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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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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

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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 view as treatment. In addition to water views, we

[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.

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 traveled, and then convert the distance to elevation. LiDAR can be used to create both Digital Elevation Models

[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.

(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 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

[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.

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 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

[6] A 5-meter buffer was chosen because these would likely cover most of a typical house without including surrounding trees.
[7] Jensen et al. (2018) focus on view as their key independent variable, but do not discuss how they calculated it.

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 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:

$$\text{(1)} \qquad \ln(price_{imt}) = \beta_1 turbineview_i + \beta_2 post_{mt} + \beta_3 post\_turbineview_{imt} + \beta_4 oceanview_i + \beta_5 pondview_i + \boldsymbol{X_i \beta_6} + \pi_m + \gamma_t + \varepsilon_{it}$$

$\ln(price_{imt})$ 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 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%

[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.

[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.

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 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:

$$\ln(price_{imt}) = \beta_1 Post\_turbineview_{imt} + \beta_2 oceanview_i + \boldsymbol{X_i \beta_3} + \gamma_t + \varepsilon_{it} \quad (2)$$

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

[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.

[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.

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 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

[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.

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.

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Figures and Tables

Figure 1: Study area

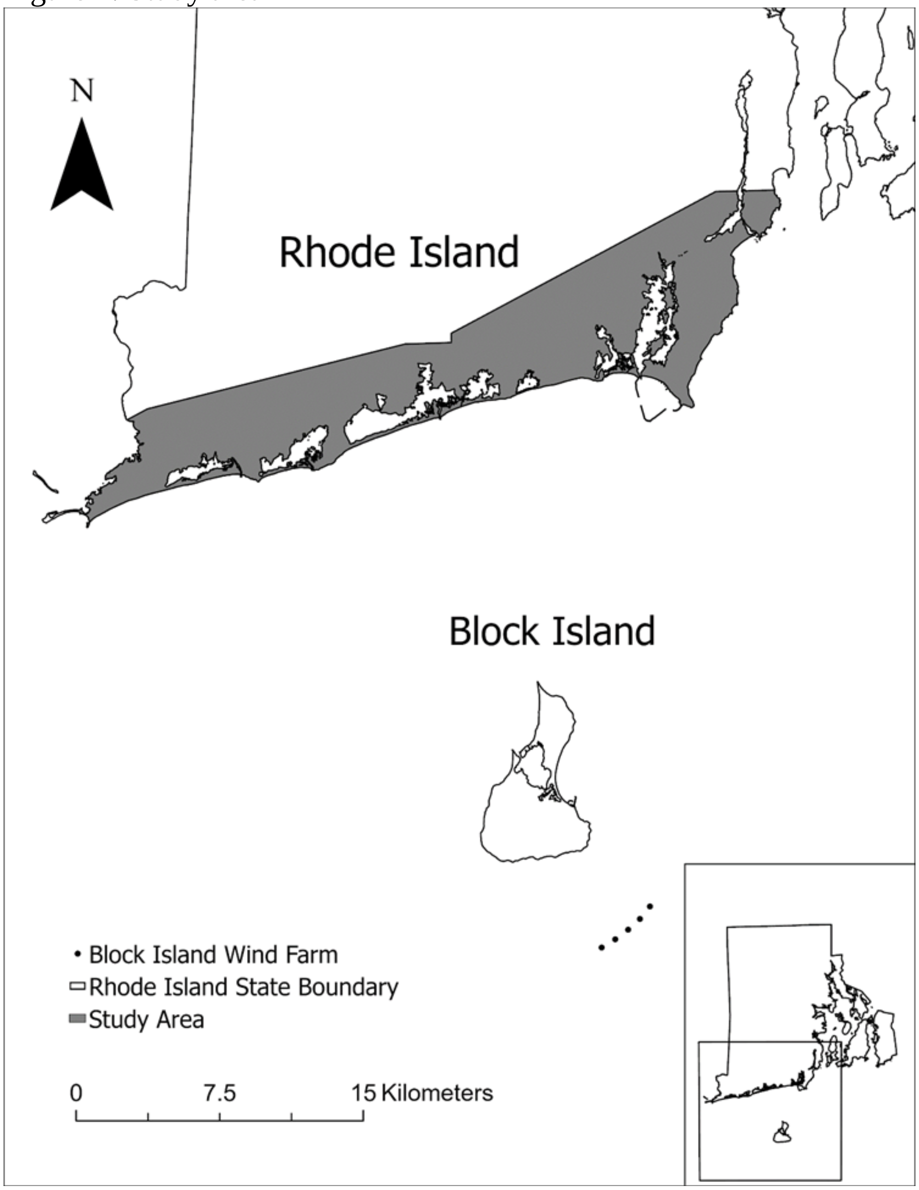


Figure 2: Turbine viewshed for small area on mainland of Rhode Island

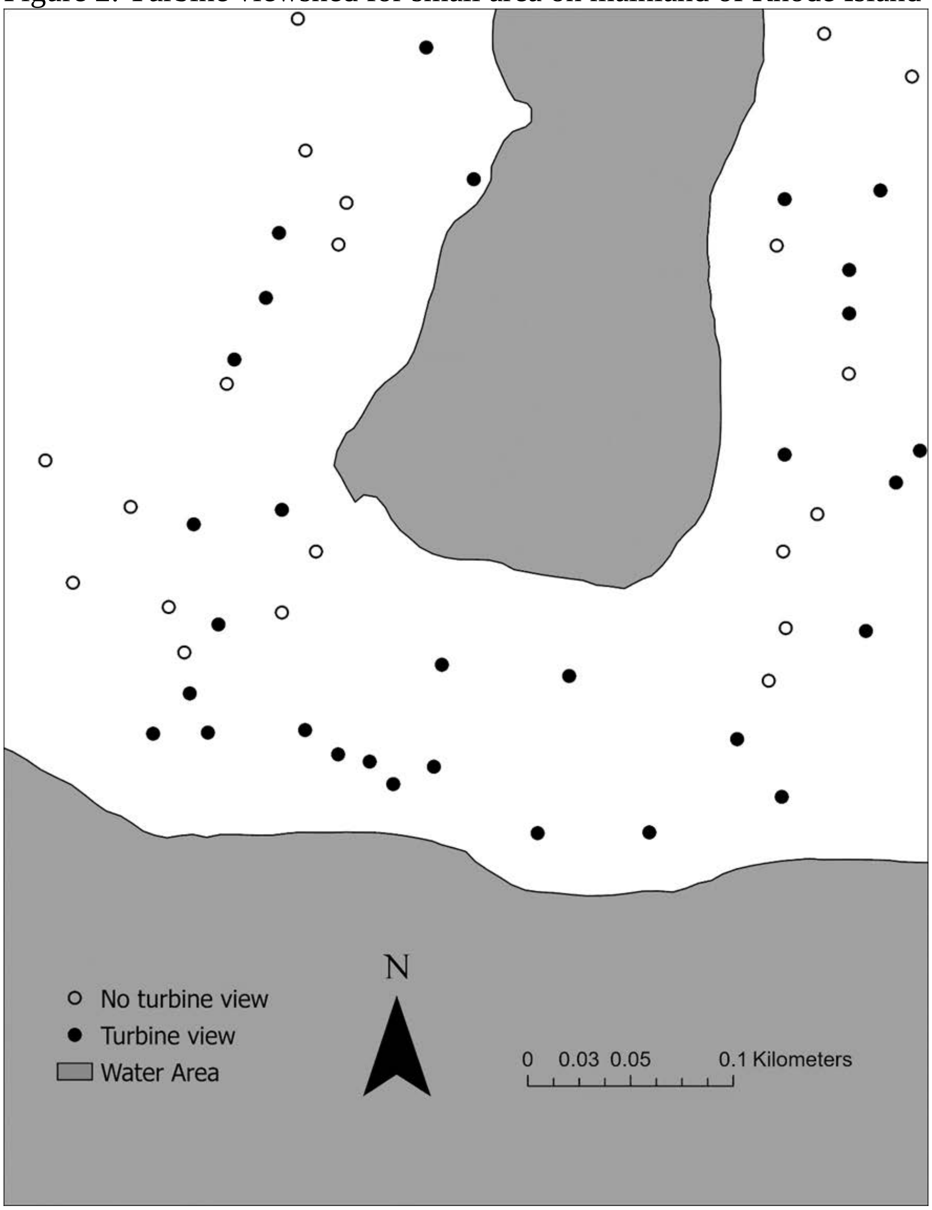
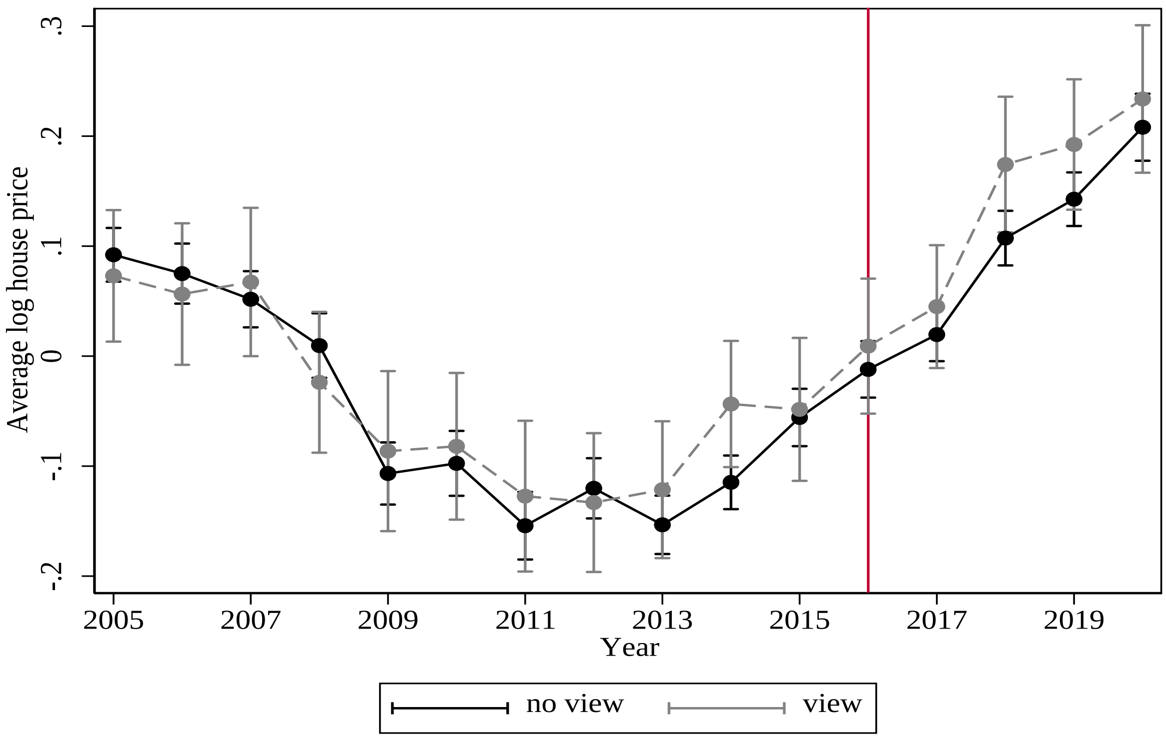


Figure 3: Housing price trends for properties with and without turbine views



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.