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Sustainability and tourism: the effect of the United States' first offshore wind farm on the vacation rental market

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SUSTAINABILITY AND TOURISM: THE EFFECT OF THE UNITED STATES' FIRST OFFSHORE WIND FARM ON THE VACATION RENTAL MARKET

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Abstract

One concern with offshore wind energy development is a negative impact to tourism. In this paper we assess this concern by examining how the Block Island Wind Farm, the first of its kind in the United States, has impacted the vacation rental market. Using data from AirBnb, we estimate a difference-in-differences model that compares Block Island to three nearby tourist destinations in Southern New England before and after construction. Our results suggest that construction of the Block Island Wind Farm caused a significant increase in nightly reservations, occupancy rates, and monthly revenues for AirBnb properties in Block Island during the peak-tourism months of July and August, but had no effect in other months. The findings indicate that offshore wind farms can act as an attractive feature of a location, rather than a deterrent.

Keywords: Offshore wind, tourism, rental market, non-market valuation, difference-in-differences
JEL Codes: Q26, Q42, Q51

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1 Introduction

Although U.S. offshore wind currently accounts for only 0.03% of the 96.5 gigawatts of installed wind capacity in the country (American Wind Energy Association 2018), future growth in wind generation will likely be more concentrated offshore. The political climate is evolving with federal policies that encourage wind power development and with aggressive, state-level renewable energy objectives to source wind power offshore.[1] The industry itself reached an important milestone on December 12, 2016 when America's first and to date only offshore wind farm (OSWF), the five turbine, 30 megawatt (MW) Block Island Wind Farm (BIWF), began generating electricity. Partially due to the success of BIWF, Massachusetts, Rhode Island, and Connecticut recently awarded contracts for 800, 400, and 200 MW OSWFs that are expected to be operational by 2021, 2023, and 2023, respectively, assuming permits are granted. Other OSWF projects along the U.S. east coast are also forthcoming, including New York's recently approved 90-MW South Fork Wind Farm that could be operational in 2022 and Maryland's 120-MW OSWF project, Skipjack Wind, whose offshore construction will likely begin in 2021 with generation set for 2022.

Despite the progress, there are several impediments to widespread growth of U.S. offshore wind energy. The high levelized cost of producing offshore wind energy makes it difficult to compete with other energy sources without subsidies.[2] At the federal level, the absence of federally mandated offshore wind energy goals, the short-term and inconsistent nature of production tax credits, and the imposition of lease and royalty fee payments can discourage development (Portman et al. 2009). At the local level, community members and other stakeholder groups have fervently opposed proposed offshore wind energy facilities, as exemplified by failed development plans of Cape Wind off the coast of Massachusetts. OSWFs have been opposed for several reasons, ranging from the impacts to marine fauna, the loss of recreational and commercial fishing grounds, the environmental and human safety risks of ship-

[1] Massachusetts requires state electricity providers to procure 1,600 MW of offshore wind capacity by 2027 (Massachusetts 2016); New York has committed to develop up to 2,400 MW of offshore wind power by 2030 (NYSERDA 2016); Maryland recently awarded two offshore wind projects the right to receive Offshore Wind Renewable Energy Credits as part of the state's Offshore Wind Energy Act of 2013 (Maryland 2013); New Jersey's governor signed an Executive Order on January 31, 2018 to promote the development of 3,500 MWs of offshore wind energy generation by 2030 (Murphy 2018).

[2] Estimates suggest that the levelized cost of offshore wind is among the highest of all sources of energy production (U.S. Energy Information Administration 2018a).

turbine collisions, and the effects on nearby property values.[3] Snyder and Kaiser (2009) discuss several of the ecological and socioeconomic arguments used in favor of and against offshore wind power.

In coastal communities, one of the most commonly voiced concerns is that OSWF development will deter tourists. Rudolph (2014) examines how stakeholders rationalized this apprehension during the planning phase of two OSWFs in Germany and Scotland. Opponents invoked several lines of reasoning for why the two OSWFs might detract for the area's desirability and therefore hurt the tourism industry, including that the wind farms would visually disturb the seascape, erode the area's cultural character and identity, or interfere with recreational activities like boating and fishing. Except for the latter, these concerns seem valid in the context of American OSWF development based on suggestive findings from a few recent studies (Parsons and Firestone 2018; Firestone et al. 2018; ten Brink and Dalton 2018). However, there exists no empirical evidence to substantiate the overall claim that OSWFs negatively affect tourism. Filling this research gap is critical because local conflicts about the impact of OSWFs on tourism can have important implications for where, and how far offshore, proposed offshore wind power facilities are located.

The purpose of this paper is to assess the effect of offshore wind development on tourism by examining the effect of the BIWF on the vacation rental market. The BIWF stands within Rhode Island state waters, approximately three miles off the coast of Block Island, and is visible from any location on Block Island that has a direct view, as well as from ferry rides to and from the mainland. We use data from AirBnb over the period October 2014 to December 2017, which spans before and after construction of the BIWF. Our method is rooted in a hedonic valuation framework, and we estimate a difference-in-differences (DD) model using three nearby tourist destinations as controls. Our specification includes property fixed effects to mitigate omitted variable bias, as well as temporal variables that control for seasonality and trends in the vacation rental market. Using this modelling approach, we focus purely on understanding visitor preferences for the BIWF and leave evaluating impacts to permanent residents for future work.

[3] The extent to which these claims materialize depend on site-specific factors, hence growing with the industry is a body of case studies investigating the ecological (Bergström et al. 2014; Lindeboom et al. 2011) and socioeconomic (Jensen et al. 2018) impacts of OSWF installations. In some sense, however, whether there is basis in the academic literature for these claims is irrelevant; valid or not, these claims can impede OSWF development.

The model yields an island-wide treatment effect, which is most relevant for assessing tourism impacts in this context for two reasons. First, there are several impacts of the BIWF's presence, like the creation of new recreational fishing opportunities or the symbolization of progress toward clean energy, that are unrelated to visibility but might nonetheless stimulate overnight visits to the island. Second, the small geographical size of Block Island—about 10 square miles—allows for easy access to the best views of the turbines from any location on the island; hence, overnight visitors need not rent properties that are in direct viewshed to experience the wind farm.[4] Moreover, it is likely that few Block Island AirBnb properties in our sample are in direct viewshed of the wind farm.

Block Island offers an excellent setting for examining visitor preferences for the BIWF because the tourism industry is the backbone of the local economy. While home to about 1,000 permanent residents, Block Island can host up to 20,000 visitors per day during peak summer season (New Shoreham Planning Board 2016). Thus, by establishing a baseline and examining post-construction movements in the vacation rental market relative to other tourist destinations, we infer how tourists, in aggregate, respond to the wind farm.[5] If the overall tourist experience changes because of the BIWF, then the vacation rental market will change accordingly.

There are two noteworthy features of this analysis. First, our study evaluates multiple margins of adjustment, which contrasts with many previous hedonic studies applied to the vacation rental market that evaluate only price adjustments.[6] We estimate our model using five different dependent variables: booked price, number of nights available, number of nights reserved, occupancy rate, and revenue. Because the speed at which vacation rental prices respond to environmental shocks is unknown,[7] it is important to evaluate other margins of adjustment that may be more elastic. Furthermore, rental market adjustments may differ in the short-run (1

[4] To put this in perspective, visitors can traverse almost the entire island on a 16-mile bike loop that stops at the BIWF and all 12 of its other major sites.

[5] Almost certainly, there are tourists that are attracted by and repulsed by the BIWF and everywhere in between. Our measures are aggregate, and we cannot distinguish preferences of individuals or even the proportion of tourists falling into different categories.

[6] Applications include hedonic pricing of: tourist activity and online reputation (Perles Ribes et al. 2018), rural recreation amenities (Nelson 2010), seascape amenities (J. M. Hamilton 2007), smoking prohibitions (Benjamin et al. 2001), access to coastal beaches (Taylor and Smith 2000), and land-uses in Spain (Bilbao-Terol et al. 2017), Belgium (Vanslembrouck et al. 2005) and France (LeGoffe 2000)

[7] To the best of our knowledge, no study has explored the dynamics of vacation rental property price responsiveness. While intuition may suggest that more transactions would lead to faster price changes, (Lang 2015) finds that amenity changes are capitalized more quickly for owner occupied housing than rental housing.

year) and the long-run (3-5 years). The price and availability of a rental property should be codetermined in the long-run. In the short-run, however, there may be a divergence in the various rental market metrics because landlords do not immediately respond to environmental shocks, but renters do. If this were the case, we would expect to see changes in the number of booked nights, occupancy rates, and revenues, but not in prices nor availability.

Second, our study is the first to empirically test the effect of offshore wind farms on tourism within a revealed preference framework. Other studies, reviewed in Section 2, have evaluated preferences for OSWFs using stated preference approaches, but these data can be biased for many reasons, including recall error, motivated reasoning, or just outright lying. Especially in the case of renewable energy development, support for which can be tied to a person's political ideology (Kennedy 2017), results may be biased as respondents seek to influence outcomes. Biases in this manner have been documented with stated preference measures in similarly politically contentious issues of gun control and climate change (Kahan et al. 2017; Goebbert et al. 2012; Howe and Leiserowitz 2013; Lang 2014).

Our results suggest that construction of the BIWF led to significant increase in nightly reservations, occupancy rates, and monthly revenues for properties in Block Island during the peak-tourism months of July and August. Specifically, we estimate that, during each peak-tourism month of July and August following construction, the BIWF caused a seven-night increase in reservations, a nineteen percentage point increase in occupancy rates, and a $3,490 increase in revenue for AirBnb properties in Block Island relative to AirBnb properties in control cities. In other months, treatments effects are statistically insignificant, though results are often consistent with positive effects. We find no significant movements in nightly price, despite this being likely the easiest margin of adjustment. Overall, there is little within-property, temporal variation in prices, suggesting prices are "sticky", and that landlords are experiencing changes to other margins of the vacation rental market. While specific to this context, these findings mitigate concerns about negative effects of OSFWs on local tourism.

The paper proceeds as follows. In the next section, we review relevant literature. Section 3 discusses the data and methodology. We provide results in Section 4 and we conclude in Section 5.

2 Literature review

Our research is grounded in hedonic price theory, which postulates that the overall price of a good is determined by the part-worth contribution from each observable attribute (Rosen 1974). Hedonic analysis is among the most popular revealed preference approaches for evaluating preferences for non-market goods and environmental amenities. Applied to a context of residential housing prices, the hedonic pricing method (HPM) relates sale prices of housing transactions to a vector of property attributes that typically include intrinsic, locational, and environmental characteristics. Intrinsic characteristics are factors such as the size of the house, the size of the lot, the number of bathrooms, and the number of bedrooms. Locational characteristics can include the condition of nearby homes, the crime rate, and quality of schools. In the field of environmental economics, regressors of interest are one or more environmental characteristic that describes a non-market amenity, such as air quality, adjacent open space, and ocean views.

HPM has been applied to estimate the implicit value of a wide range of amenities and disamenities related to energy extraction and production: power plants (Davis 2011), fracking (Muehlenbachs et al. 2015; Boslett et al. 2016), air quality (Chay and Greenstone 2005; Bento et al. 2015); and transmission lines (Hamilton and Schwann 1995). Several studies use hedonic methods to infer the external cost of onshore wind turbine facilities. Those that employ a quasi-experimental identification strategy generally find insignificant or slightly negative property value impacts from turbine proximity (Dröes and Koster 2016; Hoen and Atkinson-Palombo 2017; Hoen 2014) or turbine view (Gibbons 2015; Lang et al. 2014). However, two recent papers suggest larger housing price devaluations. Sunak and Madlener (2016) estimate a 9-14% decrease in values for properties “extremely” to “moderately” visually disturbed by wind turbines. Heintzelman et al. (2017) analyze upstate New York properties and find that the value of homes with a full or partial view of a turbine were reduced by about 17% following turbine construction. Jensen et al. (2018) is the only study to date that estimates property value impacts from offshore wind energy facilities within a hedonic valuation framework. Their results indicate that neither of two Danish OSWFs under study had any significant effect on the prices of primary or secondary homes.[8] While the bulk of HPM onshore wind studies indicate zero to

[8] The two offshore wind farms under study in Jensen et al. (2018) consist of 72 and 90 turbines and are located approximately six and two miles offshore, respectively.

negative price effect, this may not carry over to the vacation rental market because valuation may be a function of the time horizon spent around the turbines.[9] For example, utility gains from seeing the turbines for the first time or over the course of a couple of days of vacation may outweigh the loss of unfettered ocean views, but for a permanent resident, 10 years of lost views may outweigh everything else and lead to net utility losses.

Although HPM applications to offshore wind are limited, there is a substantial body of economic literature examining preferences for and tourism impacts of OSWFs. Most of these studies employ stated preference approaches, which use questionnaire responses to infer preferences and values. These approaches are appealing in the context of offshore wind development because observational data is limited or, as it was in the U.S. prior to the BIWF, non-existent. Yet the novelty of offshore wind development also raises concerns about the validity of evaluating its external cost using stated preference data. These data may be affected by the degree of respondent familiarity and experience with the good or amenity in question (Boyle et al. 1993; Cameron and Englin 1997), which is limited when it comes to OSWFs; nearly all the existing nonmarket valuation studies of OSWFs analyze stated preference data generated by individuals who lack any experience with this type of environmental amenity. Observational data, if representative of the population of interest, is not subject to this potential source of bias nor others, like sample selection bias, protest and strategic response bias, and hypothetical bias that may threaten valid inference. Moreover, it is generally argued that individuals' behavior in the market can convey information about their core preferences for nonmarket goods and amenities. We therefore believe our revealed preference approach to illumining the socioeconomic impacts of OSWFs is a critical departure from the current body of literature. Nonetheless, it is important to review the existing economic literature that uses stated preference methods to infer such impacts. This stream of literature can be classified into two groups: the first estimates the implicit cost of visual disturbances from OSWFs and the second estimates the impact of these facilities on aggregate recreational visitation and beach use.

With the exception of a few studies that find mixed preferences for OSWFs (Fooks et al. 2017a; Westerberg et al. 2013), the first group of stated preference studies generally reveal OSWFs to be an environmental disamenity. These studies find that the visual disturbance from

[9] More broadly, some amenities (e.g., local school quality) are expected to be reflected in the price of nearby housing but not in the price of nearby vacation rentals, and vice versa.

an OSWF located near the shore can generate considerable welfare losses for individuals, but these losses diminish as the distance of the OSWF from shore increases (Ladenburg and Dubgaard 2009, 2007; Krueger et al. 2011; Landry et al. 2012). Among this group, our study is perhaps most closely related to the work of Lutzeyer et al. (2018), who evaluate potential responses of the vacation rentals market to OSWF development. They survey recent renters of oceanfront and ocean-view vacation properties in North Carolina and assess their preferences for future rentals with different utility-scale wind farm configurations using a choice experiment.[10] For all visible turbine configurations, utility parameter estimates are negative and significant, which suggests that this population of renters, on average, strongly prefers unobstructed views of seascape. This result is broadly consistent with Fooks et al. (2017b), who, using an incentive compatible elicitation mechanism, find that tourists prefer hotel rooms without a view of an onshore wind turbine to those with a view of a turbine. Lutzeyer et al. (2018) also estimate utility parameters using a latent class model. These results reveal substantial heterogeneity in preferences across respondent groups, ranging from repulsion for all visible turbine configurations to indifference and even attraction to certain visible configurations, relative to the status-quo of no visible turbines. However, positive utility estimates from this model never translate to statistically significant willingness-to-pay values for moving OSWF turbines closer to shore.

The second group of stated preference studies are less conclusive about the impact of OSWFs. Landry et al. (2012) estimate an aggregate demand model to assess the behavioral response of North Carolina residents to a widespread offshore wind energy development scenario: 100-turbine OSWFs located one mile off the coast of all major beach destinations in North Carolina. They find indistinguishable differences in the expected number of annual beach trips between the hypothetical windfarm scenario and the current, no-windfarm scenario. Most recently, Parsons and Firestone (2018) employ a contingent behavior web survey to evaluate beachgoer perceptions about offshore wind development and behavioral responses to OSWFs at beaches along the U.S. east coast. Consistent with the findings from other studies, theirs suggest that wind farms located close to the shore, within about 13 miles, will lead to reductions in beach trips and economic losses in form of foregone beachgoer welfare.

[10] The most intrusive visible OSWF configuration has 144 turbines and is located five miles offshore; the least intrusive visible OSWF configuration has 64 turbines and is located 18 miles offshore.

One complication with accurately predicting the net impact of OSWFs on coastal recreational is the population of recreators may change. Parsons and Firestone (2018) estimate that, for an average beach, the first OSWF could generate nearly 13 million additional "curiosity trips" over the course of five to ten years from people who would not otherwise visit that beach. These estimates are not included in their main results, but the authors note that, if realized, an influx of curiosity trips of this magnitude would likely lead to net positive effects for many beaches. Other studies have also evidenced the potential for new OSWFs to attract tourists. In Lilley et al. (2010)'s intercept survey of Delaware beachgoers, 66% of out-of-state residents indicated being somewhat or very likely to visit a new or different beach at least once to see a 200-turbine OSWF located approximately six miles from the beach. In Firestone et al. (2009)'s mail survey, 84% of Delaware residents expressed being somewhat or very likely to visit a new or different beach at least once to see a 500-turbine OSWF located six miles from the beach.

It is difficult to draw conclusions about the projected impact of OSWFs on coastal recreation given the findings uncovered across the relevant stated preference literature. People prefer seascape horizons that are uncontaminated by wind turbines, but it remains unclear if and to what extent their behavior will change in response to OSWFs, as well as how many will be attracted to new OSWFs. Furthermore, many of the studies mentioned above capture preferences prior to OSWF installation, and preferences and support may change once OSWFs are installed. For example, Firestone et al. (2018) survey residents of Block Island, near-coastal Rhode Island, and coastal Rhode Island both before and after operation of the BIWF to understand changes in and determinants of support for the BIWF. Compared to those in the pre-installation period, levels of support in the post-operation period increased across all three strata, yet only among the coastal Rhode Island stratum were these changes in opinion found to be statistically significant. The authors also find that a respective 83% and 78% of Block Island and non-Block Island residents who saw the BIWF "[liked] the way the turbines looked", and this factor most strongly determined current support for the BIWF. In sum, the impacts of OSWFs on coastal recreation and tourism remains ambiguous. A concrete understanding of these impacts is vital for managers and developers of U.S. offshore wind resources to accurately assess externalities of OSWF development.

3 Data and Methods

In this section, we discuss the study context and data in relation to the econometric modelling strategy, sample construction, and identifying assumptions. Section 3.1 provides a timeline of events that guides our definition of the treatment period. Section 3.2 gives an overview of the data. We specify the econometric models in Section 3.3. Construction of the sample is outlined in Section 3.4 and sample characteristics are described in Section 3.5. Finally, Section 3.6 discusses the assumptions behind the DD estimator and potential threats to identification.

3.1 Timeline of Events

First established in 2004, Rhode Island's Renewable Energy Standard (RES) requires that 38.5% of the state's electricity come from renewable resources by the end of 2035. RES targets began in 2007, requiring electricity providers to source 3% of their retail sales from renewable resources, with incremental increases in target levels each year. To help meet the goals of the RES, in 2008 Rhode Island selected Deepwater Wind as the state's preferred offshore wind developer and initiated the Ocean Spatial Area Management Plan (Ocean SAMP), a marine zoning plan that provides management recommendations for developing and protecting Rhode Island's marine resources (Smythe and McCann 2018). Approved in 2011, the Ocean SAMP identified the waters off the southern coast of Block Island as having the highest wind speeds and lowest relative costs of development within RI state waters, and thus deemed this area viable for offshore renewable energy development. The Ocean SAMP designated this 13 square-mile area, which extends east to southwest of Block Island, a Renewable Energy Zone (REZ) (Coastal Resources Managment Council 2010).

Following approval of the Ocean SAMP, Deepwater Wind surveyed the sea floor within the REZ to determine potential locations for the turbine foundations and the two underwater cables, one connecting Block Island to the BIWF and one connecting Block Island to mainland Rhode Island.[11] Deepwater Wind opted to locate the turbine array within southeast portion of the

[11] A fiber optic cable for high speed-internet access was included in the undersea cable connecting Block Island to mainland Rhode Island. Block Island renters having better internet connection due to the construction of the BIWF may lead to identification problems. However, our data cover the period when the necessary on-island infrastructure was not yet built, hence renters experienced no change in internet service quality due to the BIWF over the course of the study period.

REZ to minimize environmental impacts and costs (Deepwater Wind 2012). They submitted state and federal permit applications for the wind farm in 2012 and received the final permit needed to advance the project in September 2014. In March 2015, Deepwater Wind fully financed the BIWF project by securing more than $290 million in loans.

Offshore construction of the BIWF project commenced in the summer of 2015. By the end of the 2015 offshore construction season, in early December, turbine foundations that protrude slightly from the water had been set in place. At this point, scheduled strategically to avoid overlap with the tourist season, onshore construction activities began and lasted through spring of 2016. The 2016 offshore construction season started in early August and ended soon after, on August 18, 2016, when Deepwater Wind installed the fifth and final 600-foot-tall, 6 MW wind turbine. On December 12, 2016, after several weeks of testing, the BIWF began providing wind-generated electricity to mainland Rhode Island. Block Island was connected to the BIWF's electrical grid in May of 2017, prior to which four diesel generators sourced the island's electricity needs. Now, because Block Island relies primarily on the electricity generated from the BIWF, these diesel generators operate only occasionally, which reduces air and noise pollution on one part of the island.

Our identification strategy involves comparing pre- and post-treatment rental activities, thus it is necessary to define when the treatment period begins, which is a bit ambiguous. In our case, the most important determinant of treatment-induced rental market adjustments is public awareness of the BIWF, so that tourists can take the information into account when deciding where to visit. The natural candidates are the dates of completed construction and grid connection.[12] We choose to define treatment as completed construction because that is when the turbines are visible, but the Appendix discusses results from models that use an alternative treatment date defined by grid connection.

An additional event, unrelated to BIWF, is necessary to discuss. In March 2017, corporate representatives from AirBnb visited Block Island and Nantucket Island to increase the number of AirBnb listings in those locations. They were particularly focused on encouraging owners of existing boutique hotel and bed-and-breakfast properties to use the AirBnb platform. Their visit to Block Island seems to have had the intended effect because beginning in March

[12] A simple Google Trends query for "Block Island Wind Farm" confirms these milestones as important, as the weeks including August 18, 2016 and December 12, 2016 are the two highest points of search interest.

2017, the data reveal an influx of new Block Island AirBnb properties,[13] most of which are boutique hotels or bed-and-breakfasts. This event motivates some key modelling decisions, and we discuss its relevance in more detail in Section 3.4.

3.2 Data

AirBnb is an online hospitality service that provides people with short-term lodging options from hosts seeking to rent out their rooms or properties. We obtained AirBnb rental data from AirDNA, a company that collects publicly available information about individual properties from the AirBnb website. AirDNA currently tracks the performance of roughly four million AirBnb listings worldwide through an automated scraping procedure that occurs every three days. The data cover a 39-month period starting in October 2014, when AirDNA began collecting this information, to December 2017. Both daily and monthly data is provided, but we estimate our model using the monthly-aggregated data to ease interpretation of results.[14]

The dataset contains two important types of information on each property: rental activities and property characteristics. Rental activities include nightly rates, monthly revenues, and whether nights are reserved, available but not reserved, or blocked by the host and thus unavailable for reservation. We use this information to generate our dependent variables. Property characteristics include city, number of bedrooms, number of bathrooms, minimum length of stay, maximum number of guests allowed, cleaning fee, extra people fee, security deposit, listing type (private room, entire place, etc.), and property type. There are a variety of property types included in the data and we aggregate them into four categories: bed-and-breakfasts, apartments, guest suites, and houses. Approximate latitude and longitude coordinates are also included, and we use these variables to calculate Euclidean distance to the coast. In Figure A2 in the Online Appendix, we plot these approximate locations to ascertain the visibility of the BIWF from our sample of AirBnb properties. Also included in Figure A2 is a visibility map of the area surrounding Block Island, adapted from Griffin et al. (2015). The figure suggests that few Block Island properties are in direct viewshed of the wind farm.

We estimate econometric models using five different dependent variables. These variables are measured at the monthly level and are defined as follows: (1) *Available nights*,

[13] Figure A1 in the Appendix displays this graphically.
[14] We obtain qualitatively similar results when we estimate our model using the daily data.

which equals the sum of reserved and available nights, (2) *Reservation nights,* which equals the number of nights a property was booked, (3) *Occupancy rate*, which is equal to *Reservation nights* divided by *Available nights,* (4) *Average booked rate*, which equals the average price of booked nights, and (5) *Revenue*, which is equal to total monthly AirBnb revenue.[15] Because owners determine directly the number of nights their property is available and its price, short-run changes in *Available nights* and *Average booked rate* might capture supply-side responses. Conversely, short-run changes in *Reservation nights, Revenue*, and *Occupancy rate* may be more representative of consumer demand. While these variables are of course related and determined by many of the same forces, our goal is to understand different margins of adjustment and get a broad picture of the whole story of how the vacation rental market responds to an environmental shock.

Our method is rooted in hedonic valuation; however, our data are not the standard property sales typically used with this method. As a first step to build confidence in our data and as exploration of implicit prices in the vacation rental market, we estimate a basic, cross-sectional hedonic regression with log(*Average booked rate*) on the left-hand side and property characteristics on the right-hand side. We use all observations occurring before construction of the BIWF.

The estimated coefficients in Table 1 generally follow the direction of *a priori* expectations, and thus bolster our confidence that valuable signals can be recovered from the data. Properties with greater numbers of bedrooms or bathrooms command higher rental rates. Those within 0.1 miles of the coast come with a substantial, roughly 30% rental premium. A one-person increase in the maximum number of guests allowed to stay at a property increases average booked rates by about 5%. After controlling for other rental rate determinants, rental rates for houses and bed-and-breakfasts are not statistically different than rental rates for apartments; guest suites, however, are booked at 13% lower average price than apartments. Compared to Block Island properties, rental rates are more than 40% lower in Narragansett, RI and Westerly, RI, and about 19% higher in Nantucket, MA. Average booked rates are highest relative to January in July, August, and September.

[15] *Average booked rate* and *Revenue* also include a per-visit cleaning fee, but additional fees charged for extra people are not visible on the AirBnb website and are therefore not included in the calculation of these variables.

3.3 Econometric Models

We use a DD modeling strategy to examine the effect of the BIWF on the vacation rental market. We compare rental transactions in Block Island, the treated group, to other tourist destinations, the control group, before and after construction of the wind farm. Control locations are Narragansett, RI, Westerly, RI, and Nantucket, MA. These cities are comparable to Block Island in that they are highly desirable summer vacation and tourist destinations in Southern New England. Figure 1 shows a map of all four cities and the approximate location of the BIWF. Narragansett and Westerly are located on the southern coast of mainland Rhode Island, approximately 10 miles from Block Island.[16] Nantucket is located approximately 20 miles off the coast of Cape Cod, Massachusetts and, like Block Island, offers a unique island experience to visitors. A standard DD equation applied to this context can be written as:

$$y_{ict} = \beta_1(BI_{ic} \times Post\_construction_t) + \beta_2 BI_{ic} + \beta_3 Post\_construction_t + X'_{ict}\theta + \varepsilon_{ict}, \quad (1)$$

where y_{ict} is the outcome variable for property i in city c during year-month t, BI_{ic} is a dummy variable that equals one if a property is in Block Island, and $Post\_construction_t$ is a dummy variable that equals one if an observation occurred during the post-construction period. Although construction of the BIWF was completed on August 18, 2016, we specify the post-construction period to begin on September 2016 because our data are aggregated to the monthly level.[17] Property characteristics are contained in X_{ict}. Finally, ε_{ict} is the error term. We cluster errors at the property level to allow correlation across time within individual properties. The difference in rental market outcomes between Block Island and control groups cities, and between the pre- and post-treatment period, are measured by β_2 and β_3, respectively. β_1 is the coefficient of interest, and it measures the differential change in rental market outcomes from the pre-treatment period for Block Island properties relative to changes in rental market outcomes for properties in Narragansett, Westerly, and Nantucket.

Equation (1) is a standard DD model, but we chose to strengthen it with several sets of fixed-effects and other control variables. First, we include property fixed effects that purge from the error term any unobservable time-invariant factors, such as nearby amenities and online

[16] The BIWF can be seen from a few locations on the southern portion of Narragansett. From these locations, however, the turbines appear as an extremely small cluster on the horizon and can be perceived only under certain weather and sky conditions.
[17] In the Online Appendix, we provide results from models that exclude August 2016 from the sample given this treatment status uncertainty. These results are very similar to our main results.

appeal, that both affect rental market outcomes and differ across individual properties. Second, we include year-month fixed effects that capture region-wide temporal variation in rental activity. Such variation is particularly large in this context because of the highly seasonal nature of the vacation rentals market. Third, we include city-specific time trends to control for rental market trends at the city level. These variables are critical for disentangling impacts of the BIWF from other potential location-specific growth trends. After including these variables, our new specification is

$$y_{ict} = \beta_1(BI_{ic} \times Post\_construction_t) + X'_{ict}\theta + \gamma_t + \alpha_i + \delta_c t + \varepsilon_{ict}, \quad (2)$$

where terms are as described previously with the addition of α_i, the property fixed-effects, γ_t, the year-month fixed effects, and δ_c, which estimate the city-specific time trends. We find that models which include year-month fixed effects and city-specific time trends are, across the five dependent variables, broadly superior in terms model fit and Akaike Information Criteria (AIC) than those that omit one or both of sets of controls; Table A1 of the Online Appendix discusses the results of models that add these control variables sequentially.

All time-invariant property characteristics, including property location, distance to the coast, and property type are excluded from estimation due to the inclusion of property fixed-effects. Yet for a small portion of properties, listed amenities such as minimum length of stay, maximum number of guests, security deposit, cleaning fees, and fees for extra people do change over time, and hence we include them in X_{ict}.[18] If these time-varying property amenities are endogenous to treatment, however, their inclusion in model would violate the basic identification condition $E[X\varepsilon] = 0$ and render OLS estimates inconsistent. This is a plausible source of endogeneity for our study, considering that landlords in Block Island or elsewhere may have, in response to the BIWF, sought out additional means to make their properties more attractive—by decreasing the minimum length of stay or extra-people fee, for example. To address this concern, we first examined properties in the main estimation sample (Table 2) and found that only a few properties in Nantucket or Narraganset—no Block Island properties—varied their amenities over time (Online Appendix Table A3). Next, we estimated DD models like those defined by Equations (3) and (4) below but specified the time-varying property amenities as the dependent

[18] Models for *Average booked rate* and *Revenue* exclude cleaning fees from the vector of time-varying property amenities because these fees are incorporated in the dependent variable.

variable (Online Appendix Table A4). Although these models reveal negative and significant treatment effects for one of the five property amenity variables, these effects are driven by a few properties in Nantucket and the coefficient estimates are negligible in magnitude. Based on these findings, we take all time-varying property characteristic as exogenous to treatment.

The treatment effect in Equations (1) and (2) is an average across all months of the year. Because most rental market activity occurs during the tourist season,[19] we hypothesize that treatment effects may be different during this period compared to other times of the year. Hence, we specify two models that differentiate treatment effects by time of year. In the first, we interact the treatment effect term $BI \times Post\_construction$ with indicator variables for summer and off-summer, where summer is defined as the months of June, July, August, and September. The second model is similar, but further differentiates peak (July and August) and off-peak (June and September) summer. We choose to specify these models such that the full effect of treatment in each season is represented by a single coefficient on a triple interaction term. These two models are defined below.

$$\begin{aligned} y_{ict} &= \beta_1(BI_{ic} \times Post\_construction_t \times Off\_summer_t) \\ &\quad + \beta_2(BI_{ic} \times Post\_construction_t \times Summer_t) \\ &\quad + \beta_3(BI_{ic} \times Off\_summer_t) + \beta_4(BI_{ic} \times Summer_t) \\ &\quad + X'_{ict}\theta + \gamma_t + \alpha_i + \delta_c t + \varepsilon_{ict} \end{aligned} \tag{3}$$

$$\begin{aligned} y_{ict} &= \beta_1(BI_{ic} \times Off\_summer_t \times Post\_construction_t) \\ &\quad + \beta_2(BI_{ic} \times July\_Aug_t \times Post\_construction_t) \\ &\quad + \beta_3(BI_{ic} \times June\_Sep_t \times Post\_construction_t) \\ &\quad + \beta_4(BI_{ic} \times Off\_summer_t) + \beta_5(BI_{ic} \times July\_Aug_t) \\ &\quad + \beta_6(BI_{ic} \times June\_Sep_t) + X'_{ict}\theta + \gamma_t + \alpha_i + \delta_c t + \varepsilon_{ict} \end{aligned} \tag{4}$$

3.4 Sample construction

The full dataset comprises 1,368 AirBnb rental properties and $39.5 million in rental transaction revenue. Omitted from Equations (2), (3), and (4), however, are 630 properties that

[19] To see this, Table A2 in the Online Appendix displays each month's contribution to the total sample revenue and reservation nights that accrued over 2015, 2016, and 2017.

are active only during the post-treatment period and 120 properties that are active only during the pre-treatment period because for these properties, the within-property variation in pre- and post-treatment rental market outcomes necessary to identify a treatment effect does not exist. We refrain from estimating Equations (2), (3), and (4) without property fixed-effects, which would retain these properties in the sample, because, as discussed in Section 3.1, corporate representatives from AirBnb seem to have successfully persuaded many existing Block Island bed-and-breakfast properties to begin using the Airbnb platform during the post-treatment period, and thus we are missing important pre-treatment information for these properties. We also examined the 630 properties active only during the post-treatment period and found significant differences in means between treatment groups for almost all housing characteristic variables, including a 45% higher proportion of bed-and-breakfast properties in Block Island. We would have additionally liked to examine the extensive margin by looking at new entrants into the market. However, given the coincidence of AirBnb's corporate visit to the island, we cannot separate the impact of that event from new entrants due to the wind farm. Thus, we focus only on the intensive margin, and leave the extensive for future research in a different setting.

We subsequently remove all bed-and-breakfasts from our sample because the outcome variables for these properties may be measured with error. We find an abundance of "blocked" property-nights, during both summer and off-summer months, in the rental histories of these properties. With near certainty, these properties can be rented year-round, so it is likely that some "blocked" nights indicate reservations arranged outside of the AirBnb platform.[20] If this type of measurement error is correlated with any of the independent variables, OLS estimates will biased and inconsistent (Wooldridge 2013).[21] After removing bed-and-breakfasts, we have 590 properties in our sample.

To improve comparability between treated and control group properties, we remove control group properties whose number of bathrooms, number of bedrooms, or minimum length of stay are outside the range of values observed for treated group properties. These excluded

[20] Some of these properties in Block Island do use alternative rental platforms as confirmed by members of the Block Island Chamber of Commerce who have relationships with these property owners.

[21] The independent variable most likely to be correlated with the measurement error is the treatment group indicator, because these types of properties account for a substantially higher proportion of the remaining sample properties in Block Island (30%) than in other cities (6%).

properties have more than six bedrooms, more than five bathrooms, or require a minimum stay of more than seven nights. Our final sample consists of 558 AirBnb rental properties.

3.5 Sample Characteristics

Table 2 assesses the degree of similarity between properties in the treatment and control group by displaying pre-treatment means and differences in means between groups. Variables are taken as averages across all pre-treatment months in which a property had at least one available night or reservation night. Block Island properties have fewer available and reservation nights by about 2.5 nights per month than control properties. Pre-treatment period monthly revenue is also lower in Block Island by about $1,000 per month, which is intuitive given the differences in monthly reservation nights and the mean of average booked rates for Block Island properties ($559). Pre-treatment occupancy rates and average booked rates are not statistically different between treated and control groups.

The housing characteristic control variables are well-balanced between groups. The average Block Island property has three bedrooms and two bathrooms, and requires a minimum stay of 3.6 nights, a roughly $500 security deposit, and $15 for each person above the maximum number of guests allowed. Twenty percent of properties in each treatment group are located within 0.1 miles of the coast. Each treatment group contains mostly houses, but apartments constitute a higher, though statistically insignificant, proportion of the sample in Block Island than in Narragansett, Westerly, and Nantucket.

3.6 Assumptions

While the results in Table 2 suggest that treated properties have common support along the spectrum of control group properties, the DD estimator relies on two untestable, identifying assumptions. First, we must assume that in the absence of treatment, differences in outcomes between treatment groups would remain constant over time. Support for this "common trends" assumption can be found by visually inspecting outcome trends during the pre-treatment period. Because the properties included in the sample change over time, instead of graphing raw outcome means, we estimate a version of Equation (2) that excludes the interaction term $BI \times Post\_construction$, recover the residuals, and calculate differences in residuals between treatment and control.[22] Figure 2 plots these estimated differences with 95% confidence intervals.

Figure 2 reveals that treated and control groups have similar trends in *Reservation nights*, *Occupancy rate*, *Average booked rate*, and *Revenue* during the pre-treatment period.[23] For these outcome variables, we find relatively large but statistically insignificant differences in some pre-treatment period months, but these differences likely reflect the small sample size of the treated group. Figure 2 also shows that differences in residuals for *Reservation nights*, *Occupancy rate*, *Average booked*, and *Revenue* are largest—and statistically significant for all but the latter outcome—during the post-treatment period, which is unobserved in these models. Our DD model specification serves to identify the portion of this unobserved variation attributable to the BIWF. The one concerning result in Figure 2 is the large and statistically significant deviation in *Available nights* residuals that immediately precedes treatment. One possible explanation is that the construction phase of the BIWF rendered Block Island a less attractive tourist destination, prompting landlords in Block Island to reduce monthly availability. However, this seems unlikely because we see reductions in *Available nights* during the summer of 2015, when offshore construction began, for both groups (Online Appendix Figure A3). Alternatively, Block Island landlords may use other rental platforms as their primary means of renting out rooms during the summer, resulting in a fewer number of available nights during the summer than at other times of the year. This explanation is equally questionable because we observe Block Island-specific reductions in available nights during the summers of 2015 and 2016, but not in the summer of 2017 (Online Appendix Figure A3). Nonetheless, the treated group's decrease in monthly availability during the months preceding treatment will result in DD estimators that overstate the effect of the BIWF on *Available nights*.

The second major assumption necessary for casual inference in DD models is the stable unit treatment value assumption (SUTVA), which requires that treatment does not affect the outcome of the control group (Rubin 1980). In the context of our study, this means we assume that the BIWF had no impact on rental activities in Nantucket, Narragansett, or Westerly.

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[22] For completeness, Figure A3 in the Appendix displays graphs of raw outcome means between treated and control groups.

[23] For the *Average booked rate* plot, missing values of differences in residuals reflect months in which no Block Island properties transacted; missing confidence intervals reflect months in which only one Block Island property transacted.

However, there are two plausible scenarios that would lead to a SUTVA violation. First, tourists may view the control locations as substitutes for Block Island. If they are attracted to the BIWF, then they may vacation on Block Island instead of their normal destination of Nantucket. Or, if they are repulsed by the BIWF, they may do the opposite. This substitution behavior would lead to exaggerated treatment effect estimates. A second possibility is that the BIWF is an attractive force even in control group cities. This is a concern particularly for Narragansett, as this is one of the main ports for ferries to Block Island. Tourists may be more likely to visit Narragansett knowing they can take a day-trip to Block Island to see the turbines. This SUTVA violation would lead to an underestimate of positive treatment effects. Given that we estimate positive treatment effects, the possible SUTVA violations have opposing effects, which renders any resulting bias ambiguous. While we cannot verify the SUTVA assumption holds, when we estimate models that omit Nantucket or Narragansett, the estimates change in the opposite way as would be expected if the hypothesized SUTVA violations were true. Thus, we proceed cautiously that the SUTVA holds.

4 Results

Table 3 presents our main results. Panel A reports estimates from Equation (3), and Panel B and Panel C come from Equation (4). All models include property fixed effects, property amenity variables that change over time, year-month fixed effects, and city-specific time trends.[24]

We first discuss the results in Panel A. We find positive and significant summer and off-summer treatment effects on *Available nights*, and the range of point estimates imply an increase of between 2.7 and 6 available nights per month for Block Island properties in response to the BIWF. However, these results are likely overestimates of the true effect of treatment on *Available nights* given the pre-treatment parallel trend issues discussed in Section 3.6. The summer treatment effect on *Reservation nights* is positive and statistically significant, and its coefficient indicates a 4.3-night increase in the number of reservations for the average Block Island property in each month from June through September. The coefficient representing the off-summer treatment effect on *Occupancy rate* is significant at the 10% level of confidence, indicating a seven percentage point decrease in occupancy rates for treated properties during off-

[24] Results from estimating Equation 2 are displayed in Table A1 in the Online Appendix.

summer months. In contrast, the summer treatment effect on *Occupancy rate* is positive but statistically insignificant. Estimated summer and off-summer treatment effects on *Average booked rate* are positive but insignificant, each with large standards errors.[25] Finally, Panel A shows a significant summer treatment effect on *Revenue*. The magnitude of this coefficient implies that construction of the BIWF induced monthly revenue gains of $1,721 for Block Island properties relative to control group properties during the following summer months of June, July, August, and September.

Panel B of Table 3 presents a similar story, but indicates that all treatment effects are occurring in the peak tourism months of July and August. For *Available nights*, the treatment effect is 7.416 for July and August, but just 2.519 for June and September. In the *Reservation nights* and *Revenue* models, we observe a similar pattern, but the treatment effects grow substantially in magnitude for July and August relative to Panel A. The magnitude of these coefficients implies that construction of the BIWF caused a seven-night increase in the number of nights booked and a $3,490 increase in AirBnb revenue in each of July and August for Block Island properties relative to control group properties. These effects are considerable, as the seven-night treatment effect on *Reservation nights* represents a roughly 125% increase relative to the average number of *Reservation nights* among Block Island properties during pre-treatment months of July and August. This result is somewhat comparable to Parsons and Firestone (2018)'s findings that curiosity trips to a first OSWF project at larger beaches (five million visitors per year) along the U.S. east coast could lead to a 40% annual increase in beach trips, and that at smaller beaches (half a million visitors per year), the potential market for curiosity trips could lead to a 400% increases in annual beach trips.

Panel B also lends evidence to support demand increasing rather than supply-side adjustments. By disentangling the effect of treatment during the peak-tourism months of July and August from its average effect across all four summer months, the differential increase in *Available nights* over *Reservation nights* becomes smaller. As a result, and in contrast to Panel A, the coefficient representing the treatment effect on *Occupancy rate* during July and August in Panel B is positive and highly significant, indicating a 19 percentage point increase in occupancy

[25] The large standard errors likely reflect the smaller sample size used in these models - we exclude property-month observations with zero rental transactions. Further, there is limited residual variation in prices remaining after controlling for property-specific factors, as shown in Table A1 in the Online Appendix.

rates during these months for Block Island properties, relative to the control group properties. In other months of the year, the effect of treatment on *Occupancy rate* is statistically insignificant. This finding implies that, during the peak-tourism months of July and August following construction, the BIWF yielded a disproportionately higher effect on *Reservation nights* than on *Available nights,* which suggests that treatment-induced changes in *Reservation nights* are not driven purely by treatment-induced changes in *Available nights*. In other words, this finding is evidence that our results are driven by changes in consumer demand, as measured by changes in *Reservation nights*, as opposed to supply-side responses that are reflected by changes in *Available nights*.

Because the data generating process may differ between summer and off-summer months, the models in Panel C use a sample that is restricted to observations occurring from June through September. This sample captures almost 75% of sample *Revenue* and *Reservation nights* in Panel B. Except for those pertaining to *Available nights*, estimated peak-summer treatment effects in Panel C are attenuated compared to those Panel B, but results are broadly consistent between the two panels. Panel C reveals lower but comparable peak-summer treatment effects on *Reservation nights* and *Revenue*, which is further evidence that the effect of treatment is largely confined to the peak summer months of July and August. Like in Panels A and B, we see estimate no significant change in prices, which bolsters the idea that landlords set prices and stick to them while experiencing changes to other margins of the vacation rental market.

In sum, we broadly see increases in rental activity during July and August and no change in other months. This could indicate that rental activity in the months of September through June is unresponsive to the BIWF; however, it is more likely a byproduct of the sparsity of rental activity during these months relative to July and August. Each panel of Table 3 yields similar results, yet treatment effects on *Reservation nights*, *Occupancy rate*, and *Revenue*, are most precisely estimated when differentiated between peak-summer (July and August), off-peak summer (June and September), and off-summer (October through May) months. Our preferred set of results are therefore those in Panel B.

As stated before, the focus of this paper is tourism and not impacts to permanent residents, and one reason for this is the ambiguity of our results applied to permanent residents. The positive treatment effects on *Revenue* could imply welfare gains. However, landlords may view the BIWF as a disamenity and decide to stay in their property less often and increase its availability on the rental market. If this leads to welfare losses that outweigh concurrent AirBnb revenue gains, the net effect on landowners would be negative. While this behavior is plausible, results in Figure 2 lend credence to the idea that construction of the BIWF had little effect on rental market participation. The figure shows that only in the model for *Available nights* do differences in residuals between treated and control group cities remain relatively constant during the post-construction period. We view this as additional evidence that our results driven primarily by changes in consumer demand.

4.1 Heterogeneity of impacts by property characteristics

If rental sorting behavior occurs across different segments of the population, there may be heterogeneity in the effect of the BIWF that depends on property characteristics. In Table 4, we investigate heterogeneity in the effect of treatment across two property characteristics: $Bedrooms$, which is the mean-centered number of bedrooms, and $Coast$, which is a dummy variable that equals one if a property is within 0.1 miles of the coast. Note that we examine heterogeneity with respect to $Coast$ not to illuminate the differential effects of treatment with respect to turbine visibility, as we cannot ascertain this factor from the data, but rather to discern whether different segments of the vacation rental market are more strongly affected by treatment than others. Specifically, properties located within 0.1 miles of the coast are, on average across all four cities, 27% more expensive than properties located further inland (Table 1), hence these properties are likely to accommodate a different segment of the renter population.

Each column of Table 4 shows results from two models. The models are specified by Equation (4), but they also include all two- and three-way interactions between the property amenity variable of interest, BI, $Post\_construction$, and the seasonal indicator variables that are necessary to identify differential effects of treatment by season and property characteristic. These differential effects are measured by coefficients on the four-way interactions terms displayed in the table. Because estimated Off_summer and $June\_Sep$ treatment effects have been largely insignificant, Table 4 displays the estimated coefficient on the main and interacted $July\_Aug$ treatment effect only. Other variables are not displayed in Table 4 for ease of exposition. We also report under each set of estimates the linear combination of the two coefficients displayed. These estimates indicate the effect of treatment for properties with one bedroom above the mean or properties on the coast.

Overall, we see little evidence of heterogeneity across property characteristics, but with a couple suggestive findings. Differential treatment effects on *Available nights*, *Reservation nights*, *Occupancy rate*, and *Average booked rate* are statistically insignificant for each property amenity variable. However, models that disentangle treatment effects on *Reservation nights*, *Occupancy rate*, and *Revenue* between properties with and above the sample average number of bedrooms yield an interesting result: for each outcome variable, the coefficients on ($BI \times Post\_construction \times July\_Aug \times Bedrooms$) is positive and the total effect of treatment on properties having one more bedroom than the sample average is significant at the 5% level or higher. These results imply that properties able to accommodate larger parties are more strongly affected by treatment than those able to accommodate smaller parties. They may also be an indication that treatment-induced changes in rental market outcomes are not driven purely by "curiosity trips" to the wind farm, which we would expect to be composed of smaller parties.

The coefficient on ($BI \times Post\_construction \times July\_Aug \times Coast$) in the model for *Revenue* implies a significant, $6,381 difference in the effect of treatment between properties located within and those located further than 0.1 miles from the coast. Additionally, the effect of treatment on *Reservation nights*, *Occupancy rate*, and *Revenue* for properties located within 0.1 miles from the coast properties is significant and considerably larger in magnitude than its effect on properties located further inland. Given these findings and that coastal proximity comes with a substantial rental premium, it is possible that the positive treatment impacts estimated by our preferred specification are driven largely by behavioral changes occurring among the high-income segment of the vacation renter population.

5 Conclusion

In this study we evaluate the impact of the BIWF on tourism as measured by changes in local AirBnb rental market activity. Within a hedonic valuation framework, we estimate a series of DD models using scraped AirBnb data. To uncover the full story of how the BIWF impacted the local rental market, we estimate each model using multiple dependent variables, each of which derives from a confluence of supply- and demand-side adjustments.

We find that the installation of the BIWF acted not as a tourist deterrent, but as tourist attractant. Results from our preferred specifications indicate that during each peak-tourism month of July and August following its construction, the BIWF caused a seven-night increase in the number of nights reserved, a nineteen percentage point increase in occupancy rates, and a $3,490 increase in revenue for AirBnb properties in Block Island relative to properties in control group cities.

While there are no other similar studies with which we can compare results, our findings align with several indications of public interest in the BIWF that are outside of the vacation rental market. The Block Island Ferry, local for-hire fishing boats, and helicopter charters have all capitalized on the BIWF by adding new tours around the wind farm. Because its underwater structures act as fish aggregators, the BIWF has created new fishing opportunities (ten Brink and Dalton 2018) and thus drawn praise from the recreational fishing community (Monti 2018, 2017). One for-hire fishing boat owner was pleasantly surprised about the impacts of the BIWF, saying that "the business level picked up more than [expected]" and that it "continues to grow" (Maritime Executive 2018). Representatives from other sectors of the tourism industry in Block Island expressed similar sentiments about the BIWF during recent focus group interviews (Smith et al. 2018). Another potential indicator of public interest is that information about the BIWF is emphasized on the *Block Island Times* website. Thus, taken within the broader context, our results are plausible reflections of wider interest in and economic gains from the BIWF.

Another factor that may be driving our results is the "warm glow" effect of OSWF development. Evidenced in a few recent studies, this effect is unrelated to the visibility or ecological impacts of OSWFs; rather, it derives from the positive feelings some may experience when supporting a renewable energy source. Parsons and Firestone (2018) find that the rationale behind 52% of respondents who indicated that a wind farm would improve their beach experience was knowing something good was being done for the environment; only 11% of these respondents cited as their rationale the aesthetic appeal of the turbines in the horizon. Additionally, the authors find little variation in the percentage of respondents who would switch from their current beach to an alternative one with an OSWF with respect to the distance of the OSFW from the beach, which is also consistent with the "warm glow" effect. Firestone et al. (2018) provide additional evidence of the "warm glow" effect after studying determinants of support for the BIWF, noting that "the description of the [Block Island] wind turbines that resonated most universally among both Block Island and coastal Rhode Island supporters [who had seen the turbines] was 'symbolic of progress towards clean energy'". Hence, it could be that our results are driven partly by increased visitation from individuals who like the feeling of supporting a clean energy source, but might not necessarily care about seeing the BIWF.

Our study is novel and a strong application of revealed preference data, however several limitations exist. Because the AirBnb rental property data used to proxy for tourism represents one segment of the tourist population, we are unable to capture behavioral responses from other important segments, like single-day visitors and those who book short-term lodging accommodations through other rental platforms. Research using more comprehensive data is needed to explore whether preferences for the BIWF revealed in this study are representative of the tourist population at large. The data is also confined to a relatively short, roughly one-year post-construction time horizon. Updating our analysis using additional years of data would allow us to ascertain whether BIWF-related tourism impacts are transient or persistent.

The overarching objective of this research is to understand the effects of offshore wind energy development on tourism. However, because we focus on the BIWF, there are several factors that limit the external validity of our results, in the sense that our estimates may not apply to future OSWFs. First, our estimates come from the United States' very first OSWF, which may elicit more excitement or interest than subsequent developments. Second, future OSWFs in the U.S. will differ from the BIWF in terms of the number of turbines, installed capacity, proximity to and visibility from the shoreline and beach, and the physical and socioeconomic characteristics of the surrounding community. Thus, we urge caution when trying to generalize our results to future OSWFs. However, our results provide an important data point to the ongoing debate surrounding tourism impacts of OSWFs and provide a baseline for future work.

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Table 1. Determinants of nightly booked rates: OLS estimation results.

	Dependent Variable: log(Average booked rate)	
Variable	Coefficient	Standard
Bedrooms	0.101***	(0.039)
Bathrooms	0.126***	(0.035)
Within 0.1 miles of coast (1=yes)	0.274***	(0.059)
Minimum stay	0.007	(0.006)
Maximum number of guests allowed	0.049***	(0.017)
Security deposit ($100's)	0.024***	(0.007)
Extra people fee ($100's)	0.040	(0.041)
House	0.018	(0.059)
Bed and breakfast	0.057	(0.072)
Guest suite	-0.131*	(0.075)
Nantucket	0.188**	(0.091)
Narragansett	-0.436***	(0.084)
Westerly	-0.480***	(0.106)
February	-0.017	(0.094)
March	-0.134	(0.089)
April	0.131	(0.081)
May	0.309***	(0.081)
June	0.287***	(0.082)
July	0.408***	(0.082)
August	0.406***	(0.082)
September	0.444***	(0.090)
October	0.300***	(0.094)
November	0.256**	(0.101)
December	0.312***	(0.082)
2015	0.108	(0.070)
2016	0.254***	(0.084)
Observations	2,188	
R-squared	0.701	

Notes: Sample contains property-months with at least one reservation night and is restricted to observations occurring prior to September 2016. Standard errors are clustered at the property level. *,**, and *** represent significance at the 10%, 5%, and 1% level of significance, respectively.

Table 2. Summary statistics of property characteristics.

	Pre-treatment means (standard deviations)		Difference in means
Variable	Block Island	Control cities	
Available nights	21.19 (7.61)	23.72 (6.18)	-2.53** (1.18)
Reservation nights	2.85 (2.54)	5.40 (5.22)	-2.55*** (0.96)
Occupancy rate	0.18 (0.19)	0.23 (0.21)	-0.05 (0.04)
Revenue ($)	1495.83 (1452.91)	2506.39 (3198.00)	-1010.56* (587.68)
Average booked rate ($)	559.18 (304.65)	554.97 (469.85)	4.20 (97.04)
Bedrooms	2.93 (1.28)	2.85 (1.47)	0.08 (0.27)
Bathrooms	1.95 (1.06)	2.03 (1.09)	-0.08 (0.20)
Within 0.1 miles of coast (1=yes)	0.20 (0.41)	0.20 (0.40)	-0.00 (0.08)
Minimum stay (number of nights)	3.63 (2.06)	3.63 (2.11)	0.00 (0.40)
Maximum number of guests allowed	6.63 (2.24)	6.20 (3.11)	0.44 (0.58)
Security deposit ($)	493.33 (365.24)	422.04 (521.72)	71.29 (96.61)
Extra people fee ($)	13.67 (31.43)	12.79 (34.96)	0.87 (6.53)
House (1=yes)	0.80 (0.41)	0.87 (0.33)	-0.07 (0.06)
Apartment (1=yes)	0.20 (0.41)	0.11 (0.32)	0.09 (0.06)
Observations	30	528	558

Notes: Property characteristic variables are taken as average values across all pre-treatment months in which a property had one or more available or reservation night. For the variable Average booked rate, the number of observations across columns is 24, 447, and 471 due to some properties having zero rental transactions during the pre-treatment period. Standard errors below in parenthesis in the difference in means column. *,**, and *** represent significance at the 10%, 5%, and 1% level of significance, respectively.

Table 3. The effect of BIWF on the vacation rental market.

Panel A: Summer and off-summer treatment effects

	Available nights	Reservation nights	Occupancy rate	Average booked rate	Revenue
BI×Post_construction×Off_summer	2.675*	-0.164	-0.069*	47.960	-55.881
	(1.494)	(0.809)	(0.039)	(34.959)	(436.147)
BI×Post_contsruction×Summer	6.010***	4.312***	0.083	7.787	1721.120**
	(1.621)	(1.264)	(0.052)	(47.337)	(869.615)
Observations	10,019	10,019	10,019	4,385	10,019
R-squared	0.254	0.481	0.512	0.930	0.412

Panel B: Off-summer, peak-summer, and off-peak summer treatment effects

	Available nights	Reservation nights	Occupancy rate	Average booked rate	Revenue
BI×Post_construction×Off_summer	2.065	-0.266	-0.055	32.351	-32.868
	(1.582)	(0.791)	(0.037)	(30.877)	(378.234)
BI×Post_construction×July_Aug	7.416***	7.081***	0.188***	-18.750	3489.919**
	(2.280)	(1.837)	(0.071)	(55.573)	(1451.393)
BI×Post_construction×June_Sep	2.519	1.248	0.028	-5.771	75.870
	(1.766)	(1.263)	(0.052)	(36.469)	(798.076)
Observations	10,019	10,019	10,019	4,385	10,019
R-squared	0.255	0.482	0.512	0.930	0.413

Panel C: Restricted sample, June through September

	Available nights	Reservation nights	Occupancy rate	Average booked rate	Revenue
BI×Post_construction×July_Aug	8.935***	6.010***	0.131	-10.265	3398.752**
	(3.001)	(2.119)	(0.085)	(70.513)	(1687.622)
BI×Post_construction×June_Sep	4.339*	-0.556	-0.068	-13.724	-550.277
	(2.262)	(1.763)	(0.075)	(36.679)	(989.486)
Observations	3,923	3,923	3,923	2,649	3,923
R-squared	0.358	0.505	0.542	0.946	0.490

Notes: 'BI' stand for Block Island, 'Post_construction' is an indictor variable for the post-construction (treatment) period, 'Summer' is an indicator variable for the months of June, July, August, and September, 'Off_summer' is an indicator variable for the months of October through May, 'July_Aug' is an indicator variable for the months of July and August, and 'June_Sep' is an indicator variable for the months of June and September. Included in all regressions as controls are minimum stay (number of nights), maximum number of guests, security deposit ($), extra people fee ($), and cleaning fee ($); however, regressions for Average booked rate and Revenue exclude cleaning fees, as these fees are incorporated in the outcome variable. All regressions include property fixed-effects, year-month fixed effects, city time trends, and a constant term. Standard errors are shown below in parenthesis and clustered at the property level. *,**, and *** represent significance at the 10%, 5%, and 1% level of significance, respectively.

Table 4. Heterogeneity of BIWF treatment effects by property characteristic.

Variable	Available nights	Reservation nights	Occupancy rate	Average booked rate	Revenue
β_1(BI×Post_construction×July_Aug)	5.025**	6.943***	0.213***	-64.411	2600.966**
	(2.094)	(2.130)	(0.076)	(45.133)	(1191.415)
β_2(BI×Post_construction×July_Aug×Bedrooms)	0.950	0.666	0.057	39.547	1397.293
	(1.606)	(1.331)	(0.052)	(55.504)	(1407.110)
$\beta_1 + \beta_2$	5.975***	7.609***	0.270***	-24.863	3998.258**
	(2.273)	(1.863)	(0.069)	(81.244)	(1869.507)
β_1(BI×Post_construction×July_Aug)	5.959***	6.898***	0.199***	-44.627	3102.638*
	(2.172)	(2.126)	(0.076)	(56.675)	(1640.852)
β_2(BI×Post_construction×July_Aug×Coast)	-3.290	4.213	0.382	-7.015	6381.021**
	(4.371)	(4.785)	(0.301)	(86.818)	(2736.047)
$\beta_1 + \beta_2$	2.668	11.110***	0.581**	-51.642	9483.660***
	(3.795)	(4.327)	(0.292)	(69.043)	(2200.988)

Notes: Estimated interaction coefficients from two separate regressions, delineated by horizontal lines, are shown in each column. Estimated coefficients on other variables are not displayed, but a full table of results is available upon request. 'BI' stand for Block Island, 'Post_construction' is an indictor variable for the post-construction (treatment) period, 'July_Aug' is an indicator variable for the months of July and August, 'Bedrooms' is the mean-centered number of bedrooms, and 'Coast' is a dummy variable that equals one if a property is within 0.1 miles of the coast and zero otherwise. Numbers of observations across columns are listed in Panel B of Table 4. Included in all regressions as controls are minimum stay (number of nights), maximum number of guests, security deposit ($), extra people fee ($), and cleaning fee ($); however, regressions for Average booked rate and Revenue exclude cleaning fees, as these fees are incorporated in the outcome variable. All regressions include property fixed-effects, year-month fixed effects, city time trends, and a constant term. Standard errors are shown below in parenthesis and clustered at the property level. *,**, and *** represent significance at the 10%, 5%, and 1% level of significance, respectively.

Figure 1. Geographic location of treated and control locations and the BIWF turbines.

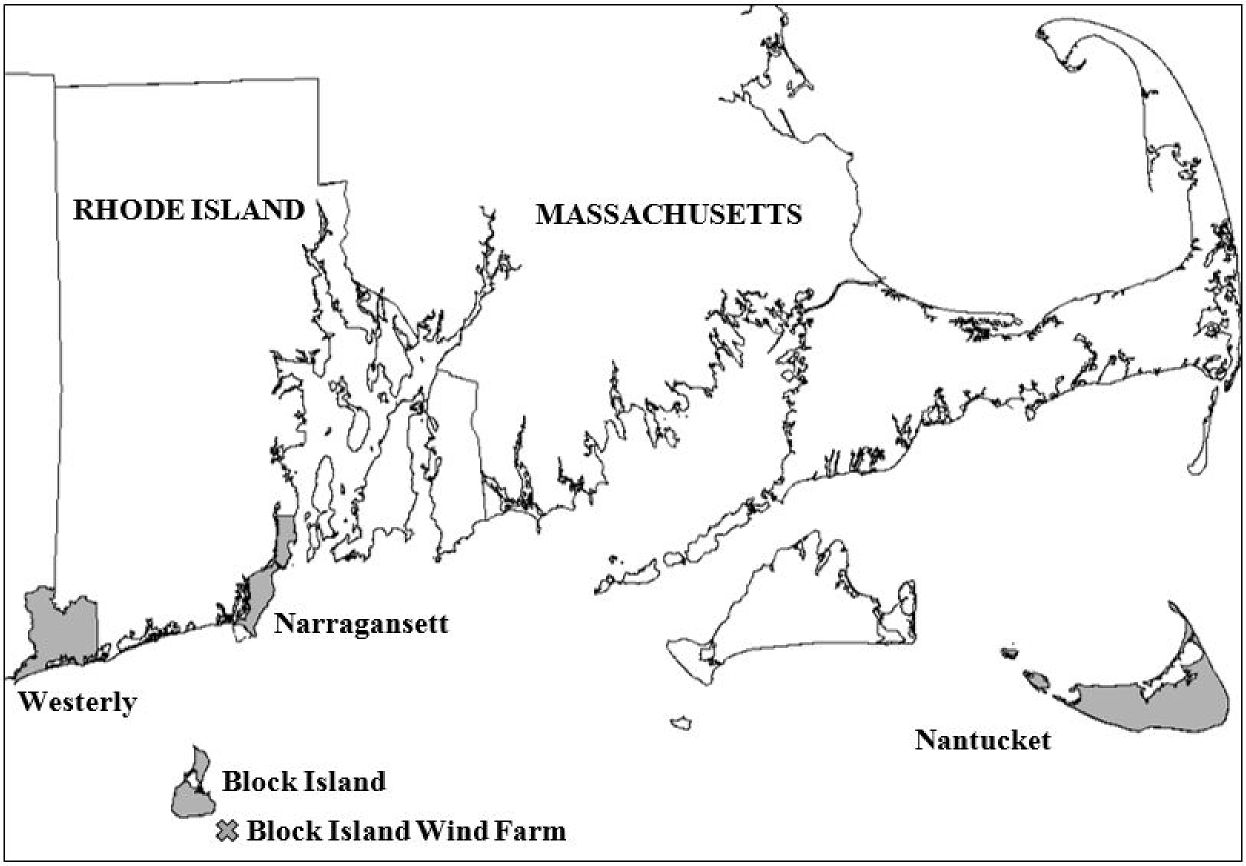

Figure 2. Pre-treatment trends in dependent variables.

Notes: A version of Equation (2) that excludes the interaction term $BI \times Post\_construction$ is estimated for each dependent variable and residuals are calculated. Figures plot differences in residuals between treatment and control by month. 95% confidence intervals plotted in gray. Vertical red lines indicate the onset of the treatment period.