogeneity of treatment effect by time for Cape Cod and Nantucket

Time interval, post construction	Distance bins		
	0-1 km	1-2 km	2-3 km
years [0, 3)	-0.140	-0.129	0.040
	(0.022)***	(0.064)*	(0.028)
years [3, 6)	-0.146	-0.062	0.046
	(0.041)***	(0.046)	(0.043)
years [6, 9)	-0.078	-0.076	0.021
	(0.018)***	(0.030)**	(0.040)
years 9 plus	-0.092	-0.058	0.027
	(0.017)***	(0.031)*	(0.047)

Notes: All estimates are obtained from a single regression that includes month-year, county-year, and property fixed effects. Distance bins indicate the distance of a property from the nearest turbine. Time interval refers to the time elapsed post turbine construction, for the nearest wind turbine. The number of observations is 14,743. R-square is 0.851. Year 12 plus was dropped due to the lack of observations. Standard errors are clustered at the tract level and shown in parentheses. ***, **, and ** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A9: Demographics by region

Socioeconomic characteristics	Western Massachusetts	Eastern Massachusetts	Cape Cod and Nantucket Massachusetts	Rhode Island
Black (%)	5.6	8.5	3.2	6.8
Hispanic (%)	14.0	11.5	3.2	15.4
Household Income ($)	85,584	115,878	123,954	101,212

Notes: Income and population data are obtained from ACS 5-year 2017-2021 estimate from US Census Bureau.

Chapter – 3

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Focusing the View: Improved Methods for Assessing Viewshed Impacts of Onshore Wind Turbines

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Abstract

The purpose of this paper is to improve methods of assessing viewshed impacts of onshore wind turbines. The preferred viewshed metrics are calculated using LiDAR Digital Surface Model GIS data, which account for trees and buildings, which obstruct distant turbines. I additionally measure views from not only a particular house, but also the surrounding roads. For comparison, I measure views using elevation data of bare earth only, which has been used in other studies. Using data from New England, USA, I use a difference-in-differences identification strategy with treatment defined by the visibility of a wind turbine, while also controlling for proximity-based treatment effects. The results suggest that property values decline when a wind turbine is visible. Previous viewshed methods underestimate the level of disamenity and reduce the significance level.

Keywords: Onshore wind energy, hedonic valuation, property values, viewshed analysis, LiDAR, Digital Surface Model

JEL Codes: Q42, Q51

1. Introduction

Renewable energy to combat global warming and air pollution continues to grow. Wind energy as a key renewable energy source has increased significantly around the world. In 2010, the total wind capacity installed was 181 GW while in 2021 the total capacity was 830 GW, over 4 times greater than that in 2010, and 92% of the growth is attributed to onshore wind (IEA). In 2021, 93% of wind capacity installed were onshore systems while offshore wind farms accounted for only 7% (IEA). Therefore, onshore wind has dominated both the growth and the distribution of wind energy.

While wind energy generates positive benefits through carbon mitigation, wind turbines are not free from negative externalities. Two major negative externalities for human beings are noise and visual disamenities. The low-frequency noise generated by a wind turbine may contribute to health problems such as headaches, sleep difficulties, and mood problems (Chiu et al., 2021). In terms of visual impacts, there are four main concerns. First, a wind turbine may ruin a gorgeous view. Some residents value the unspoiled views and the natural character of landscapes. However, the sight of a wind turbine could make the scenery less pristine and seem more industrial. Second, the movement of wind turbines can be a distraction, which makes the experience of a rural landscape less peaceful and tranquil. Third, spinning turbine blades can cause shadow flicker, a regular, intermittent light-dark flashing effect occurs when the turbine is in between the Sun and viewer. This can be distracting when it occurs in a room. Last, the blinking red lights on wind turbines generate light pollution during nighttime, potentially disturbing sleep or distracting drivers.

The purpose of this paper is to quantify the negative externalities of viewing turbines from one's residence, and in doing so explore best practices for measuring viewshed of turbines. We apply the hedonic pricing method (HPM), which is a commonly used revealed preference method. By examining where people choose to live, the amenities and disamenities around that location, and the housing price of that location, HPM can estimate the implicit price of each amenity or disamenity (Rosen, 1974). If there are disamenities associated with wind turbines, then those disamenities will be capitalized into housing prices. We use GIS to measure viewshed and incorporate this measure into our hedonic price model.

Many prior studies have also used HPM to examine wind turbine externalities. The simplest such studies use Euclidian distance to measure the extent of externalities. Some HPM studies find negative effects of wind turbines on property values (Heintzelman and Tuttle, 2012; Heintzelman et al., 2017; Dröes and Koster, 2016; Jarvis, 2021; Dröes and Koster, 2021; Eichholtz et al., 2021), but others find no effect (Lang et al., 2014; Hoen et al., 2015; Hoen and Atkinson-Palombo, 2016), while Vyn (2018) and

Dong et al. (2023) find spatial heterogeneity of price impacts. When proximity is the only measure of externalities, it will measure the combined impact of noise and visual disamenities. However, using proximity to proxy for views introduces substantial measurement error because not all houses at a given distance have the same viewshed. Research has been conducted to evaluate the externality of turbine view specifically, using the visibility of the turbine as the treatment status instead of the adjacency to the wind turbine. Regarding onshore wind turbine view impact, there is no consensus. Hoen et al. (2011), Vyn and McCullough (2014), Lang et al. (2014), and Dröes and Koster (2016) find no visual impact, but others find negative impact (Jensen et al., 2014; Gibbons, 2015; Sunak and Madlener, 2016). Heintzelman et al. (2017) find negative impact in New York but no impact in Ontario. For offshore turbines, both Jensen et al. (2018)[21] and Dong and Lang (2022) find no price effect of views.[22]

There are several different methods that can be used to calculate turbine viewshed. The most straightforward way is field visits (Hoen et al., 2011; Lang et al., 2014; Vyn and McCullough, 2014; Heintzelman et al., 2017). Vyn and McCullough (2014) visit 79 rural residential properties and 27 farm properties, 106 in total. Heintzelman et al. (2017) visit 47 parcels in Ontario and 58 parcels in New York, 105 in total. Lang et al. (2014) completes site visits to 1354 properties in Rhode Island. Hoen et al. (2011) go to 6,194 homes, which took them more than a year to finish. This method can apply to small sample sizes within a small study area only. It is very time-consuming and costly, even impossible, to conduct site visits for a large sample in a widespread study area. Additionally, some properties are constrained by private roads, which could lead to loss of relevant observations due to inaccessibility. Lastly, field visits are problematic if there are low visibility conditions (e.g., fog) on the day of the visit.

Due to the limitations of site visiting, some researchers have turned to GIS software to calculate turbine viewshed. Dröes and Koster (2016) draw a line from the geometric center (i.e., the centroid) of each property to the nearest wind turbine. If the line is obstructed by other buildings, they assume that there is no direct view. Based on this measure, 0.69% of the treated 80,000 houses have a direct view on a wind turbine. It is likely that this method will inaccurately estimate the number of houses having a turbine view. First, this method does not account for any change in the elevation of the bare ground, and thus is only suitable for flat areas. Second, buildings may not necessarily block the view if they are short and far away from the observer. Third, the method does not account for trees or other natural vegetation that could block views.

[21] Jensen et al. (2018) do not discuss how they calculated the viewshed.
[22] Carr-Harris and Lang (2019) examine tourism impacts of offshore wind using the case study of the Block Island Wind Farm, where the turbines are very prominent at just 3 miles off the coast. They find tourism increases following construction, suggesting views may even attract tourists.

The most rigorous, automated way to calculate turbine viewshed is using LiDAR (Light detection and ranging) point cloud data. A LiDAR system measures the time it takes for emitted light to travel to the target and back. That time is used to calculate the distance traveled and then to convert the distance to elevation. LiDAR data can be converted to two elevation models — the Digital elevation model (DEM) and the Digital Surface Model (DSM). DEM accounts only for the elevation of bare earth without trees and buildings, while DSM incorporates any object on the earth's surface, including trees and buildings.

Several prior hedonic studies have applied LiDAR data. Gibbons (2015) calculates viewshed using DEM, which means no-view houses are only those where turbines are hidden by the terrain. Therefore, DEM misclassifies many properties as having turbine views by ignoring trees and buildings. Jensen et al. (2014), Sunak and Madlener (2016), and Dong and Lang (2022) use DSM, the most accurate tool, to calculate viewshed. Sunak and Madlener (2016)[23] identify houses as having a turbine view if the housing point feature is located within the turbine viewshed. The viewshed will be overestimated since the observer is the rooftop. Jensen et al. (2014) define houses as having a turbine view if at least one corner of the building footprint polygon 2 meters above the ground is in the turbine viewshed, but the viewshed zone is captured by only 4 points instead of an area. Dong and Lang (2022) draw a 5-meter buffer of each housing point and consider a house as having a turbine view if a turbine is visible in its buffer zone. This method incorporates the visibility of a turbine in the empty area around the house. However, this will still overestimate the viewshed since the rooftop and trees in the buffer zone can "see" a turbine.

The primary research objective of this paper is to develop a best practice for automated viewshed estimation. I use DSM with adjustments for on property trees and buildings that could result in a false positive for viewshed. Further, I estimate viewshed from the property and from nearby roads to more holistically capture the homeowners experience, and eventually combine these measures for the best approximation of true views. Then, I incorporate the estimated viewshed into a hedonic model to assess people's valuation of turbine views. Lastly, I additionally estimate viewshed using inferior, but previously used DEM methods, to assess the extent of misclassification and the extent of bias in the valuation estimates. Finally, this article discusses how previous methods yield biased estimates of the visual impacts and how to accurately measure turbine viewshed.

The application of methods focused on turbine and housing data from Massachusetts and Rhode Island. The sample size is 118 turbines and 60,300 property

[23] Their article does not mention details of GIS analysis, but their Figure 2 suggests that the circles are point features instead of buffer zones since some highly overlapped circles represent very different viewshed results.

transactions. The GIS analysis suggests that over 50% of the observations are misclassified as having a view using DEM. To assess valuation of turbine externalities, I estimate a difference-in-differences model that incorporates both proximity to and viewshed of turbines. Using the preferred DSM viewshed measure, the results suggest that visibility of a wind turbine causes property values to decline by 2.7% to 5.2%. Given the average house price for properties before turbine installation was $361,374, the point estimates imply property value losses ranging from $10,841 to $18,069. In contrast, when using the DEM viewshed measure, the results suggest visibility of a wind turbine causes property values to decline by 0.6% to 2.2%. While not the primary focus of this article, I find that proximity to the wind turbine within 1 km does not have a statistically significant negative impact on housing prices relative to 2-3 km. This suggests that views of turbines are more important to homeowners and potential buyers than proximity. However, I also explore heterogeneity by county, and find that in some areas proximity does matter more than viewshed.

This article makes several contributions. First, it uses DSM and a variety of GIS tools to accurately measure the direct view, and it also analysis the impact of indirect view from the road on housing prices. Second, it bridges the gap between the inconsistencies of the visual impacts of onshore wind turbines. Third, it finds that DEM yields biased results due to viewshed misclassification. Last, it discusses the problem of turbine viewshed measurement in previous articles and provides guidance on how to accurately measure turbine view.

The rest of the paper is structured as follows. Section 2 outlines the methodology used for the analysis. Section 3 describes the data and Section 4 the results. The final section includes the conclusion and the limitations of the study.

2. Methodology

2.1 Viewshed analysis

Viewshed can be calculated in two models using GIS: Digital Elevation Models (DEM) and Digital Surface Models (DSM), both of which are generated using LiDAR data. DEM is generated using ground returns, which measures only the elevation of the bare earth, while DSM is generated using first returns, which incorporates any object on the earth’s surface, including trees and buildings. Therefore, DSM is more accurate than DEM for viewshed calculation. I define the spatial resolution (pixel size) for both DSM and DEM as 2 meters, which was substantially larger than the average point spacing to minimize the occurrence of pits and the need for interpolation.[24]

[24] A one-meter pixel size would be the best, but not feasible due to the memory limit of the computer.

First, I generated the Digital Height Model (DHM) by subtracting the DEM raster from the DSM raster. The DHM model represents the height of the objects on the earth. I defined pixels with the value of the DHM greater than 160 m as anomalies since the tallest building within 3km of any turbine is less than 160 m. I removed the anomalous pixels from the DSM raster and filled the gap by taking the median of the neighboring pixels.

I used wind turbines as the observers to calculate viewshed. The actual observers are people from the yard or the road. Since viewshed is symmetric, however, using turbines as the observer yields identical results in far less computational time. Next, I removed the turbine pixels from the DSM model.[25] The height of the viewshed observer is required for viewshed calculation in GIS. In this analysis, the observer height should be the ground elevation of the turbine plus the turbine height. The turbine height will be added to the pixel of the DSM raster where the turbine points are located. If the turbine pixels are not removed, the turbine height will be twice its actual height, and the viewshed raster will be overestimated when the turbine point feature is on the pixel. The viewshed raster will be underestimated when the turbine point feature is not on the turbine pixel but located on any of the surrounding pixels due to measurement error, since turbine pixels will block part of the viewshed. To remove the turbine pixel, I set the DSM pixels corresponding to heights ≥ 30 m (i.e., the minimum height for turbines) within 50m (i.e., the maximum rotor radius) buffer zone of a turbine point feature to a null value. Then, I replaced the null value with the coinciding DEM elevation value.

For viewshed analysis, I used the DSM raster with anomalies and turbine pixels removed as the input raster and turbine point features as observers. I used two different observer heights to calculate turbine viewshed. The first observer is turbine hub, which means that the visibility of only blades will not be considered turbine view. The second observer is the tip of the blade at the twelve o'clock position, which means the visibility of any part of a turbine will be considered turbine view. The reason why I use two different observers is because first some researchers use hub height (Jensen et al., 2014; Dong and Lang, 2022), while other researcher uses tip height (Gibbons, 2015). Second, I use two observation points to test if there is a difference in valuation. The elevation of the observers is the pixel values of the DSM raster plus the turbine height (hub height or total height). I limit the radius of turbine viewshed to 3 km from each wind turbine.[26] I generated the Above Ground Level (AGL) raster to identify locations that would be visible to a human observer. In an AGL raster, each cell value represents the minimum height required to be added to the cell to make it visible by at least one observer. Cells that are already visible have a value of 0. I define AGL raster value below 2 meters as

[25] Turbine pixels represent the elevation of turbines built before the acquisition date of the LiDAR data.
[26] Extending the range of viewshed would be better, but requires more LiDAR data, and is not feasible to conduct due to the memory limit of the computer.

turbine-visible since the median human height is just below 2 meters.

There are 2 turbine viewshed locations for each house. The first location is defined as empty area[27] within 10 m buffer of a housing building footprint (i.e., yard, driveway, or adjacent road). After generating the AGL rasters, I removed the pixels in the AGL rasters where the pixel values in the DHM are greater than 2 meters. I assumed that any objects on the ground above 2 meters are fixed features like trees and buildings, and thus the turbine observer seeing those points would not constitute a true view because people do not typically stand on trees or sheds. The remaining pixels represent the empty area where people can stand within 10 m buffer of their house. The second location is defined as roads within 100 m buffer of a housing building footprint. I converted AGL raster to polygon and intersect AGL polygon with road line features. Then I calculated the sum of road length where AGL value is below 2 meters within 100 m buffer of a housing building footprint. Road view serves as a good second measure that is meant to complement yard view. The value in this measure is it expands the possible viewshed to a small neighborhood around a house, which will capture what residents might see when they drive somewhere or take a walk. Further, roads do not have trees or buildings on them, so there no concern about a false positive. My goal is not to test differences in valuation between these two measures; I see them as different approaches to measure the same thing. Instead, in my preferred viewshed measure, I combine these two measures to have a more holistic sense of viewshed. I calculated the turbine viewshed in the same way using DEM except the anomaly and turbine pixel removal steps. These steps were omitted because is because no anomaly is detected visually on the DEM raster and DEM raster does not have pixels representing turbine height. Figure 1 displays the workflows of turbine viewshed calculation for both DSM and DEM.

The final dataset includes 8 different viewshed variables. I calculated the viewshed from two different locations (yard view and road view), two different elevation models (DSM, DEM), and two different observers (turbine hub, turbine tip at the 12 o'clock position). Figure 2 is an example of different viewshed results between DSM and DEM. DEM has a larger viewshed than DSM does since trees and buildings are not accounted for in DEM's viewshed.

2.2 Regression model

Consistent with recent research, I use a difference-in-difference (DID) model to estimate the impact of wind turbines on property values. The model allows for both a proximity effect and a viewshed effect. For proximity effect, the treatment group is the transacted properties between 0-1 or 1-2 km from the closest wind turbine, while the control group is the transacted properties between 2-3 km from the closest wind turbine.

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[27] I define empty area as where people are able to stand outdoors.

For viewshed effect, the treatment is the transacted properties having a turbine view, while the control group is the transacted properties not having a turbine view, within 3 km of the closest wind turbine. The model is defined as follows:

$$\ln(price_{icmt}) = \beta_0 + \sum_{k=1}^{2} \beta_1^k \left(dist_i^k\right) + \beta_2 Sited_{imt} + \beta_3 Constructed_{imt} + \sum_{k=1}^{2} \beta_4^k \left(dist_i^k \times Sited_{imt}\right) + \sum_{k=1}^{2} \beta_5^k \left(dist_i^k \times Constructed_{imt}\right) + \beta_6 view_i + \beta_7 (Sited_{imt} \times view_i) + \beta_8 (Constructed_{imt} \times view_i) + \boldsymbol{X_i \beta_9} + \gamma_{mt} + \delta_{ct} + \varepsilon_{icmt} \quad (1)$$

where $\ln(price_{icmt})$ 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 property i is located within the k^{th} distance band to the nearest turbine site. The distance bands are defined as 0-1 km and 1-2 km; the 2-3 km distance band is the omitted. $Sited_{imt}$ is a binary variable equal to one if the transaction occurs between 30 and 8 months prior to generation commencing. $Constructed_{imt}$ is a binary variable equal to one if the transaction occurs in the time after wind turbine construction is complete, which I assume is 8 months prior to generation commencing.[28] $\boldsymbol{X_i}$ is a set of property-specific, time-invariant control variables (e.g., bedrooms and bathrooms). γ_{mt} is month-year fixed effects to control for common price fluctuations in the whole housing market. δ_{ct} is county-year fixed effects to control for localized price variation.

First, this model tests whether the proximity of wind turbine affects housing prices by comparing transactions within 1 km and 1-2 km from the closest wind turbine with transactions between 2 to 3 km from the closest wind turbine. This model assumes that there are no impacts beyond 2 km, which is supported by the results of Dong et al. (2023). Second, this model tests whether the visibility of wind turbines has an additional impact on housing prices beyond the impact of proximity. The null hypothesis is that the visibility of wind turbines has no impact on housing prices, while the alternative hypothesis is that the visibility of wind turbines has an impact on housing prices. $view_i$ is a binary variable equal to one if a transacted property has a turbine view at the time of sale. I estimate this model for each of the eight viewshed variables using block fixed effect model (Equation 1), as well as a repeat sales model that includes property-specific fixed effects.

3. Data

3.1 Wind Turbines and Viewshed

Turbine data are from the Energy Information Administration's (EIA's) report

[28] The assumed timeline follows Dong et al. (2023), which they base on average turbine construction timelines from Hitachi Velocity Suite.

EIA-860M, or the Monthly Update to the Annual Electric Generator Report and the U.S. Wind Turbine Database (USWTDB). I gather data on all onshore wind turbines in MA and RI that were constructed between January 2001 and December 2019. The USWTDB includes information on capacity, location (latitude and longitude), and the year of operation. One drawback of this dataset is that only the year of turbine operation is reported and not the month, a practice which results in imprecision. I therefore use the EIA-860M dataset, which includes information on the month of operation for 89 onshore turbines in MA and RI with a wind farm capacity greater than or equal to 1 megawatt (MW).[29] For the remaining 29 turbines with a wind farm capacity below 1 MW, I assume that the operation month is July. Four turbines below or equal to 100 kW in the dataset had unknown turbine heights, so I assigned 37 meters for their hub heights and 48 meters their total heights, which are the modal values for turbines smaller than 100 kW. Our dataset consists of 118 turbines (see Figure 3).[30]

Table 1 displays the summary statistics of wind turbines. The average capacity is 1.4 MW, ranging from 0.05 MW to 3 MW. The average hub height and tip height are 71.5 and 108.8 meters, respectively. The difference between the average hub height and tip height is large, suggesting that turbine blade might be long enough to have a view impact. All these attributes have a big range and a large standard deviation, which means turbines are different in size. Figure 3 represents a map of our sample turbine locations.

GIS data (LiDAR point clouds, state boundaries, building footprints, and roads) were acquired from the Rhode Island Geographic Information System (RIGIS), MassGIS, and the National Oceanic and Atmospheric Administration (NOAA). Distance to the nearest turbine along with turbine view were calculated using ArcGIS Pro 3.0.

3.2 Housing transactions

Housing transaction data were obtained from Zillow (http://www.zillow.com/data) for MA and RI for years 2000 to 2019. The dataset includes sales prices, street addresses, geographic coordinates, Census divisions, transaction dates, and housing characteristics (bedrooms, bathrooms, etc.). Sales prices are adjusted to 2019 levels using the Northeast regional housing Consumer Price Index from the Bureau of Labor Statistics. I made the following sample cuts. I include only single-family housing and exclude condominiums. I dropped transactions with prices of $100 or less, since these are clearly not arm's length transactions, I also dropped transactions in the bottom and top 5% of the sales price distribution to eliminate outliers. Further, I dropped observations that have more than

[29] The EIA-860M does not record information on any energy generation plants that have a capacity less than 1 MW.

[30] I excluded Block Island, Martha's Vineyard, and Nantucket.

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. I excluded homes that were sold before they were built, as there is evidence that these are lot sales without improved property. Properties that transact more than once on the same date are likely to be subdivisions and are therefore excluded. I detected that Zillow geographic coordinates were inaccurate based on overlay with satellite imagery. Therefore, I geocoded properties using Google Sheets to create point features for all sample properties within 3km from the closest wind turbine and confirmed that these were accurate by comparing the location of housing point feature with that in the satellite imagery. I discarded the housing points located more than 5 meters from the closest building polygon. This was done because of the inaccuracy of the addresses in the original dataset or the inaccuracy of geocoding. This step dropped 4468 properties from the total of 48,939, leaving 44,471 properties. I spatially merge the turbine data with the housing dataset by matching every property to the closest wind turbines within 3km since the viewshed data are available only in that range. The final dataset used for regression includes 60,300 transactions.

3.3 Summary statistics

Table 2 presents summary statistics for sample properties including both housing characteristics and viewshed. The first panel is the viewshed binary variables calculated by DSM. Only 8% of the transactions either have or will have a yard view of the turbine tip after the construction of a nearby turbine, and 5% of the turbine hub. In terms of road view, the percentage of transactions increases to 18% and 11%, respectively. The second panel is the viewshed binary variables using DEM, the magnitude increases to 60% approximately for all variables. This disparity between DSM and DEM measures implies that the DEM method results in about 50% percent of the observations being misclassified as having a yard view or road view.

Panel 3 is the housing characteristics for the sample. The average sales price of all the transactions is $343,090; the average living area is 2,970 square feet; the average number of bedrooms is about 3; and the average number of bathrooms is slightly below 2.

3.4 Assessing the DID Assumption

A key assumption of the DID method is that treatment and control outcome trends would be parallel in the absence of treatment. I examined pre-treatment trends to assess the likelihood that this assumption holds. Figure 4 displays estimated differences between housing prices where houses have a turbine view on the road and housing prices where houses do not have a turbine view on the road for one-year increments. Time zero represents the starting year of generation, and the first vertical line represents the approximate announcement date of the wind turbine; the second vertical line represents the approximate completion of the construction of the wind turbine. I use the estimates before the beginning of the construction period to assess parallel trends. All estimated coefficients before the treatment period are not significantly different from zero, which suggests that the parallel trends assumption holds in this case. Figure A1 displays estimated differences between housing prices by distance in the 0–1 km distance bin and the 2–3 km distance bin for one-year increments. All estimated coefficients suggest that the parallel trends assumption holds.

4. Results

4.1 Classification of treatment status

Table 3 illustrates the classification of treatment status (viewshed) between DEM and DSM for yard view and road view after the construction of wind turbine. The DEM method classifies many properties as having a view that are classified as not having a view by the DSM method. We assume this is a misclassification by the DEM method because it does not account for trees and buildings that block views. For yard view, 13,821 observations (86% of the treated properties) are misclassified by DEM; for road view, 12,383 observations (72% of the treated properties) are misclassified. Numbers are similar for hub view.[31] Figure 5 is the visualization of misclassification of DEM. As the figure displays, a large portion of observations in the treatment group is misclassified. Given that properties without a view are classified as having a view by DEM, I expect that the coefficients in the hedonic model using DEM views will be biased relative to DSM. Specifically, I expect the DEM coefficients to be attenuated towards zero.

As alluded to above, the DSM yard view and road view do not always classify properties the same way. Table 4 illustrates the DSM classification using turbine tip as the observer. Of the 29,104 transactions that are classified as not having a yard view, 2,758 (9%) are classified as having a road view. Of the 26,588 transactions that are classified as not having a road view, 242 (1%) are classified as having a yard view.[32] These observations are not misclassified if the treatment status is yard view or road view, specifically, but are misclassified if the treatment status is turbine view in general. Figure 6 is the visualization of misclassification for yard view and road view using DSM. I expect that the road view coefficients in the hedonic regression will be larger in magnitude and more significant than yard view coefficients, assuming yard view and road view have the same visual impact. This is because there are less misclassified observations having a turbine view for the non-treated of road view variable than those having a turbine view for the non-treated of yard view variable. Given these differences

[31] See Table A1

[32] Table A2 illustrates the DSM classification using turbine hub as the observer. Of the 30,028 transactions that are classified as not having a yard view, 1,991 (7%) are classified as having a road view. Of the 28,223 transactions that are classified as not having a road view, 186 (1%) are classified as having a yard view.

in classification, in addition to presenting hedonic models that use either road view or yard view, I also combine these measures into a single measure for a more inclusive measure of viewshed. This combined measure is my preferred measure.

4.2 Preliminary results

Table 5 presents preliminary results from the estimating Equation (1). Columns 1 and 3 use Census block fixed effects and Columns 2 and 4 include property fixed effects instead. All columns include county-year fixed effects. Results suggest that the DID coefficients for the 0-1 km bin are negative but generally insignificant. The coefficients of the viewshed variables are consistent with expectations. In terms of road view, the coefficients estimated using DEM have smaller magnitude than those using DSM, and the statistical significance for the coefficients estimated using DEM are lower than those using DSM. This is due to the large portion of misclassified observations for the treated using DEM, while the misclassified observations for the non-treated having a turbine view using DSM are negligible. For DSM, the coefficients for yard view have smaller magnitude than those for road view, and the statistical significance for yard view coefficients is lower than that for road view coefficients. This is due to the larger proportion of misclassified observations having a turbine view for the treated for yard view. As for yard view, the coefficients and statistical significance between DSM and DEM are mixed. The DSM tip coefficients have larger magnitude than DEM tip coefficients have, but the statistical significance is lower. The DSM hub coefficients have smaller magnitude than DEM hub coefficients have, and the statistical significance is lower. The mixed results are attributed to the misclassification for the treated for DEM and the misclassified observations having a turbine view for the non-treated for DSM.

4.3 Main results

Since there is significant overlap between yard view and road view for the treated and misclassification of turbine view for the non-treated, the results using the DSM model in Table 5 are not a clean test of viewshed valuation. I estimated several models with modifications to the sample or the definition of viewshed to improve the tests. First, I reran Model (1) by excluding the overlapped and misclassified observations. For the yard view regression, 11,229 observations are dropped; for the road view regression, 5,179 observations are dropped using tip as the observer.[33] These models test how yard view or road view alone affects the housing prices, with no overlap or misclassification.

[33] For the yard view regression, 7,152 observations are dropped; for the road view regression, 2,981 observations are dropped using hub as the observer.

In addition, I generate a new binary variables, “turbine view”. “Turbine view” is equal to one if a house has either a yard view or a road view. This tests whether a turbine view around the house or on the nearby road affects housing prices. The results are displayed in Table 6. With regard to pure yard view, all estimates are positive and insignificant, suggesting that houses having a yard view experience no price change. This could possibly be due to the lack of observations; only 242 observations have a yard view with no road view. In terms of pure road view, all coefficients are negative and significant, ranging from -0.033 to -0.059. This suggests that houses having a turbine view from a nearby road experience loss of value ranging from about 3% to 6%. In terms of turbine view, all coefficients are negative and significant, ranging from -0.027 to -0.052. This suggests that houses having a turbine view from the yard or a nearby road experience loss of value ranging from about 3% to 5%.[34]

4.4 Heterogeneity by strength

This article also tests whether the impact is the same between different viewshed strengths. The viewshed strength for each house is calculated by the sum of the length of road segment multiplied by the number of visible turbines in that segment.

$$viewshed\ strength_i = \sum_{j=1}^{n} road\ length_{ij} \times number\ of\ visible\ turbine_{ij}$$

where i refers to houses and j refers to road segments within a 100-meter buffer of the house. I generated two dummy variables for each observer. The “above median” that equals 1 means that the viewshed strength is above the median value; “below median” that equals 1 means that the viewshed strength is below the median value; the reference group is transactions where houses have no road view.

Table 7 displays the results of the impact of road view strength on housing prices using the DSM model. The first panel uses tip as the observer while the second panel uses hub as the observer. All the 8 coefficients of viewshed strength are negative. In the first panel, the magnitude of coefficients increases from 0.009 insignificantly to 0.026 at the 1% significance level in the block fixed effect DID model and from 0.016 at the 10% significance level to 0.034 at 1% significance level in repeat sales model. In the second panel, the magnitude of coefficients increases from 0.017 to 0.032 in the block fixed effect DID model and from 0.031 to 0.036 in the repeat sales model, all coefficients are

[34] In the results so far, I have assumed that the effect of viewshed on housing prices is the same regardless of how far a property is from a turbine. Table A3 displays the results that test heterogeneity of viewshed impacts by distance. All coefficients on interactions between viewshed and distance are insignificant suggesting that there is no heterogeneity of viewshed impacts by distance within 3 km from the closest wind turbine.

significant at the 1% level. The increase of the magnitude and significance levels suggests that houses having stronger view impacts experience a larger decrease in prices.

This finding aligns with Gibbons (2015) and Sunak and Madlener (2016). Gibbons (2015) finds that visual impact on housing prices of wind farms is proportional with the number and proximity of visible turbines. Sunak and Madlener (2016) find that houses having an extreme to medium turbine view experience a decrease in price by about 9–14%, but properties having a minor or marginal view do not experience any statistically significant negative effect on the value.

4.5 Heterogeneity by county

Dong et al. (2023) find that the decrease of housing prices in Massachusetts and Rhode Island due to the proximity of a wind turbine is driven by Cape Cod and Nantucket. It is possible that there are spatial heterogeneous treatment effects of visual impact as well. Table 8 displays the results by county using tip as the observer, but we omit any county with less than 1,000 observations from this analysis.[35] There are 11 counties in total in the table. For each county, the coefficients are estimated using the Block fixed effect DID model using tip as the observer. Only Bristol, Essex, and Middlesex County have negative and significant estimates for both observers. The results suggest that there is heterogeneity of view impact by county, mostly driven by Bristol, Essex, and Middlesex County. The visibility of wind turbines does not add additional impact to the proximity of wind turbines on housing prices in Cape Cod. This is consistent with the idea of a localized culture that dislikes turbines.

4.6 Discussion of previous articles

Among the studies that concentrate on the impact of turbine view on housing prices, there have been four published journal articles that calculated turbine view using LiDAR data. Jensen et al. (2014) define houses as having a turbine view if at least one corner of the building footprint 2 meters above the ground is in the turbine viewshed using DSM. This method is similar to the calculation of yard view in this article, except that yard view is represented by four points of the building instead of the entire empty area around the house. There are probably non-treated transacted properties that actually have a view from a nearby road, which the article does not consider, and may bias the results. Gibbons (2015) calculates the viewshed using DEM. The first identification strategy is to compare the price changes when a wind farm becomes visible and operational to the price changes occurring in comparable areas where wind farms are already visible and operational or where they will become so in the future (see Figure A2 that shows viewshed treatment status of Gibbons (2015)). The viewshed measurement is likely misclassified due to the unrealistic assumptions of DEM (see Figure A3 that shows the misclassification for the treated of Gibbons (2015)). However, Gibbons (2015) finds

[35] Table A4 displays the results using hub as the observer.

consistent negative and significant estimates, which are very different from my results. There are several explanations. First, his study area is England and Wales, and preferences may be different. Specifically, based on area, there are almost three times as many turbines in that study area as in mine, and the preponderance may influence valuation. Second, even if the DEM misclassification is large, his identification strategy can detect causal relationship of the proximity to the wind turbines, either visible or non-visible, on housing prices (see Figure A4 that shows proximity treatment status of Gibbons (2015)). Third, Gibbons (2015) estimates the visual impact at postcode level (geographical unit with about 17 houses) instead of property level, meaning viewshed is measured at a postcode level, instead of something specific to an individual property. Sunak and Madlener (2016) estimate valuation of five discrete visual impact levels to no view. Their results show that the coefficients for houses with an extreme view (highest) are lower in both magnitude and significance level than those with a dominant view (second highest). They explain that this is due to the lack of observation for houses having an extreme view. However, this could also result from misclassification of viewshed since they use DSM with rooftop as the viewer. Table A5 explains this misclassification using my sample. There are houses where a turbine is visible from the rooftop but not from a nearby road. There are also houses where a turbine is visible from a nearby road but not from the rooftop. Dong and Lang (2022) draw a 5-meter buffer of each housing point, and the viewer is rooftop and trees in the buffer zone. This could suffer from similar or even greater misclassification than rooftop view (see Table A5). Their results suggest no impact of an offshore wind farm about 26 km away. Jensen et al. (2014) and Dong and Lang (2022) use hub as the observer instead of turbine tip, which could underestimate the extent of viewshed, since a single turbine blade is about 1/3 of the total height.

5. Conclusion

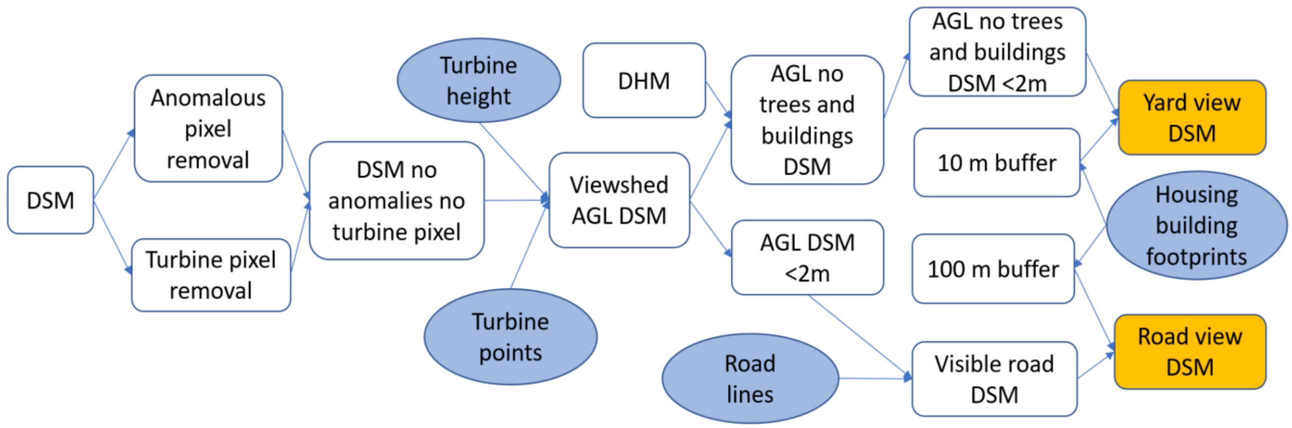
This study explored the visual impact of wind turbines on housing prices in Massachusetts and Rhode Island. The results suggest that houses having a turbine view from nearby road experience a loss of value from about 3% to 5%, but the impact on the housing price if a turbine is visible around the house is inconclusive. Stronger turbine viewshed has stronger negative impacts on housing prices, and there exists heterogeneity of view impact by county. If either direct view or indirect view has an impact on housing price, in order to get accurate results, we should first use the DSM method instead of DEM and then consider not only direct view from the house but also indirect view from the public road nearby.

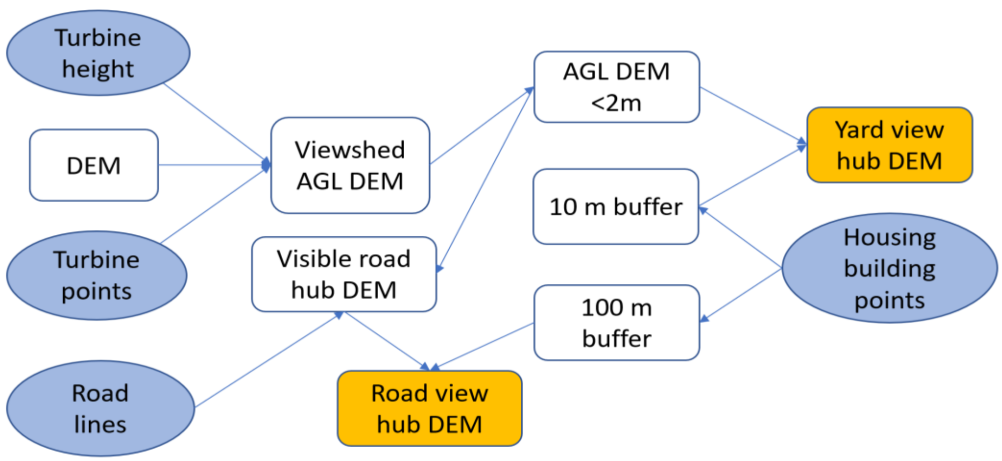
The viewshed measurement methods in this article also give insights into the viewshed measurement in other research fields, such as ocean view or park view. Walls et al. (2015) evaluates the value of natural landscape views on housing prices using DEM, which biases the estimates due to the misclassification in the treatment group. Dai et al. (2023) estimates the viewshed effects of the natural landscape on house prices using augmented DEM with building obstruction, which is less accurate than DSM. Even if the modified DEM method generates the viewshed similar to DSM viewshed, the observer is a housing point, which ignores the possible visibility of the natural landscape from the yard or the road. Yamagata et al. (2016) assess the value of open view (goodness of visibility), green view (visibility of open space), and ocean view (visibility of ocean) on condominium prices using DSM. However, the research only considers the visibility from the room. If an apartment building has a great ocean from the nearby road, the price difference between the condo having a great ocean view and the one having a poor or moderate ocean view might be mitigated by the great outdoor indirect ocean view.

There are some limitations in this research. The study area is limited to 3km due to memory capacity limitation. The viewshed impact may be beyond that range. This research does not account for view angle since turbines can rotate. Even if turbines are fixed, it is very difficult to calculate view angle using GIS in a large sample. The viewshed analysis does not incorporate the visibility of wind turbine from the window in the house. However, the dataset only includes single-family houses, which are not tall, and hence if a turbine is visible from the room, it is probably visible from the yard or nearby road. In addition, it is difficult to accurately calculate the turbine view from the room since it depends on the dimension, elevation, and the facing direction of the window. The article does not explain the difference in impact between counties.

Tables and Figures

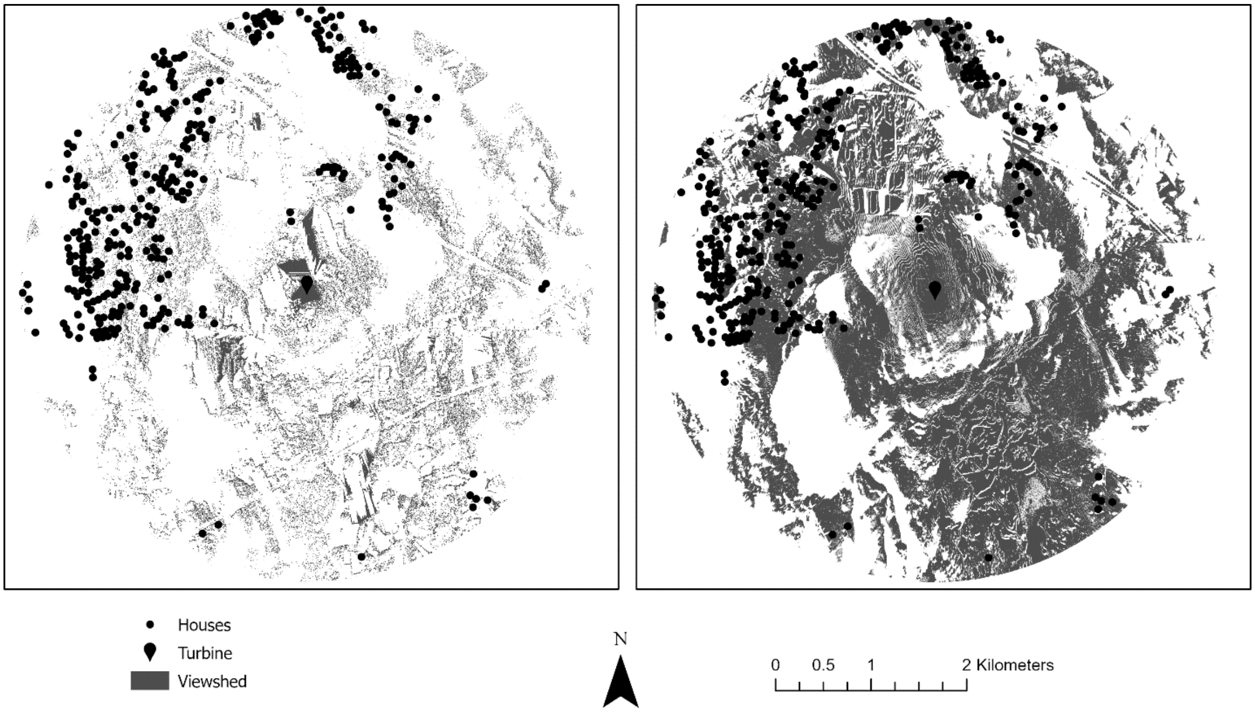
Figure 1. GIS workflow of turbine viewshed calculation.





Note: The top workflow is for DSM viewshed; the bottom workflow is for DEM viewshed.

Figure 2. Map of DSM and DEM viewshed.



Note: The two maps displace the same area. The left map is DSM viewshed; the right map is DEM viewshed. The observer is turbine tip for both.

Figure 3. Map of wind turbines across Massachusetts and Rhode Island.

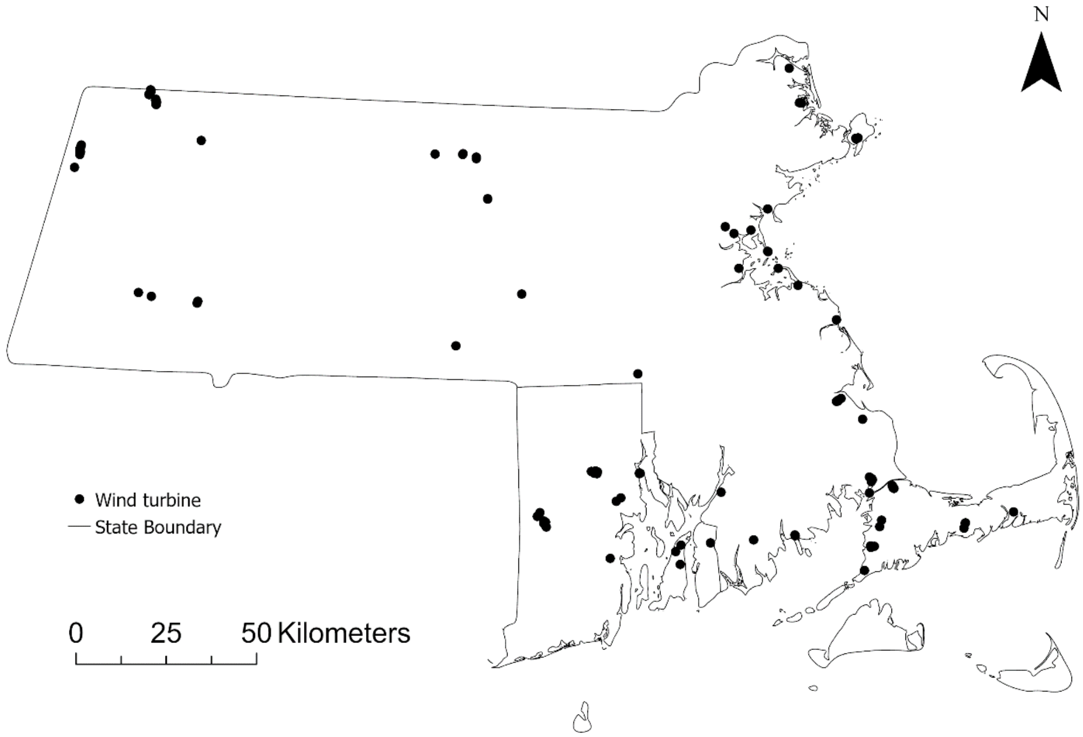
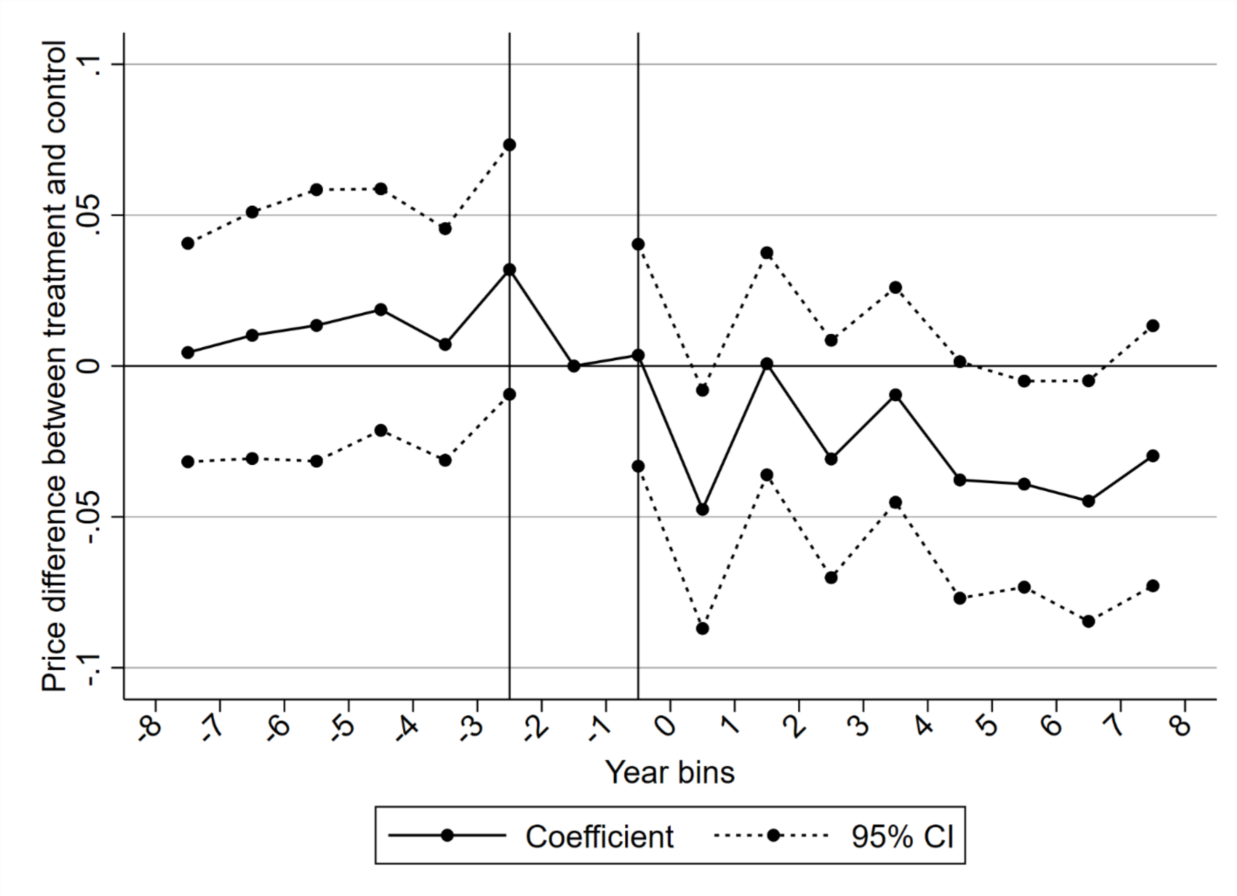


Figure 4. Price trend differences by viewshed



Notes: The treatment group is houses having a turbine view from the road using the tip of the turbine as observers; the control group is houses not having a turbine view from the road using the tip of the turbine as observers. The sample is limited to within 3km from 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 1-2 years prior to the operation date of the wind turbine. The first vertical line represents the approximate announcement date 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. N= 60,300. Standard errors are clustered at the tract level. Resulting coefficients and 95% confidence intervals are graphed.

Figure 5. The misclassification for DEM for the treated

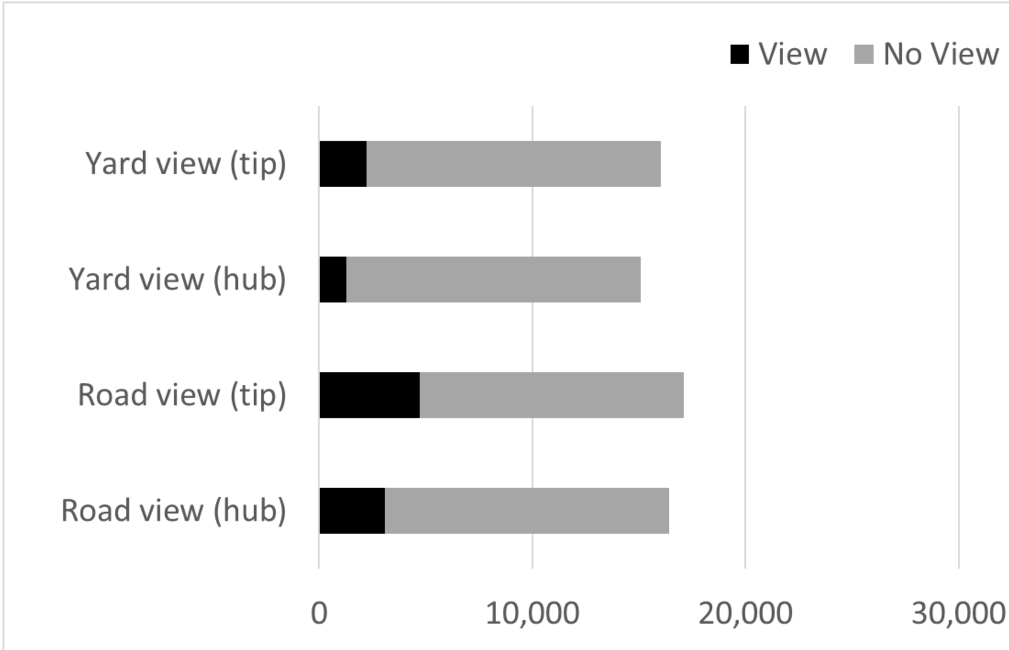


Figure 6. The misclassification for DSM for the non-treated

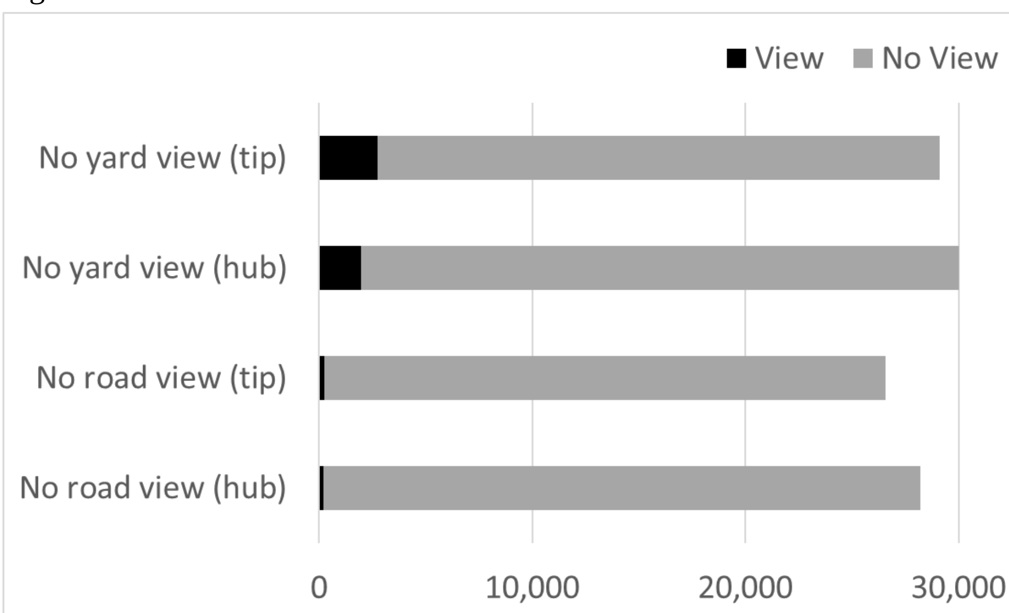


Table 1: Turbine summary statistics

Variable	Mean	S.d.	Min	Max
Capacity (MW)	1.4	0.7	0.05	3
Hub height (m)	71.5	18.2	30	100
Tip height (m)	108.8	29.9	41	158
Observations	118			

Notes: Capacity is single turbine capacity instead of wind farm.

Table 2: Summary statistics for sample properties

Variable		Mean
DSM		
	DSM yard view tip	0.08
	DSM yard view hub	0.05
	DSM Road view tip	0.18
	DSM Road view hub	0.11
DEM		
	DEM yard view tip	0.61
	DEM yard view hub	0.57
	DEM yard view tip	0.64
	DEM yard view hub	0.62
Housing characteristics		
	Sales price ($1000)	343.09
	Lot size (acres)	12.30
	Bathroom	1.73
	Bedrooms	3.01
	Fireplace number	0.23
	Living area (1000 sq. ft.)	2.97
	Age of home (years)	62.39
	Pool (1 = yes)	0.04
	Air conditioner (1 = yes)	0.28
Observations		60,300

Notes: All the view variables are binary.

Table 3: Visibility classification after treatment occurred between DSM and DEM by treatment status using tip as the observer

	Yard view (DSM)		
Yard view (DEM)	No view	View	Total
No view	15,283	0	15,283
View	13,821	2,220	16,041
Total	29,104	2,220	31,324
	Road view (DSM)		
Road view (DEM)	No view	View	Total
No view	14,205	0	14,205
View	12,383	4,736	17,119
Total	26,588	4,736	31,324

Notes: This table compares the classification of transactions between DSM and DEM after the construction of wind turbine. The first panel compares yard view, and the second panel compares road view. All coefficients are estimated using tip as the observer.

Table 4 Visibility classification after treatment occurred for DSM between yard view and road view by treatment status using tip as the observer

	Road view (DSM)		
Yard view (DSM)	No view	View	Total
No view	26,346	2,758	29,104
View	242	1,978	2,220
Total	26,588	4,736	31,324

Notes: This table compares observations between yard view and road view for DSM. All coefficients are estimated using tip as the observer.

Table 5: Difference-in-differences estimates of the impact of wind turbine viewshed on housing prices

	(1)	(2)	(3)	(4)
	Yard view		Road view	
DSM tip	-0.012	-0.039	-0.033	-0.055
	(0.010)	(0.015)**	(0.009)***	(0.014)***
PC * [0, 1) km	-0.017	-0.027	-0.010	-0.026
	(0.013)	(0.017)	(0.014)	(0.017)
DSM hub	-0.011	-0.015	-0.029	-0.044
	(0.015)	(0.020)	(0.011)***	(0.016)***
PC * [0, 1) km	-0.017	-0.030	-0.013	-0.028
	(0.013)	(0.016)*	(0.014)	(0.017)*
DEM tip	-0.010	-0.019	-0.006	-0.015
	(0.006)*	(0.009)**	(0.006)	(0.009)
PC * [0, 1) km	-0.020	-0.037	-0.020	-0.037
	(0.013)	(0.017)**	(0.013)	(0.016)**
DEM hub	-0.012	-0.022	-0.007	-0.018
	(0.006)*	(0.009)**	(0.006)	(0.009)**
PC * [0, 1) km	-0.019	-0.038	-0.021	-0.038
	(0.013)	(0.017)**	(0.013)	(0.016)**
Year by month FEs	Y	Y	Y	Y
Block FEs	Y	N	Y	N
Property FEs	N	Y	N	Y
County by year FEs	Y	Y	Y	Y
Observations	60,300	36,572	60,300	36,572

Notes: There are 16 regressions in total. Each column displays the view DID coefficients from 4 different regression models. ‘PC’ stands for post-construction. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 6: Difference-in-differences estimates of the impact of wind turbine viewshed on housing prices

	(1)	(2)	(3)	(4)	(5)	(6)
	Yard view		Road view		Turbine view	
DSM tip	0.009	0.006	-0.037	-0.059	-0.030	-0.052
	(0.019)	(0.035)	(0.009)***	(0.016)***	(0.008)***	(0.013)***
Observations	49,071	29,635	55,121	33,397	60,300	36,572
R-squared	0.791	0.872	0.788	0.870	0.785	0.870
DSM hub	0.009	0.055	-0.033	-0.052	-0.027	-0.038
	(0.026)	(0.045)	(0.011)***	(0.018)***	(0.010)***	(0.016)**
Observations	53,148	32,176	57,319	34,817	60,300	36,572
R-squared	0.790	0.871	0.788	0.870	0.785	0.870
Year by month FEs	Y	Y	Y	Y	Y	Y
Block FEs	Y	N	Y	N	Y	N
Property FEs	N	Y	N	Y	N	Y
County by year FEs	Y	Y	Y	Y	Y	Y

Notes: There are 14 regressions in total. Turbine view means a house have either yard view or road view. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 7: Heterogeneity by strength

	(1)	(2)
Above median tip	-0.026	-0.034
	(0.008)***	(0.012)***
Below median tip	-0.009	-0.016
	(0.006)	(0.009)*
Above median hub	-0.032	-0.036
	(0.008)***	(0.013)***
Below median hub	-0.017	-0.031
	(0.006)***	(0.009)***
Year by month FEs	Y	Y
Block FEs	Y	N
Property FEs	N	Y
County by year FEs	Y	Y
Observations	60,300	36,572
R-squared	0.786	0.871

Notes: All coefficients are road view using DSM. "Above median" equals 1 if viewshed strength is above the median value; "Below median" equals 1 if it is below the median value; the reference group is transactions where houses have no road view. Viewshed strength is defined by the sum of the length of road segment multiplied by the number of visible turbines in that segment. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 8: Heterogeneity by county using tip as the observer

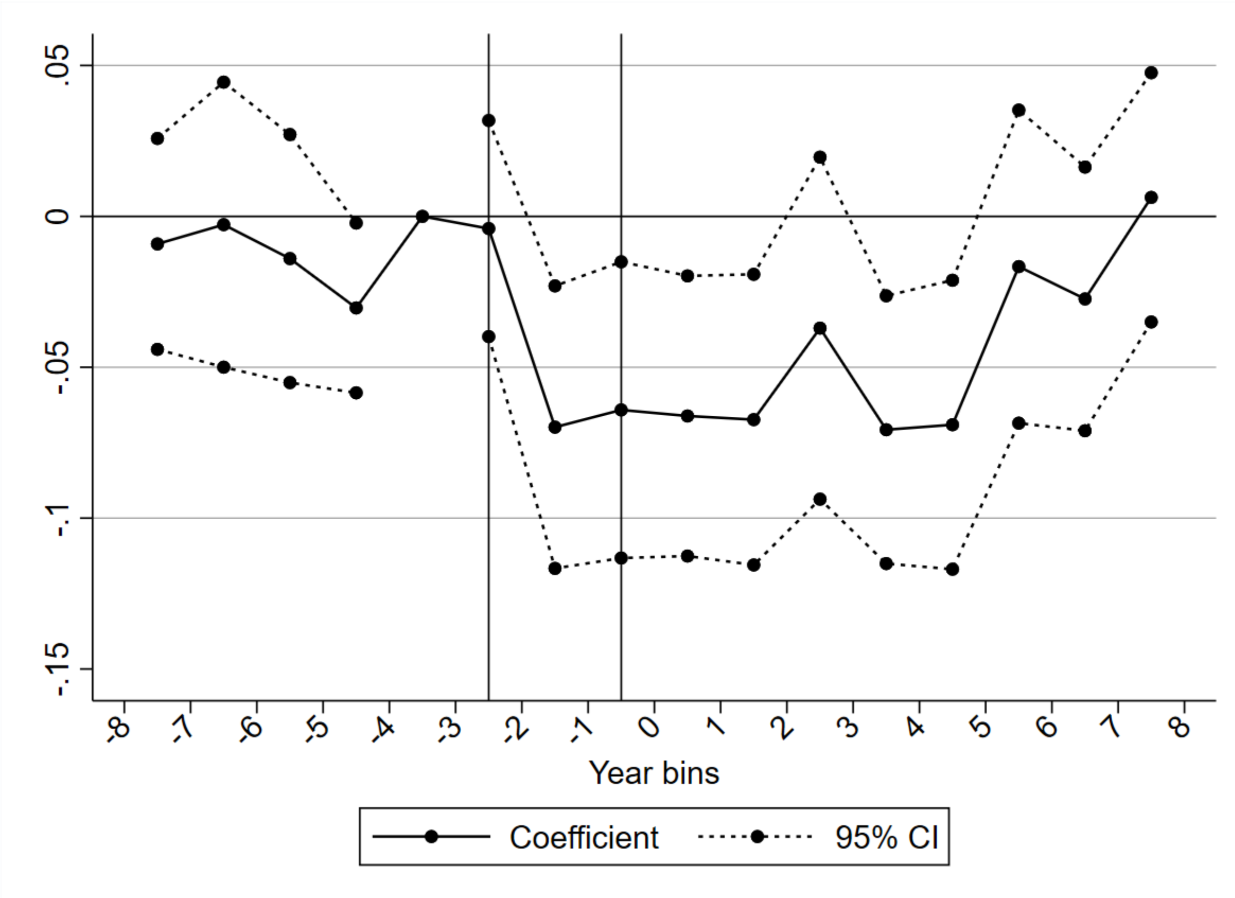
	BARNSTABLE	BRISTOL	ESSEX	KENT	MIDDLESEX	NEWPORT
	(1)	(2)	(3)	(4)	(5)	(6)
Turbine view tip	0.016	-0.032	-0.076	-0.036	-0.113	-0.011
	(0.016)	(0.011)**	(0.030)**	(0.051)	(0.026)***	(0.023)
PC * [0, 1) km	-0.113	0.017	-0.033	0.050	0.029	0.007
	(0.042)**	(0.018)	(0.063)	(0.028)*	(0.037)	(0.024)
Observations	6,485	4,997	5,209	4,102	6,889	2,591

	PLYMOUTH	PROVIDENCE	SUFFOLK	WASHINGTON	WORCESTER
	(7)	(8)	(9)	(10)	(11)
Turbine view tip	0.003	-0.036	-0.022	0.031	0.024
	(0.015)	(0.010)***	(0.017)	(0.040)	(0.019)
PC * [0, 1) km	-0.033	-0.054	0.032	0.167	-0.018
	(0.021)	(0.042)	(0.037)	(0.024)***	(0.024)
Observations	5,430	8,658	5,955	1,168	7,721

Notes: ‘PC’ stands for post-construction. All regressions include block, year by month, and county by year fixed effects as well as housing characteristics. All coefficients are turbine view from the road or the yard using DSM. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

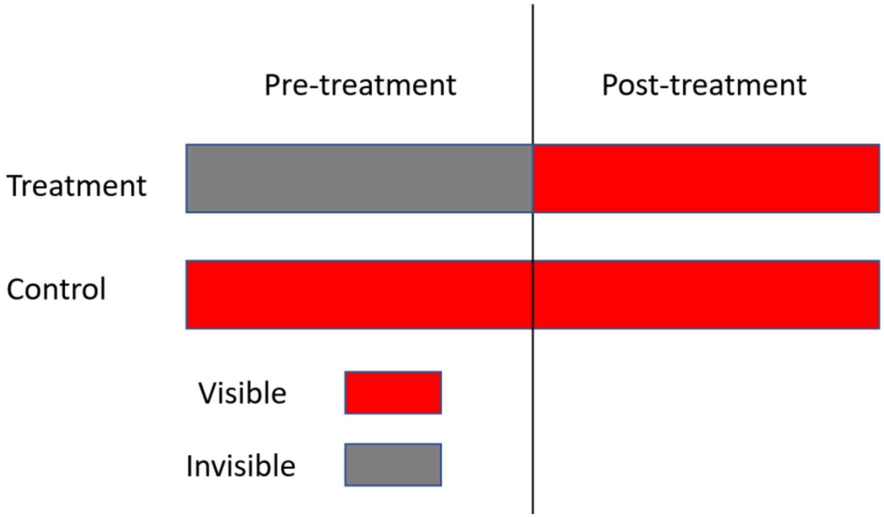
Appendix

Figure A1. Price trend differences by distance



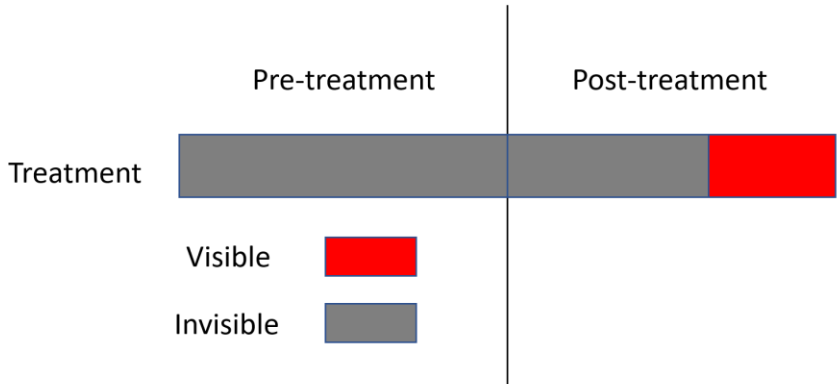
Notes: The treatment group is houses within 1km from the closest wind turbine; the control group is houses between 2km and 3km of the closest wind turbine. Year bins represent the number of years before (negative) or after (positive) the operation date of the wind turbine. The reference time period is 3.5 years prior to the operation date of the wind turbine. The first vertical line represents the approximate announcement date 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 2km are dropped. Data are from ZTRAX, USWTDB, and EIA for years 2000-2019. N= 60,300. Standard errors are clustered at the tract level. Resulting coefficients and 95% confidence intervals are graphed.

Figure A2. DEM viewshed treatment status of Gibbons (2015)



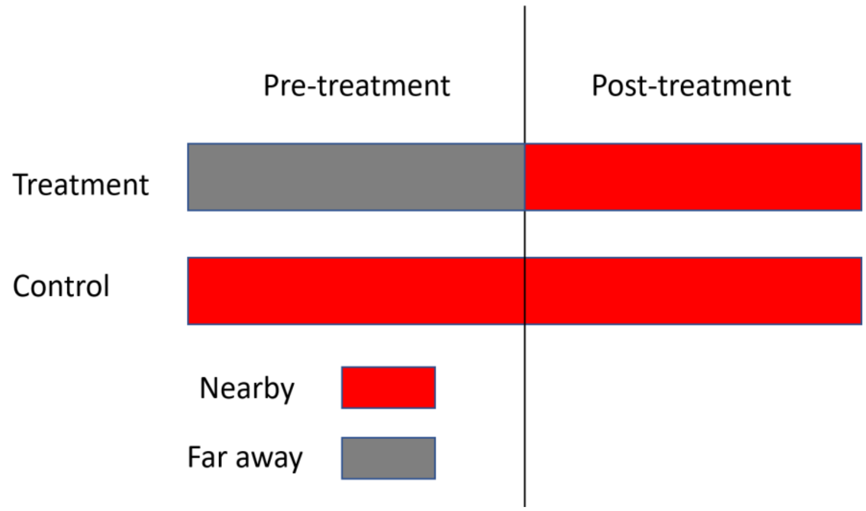
Notes: In terms of Gibbons (2015)'s first identification strategy, the treatment group is postcodes that will have a turbine become visible after the construction of the wind turbine; the control group is postcodes having a turbine visible all the time.

Figure A3. Misclassification for the treated of Gibbons (2015)



Notes: In terms of Gibbons (2015)'s first identification strategy, the red area represents the misclassified observations after the construction of a wind turbine due to the inaccuracy of DEM.

Figure A4. Proximity treatment status of Gibbons (2015)



Notes: In terms of Gibbons (2015)'s first identification strategy, the treatment group is also postcodes that will have a turbine become proximate after the construction of the wind turbine; the control group is postcodes having a proximate turbine all the time.

Table A1: Visibility classification after treatment occurred between DSM and DEM by treatment status using hub as the observer

	Yard view (DSM)		
Yard view (DEM)	No view	View	Total
No view	16,249	0	16,249
View	13,779	1,296	15,075
Total	30,028	1,296	31,324
	Road view (DSM)		
Road view (DEM)	No view	View	Total
No view	14,895	0	14,895
View	13,328	3,101	16,429
Total	28,223	3,101	31,324

Notes: This table compares the classification of transactions between DSM and DEM after the construction of wind turbine. The first panel compares yard view, and the second panel compares road view. All coefficients are estimated using hub as the observer.

Table A2: Visibility classification after treatment occurred for DSM between yard view and road view by treatment status using hub as the observer

	Road view (DSM)		
Yard view (DSM)	No view	View	Total
No view	28,037	1,991	30,028
View	186	1,110	1,296
Total	28,223	3,101	31,324

Notes: This table compares observations between yard view and road view for DSM. All coefficients are estimated using hub as the observer.

Table A3: Heterogeneity of viewshed impact by distance

	(1)	(2)	(3)	(4)
	0-1 km		1-2 km	
Turbine view tip	0.014	0.015	-0.000	0.011
	(0.021)	(0.032)	(0.018)	(0.024)
Observations	60,300	36,572	60,300	36,572
R-squared	0.780	0.866	0.780	0.866
Turbine view hub	0.010	0.020	-0.002	0.033
	(0.025)	(0.038)	(0.022)	(0.032)
Observations	60,300	36,572	60,300	36,572
R-squared	0.780	0.866	0.780	0.866
Year by month FEs	Y	Y	Y	Y
Block FEs	Y	N	Y	N
Property FEs	N	Y	N	Y
County by year FEs	Y	Y	Y	Y

Notes: This table compares the visual impact within 1 km of the closest wind turbine and 1-2 km from the closest wind turbine with 2-3 km from the closest wind turbine. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A4: Heterogeneity by county using hub as the observer

	BARNSTABLE	BRISTOL	ESSEX	KENT	MIDDLESEX	NEWPORT
	(1)	(2)	(3)	(4)	(5)	(6)
Turbine view hub	0.032	-0.054	-0.077	-0.110	-0.064	-0.022
	(0.041)	(0.024)**	(0.033)**	(0.056)*	(0.026)**	(0.028)
PC * [0, 1) km	-0.112	0.023	-0.045	0.057	0.020	0.014
	(0.042)**	(0.020)	(0.061)	(0.024)**	(0.037)	(0.023)
Observations	6,485	4,997	5,209	4,102	6,889	2,591

	PLYMOUTH	PROVIDENCE	SUFFOLK	WASHINGTON	WORCESTER
	(7)	(8)	(9)	(10)	(11)
Turbine view hub	0.031	-0.026	-0.039	0.021	0.016
	(0.024)	(0.020)	(0.023)*	(0.098)	(0.017)
PC * [0, 1) km	-0.042	-0.061	0.044	0.174	-0.012
	(0.022)*	(0.041)	(0.039)	(0.020)***	(0.023)
Observations	5,430	8,658	5,955	1,168	7,721

Notes: ‘PC’ stands for post-construction. All regressions include block, year by month, and county by year fixed effects as well as housing characteristics. All coefficients are turbine view from the road or the yard using DSM. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A5: Post-treatment visibility classification by treatment status

	Road view (DSM)		
Rooftop view (DSM)	No view	View	Total
No view	25876	3075	28951
View	712	1661	2373
Total	26588	4736	31324
Rooftop view buffer (DSM)	No view	View	Total
No view	24350	1842	26192
View	2238	2894	5132
Total	26588	4736	31324

Notes: The first panel compares the number of observations of rooftop view (i.e., whether a turbine is visible from the rooftop) with road view; the second panel compares 5-meter buffer of rooftop view (i.e., whether a turbine is visible within in 5-meter buffer of the rooftop) with road view. All variables are calculated using DSM and turbine tip as the observer.

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