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The impact of on-shore and off-shore wind turbine farms on property prices

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ABSTRACT

We present the results of a large-scale analysis on how on-shore and off-shore wind turbines affect the property prices of nearby single family residential and vacation homes in Denmark. We find that on-shore wind turbines negatively affect the price of surrounding properties to a distance of three kilometers. The negative impact increases with the number of wind turbines at a declining marginal rate but declines with distance. In the case of off-shore wind turbine farms, we do not find a significant effect of having an off-shore wind farm in view from a property itself or from the nearest beach, likely because the closest off-shore turbine is 9 km from the closest traded home. We illustrate the policy relevance of our findings by providing maps showing how the marginal impact of a wind turbine varies across the landscape according to the spatial distribution of home density and homes values in the proximity of a wind turbine site. The results suggest that *ceteris paribus*, wind turbine farms should be built quite far away from residential areas with turbines gathered in larger wind farms rather than installed as single turbines.

1. Introduction

The increasing presence of wind turbines in the landscape both on- and off-shore has grown more contentious as investments in renewable energy have surged, creating local conflicts regarding where to place key energy infrastructure (Wolsink, 2000; Goetzke and Rave, 2016). The negative externalities associated with wind turbine farms include reductions in aesthetic amenity values, light flickers from blades and noise pollution (Devine-Wright, 2005) and in some places, even threats to migrating and foraging birds (Drewitt and Langston, 2006).

Environmental economists and other social scientists have studied people's preferences regarding wind turbine farms as a source of energy and their preferences for living in close proximity to wind farms. The latter is the focus of this study. Stated preference studies have documented that people view wind energy itself as a positive thing (Borchers et al., 2007) but also express a disutility from externalities such as visual impact and noise (Ladenburg, 2009; Meyerhoff et al., 2010; Ladenburg and Möller, 2011; Brennan and Van Rensburg, 2016; García et al., 2016). Stated preference studies can be designed flexibly enough to capture the possible externalities experienced by people living or working in close proximity to wind farms and those experienced by people just travelling through or visiting the area. However, the values are derived on stated preferences, which can be subject to different biases (Carson, 2012; Hausman, 2012).

These issues have also been investigated with the revealed preference technique of hedonic pricing, but so far, this investigation has occurred only in a modest number of studies and with mixed evidence (Sims and Dent, 2007; Sims et al., 2008; Hoen et al., 2011, 2015; Heintzelman and Tuttle, 2012; Vyn and McCullough, 2014; Jensen et al., 2014; Lang et al., 2014; Hoen and Atkinson-Palombo, 2016; Sunak and Madlener, 2016). The literature takes different approaches to handle challenges of omitted variables and in particular endogeneity, which may hamper proper identification. Concerning endogeneity, a particular concern has been if wind turbine farms are more likely to be placed in areas with lower property prices. These conclusions could be incorrect about both causality and magnitudes of effects if they are not controlled for. Greenstone and Gayer (2009) and Kuminoff et al. (2010) show that, e.g., spatial fixed effects or similar specification may solve both omitted variable and endogeneity issues under certain conditions, and studies such as Heintzelman and Tuttle (2012) and Jensen et al. (2014) pursue this strategy in identification. A different and potentially more potent approach taken in recent studies such as Hoen et al. (2015, 2016) and Sunak and Madlener (2016) is the difference-in-differences approach. This approach can be a strong identification tool when

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suitable data are available. In this study, we apply both of these identification strategies because we believe both are suitable.

We add to and extend this still scarce literature in the following ways. First, we undertake analyses of the negative cumulative effect of on-shore and off-shore wind turbine farms, with the latter analysis being a first in the literature to our knowledge. Second, we add to the literature by presenting analyses of dwellings bought as a property for permanent residential use (residential homes) and dwellings bought as a property for part-time use (vacation homes). Our analysis covers parts of the Danish landscape in which the majority of new wind turbines have been installed.

For on-shore wind turbines, we present further evidence of effects of a wider set of spatially distinct housing markets in rural Denmark based on a cross-sectional analysis, taking an identification strategy similar to Heintzelman and Tuttle (2012) and Jensen et al. (2014). We also pursued the difference-in-differences identification strategy for on-shore turbines but faced limited data availability for treatment variables, as we discuss further below. As a further addition to the literature, we investigate if the effect of proximity to on-shore wind turbines is sensitive to the number of wind turbines in the surrounding area. We find that it is and that there is also a strongly decreasing effect of an additional wind turbine in the surrounding area. This is an important finding for policy because it suggests that clustering of turbines is preferred.

The Danish off-shore wind production is less developed, more recent and on-going than on-shore wind production. Here, we a purse a difference-in-differences identification strategy to analyze the effect in a case area in the Southern part of the Baltic Sea. The effect of off-shore wind farms on property prices has never been studied before, but the growing number of wind farms visible from the shore calls for such analyses to be undertaken. The identification of an effect from off-shore wind turbines can be difficult due to the spatial structure of data. We find no effects of being able to see the off-shore wind farm from houses or beaches, but we note that the closest wind farm is placed 9 km from the coast and thus even farther away from the majority of houses. Thus, the results cannot be extrapolated to, e.g., wind farms closer to land.

We illustrate the potential value of our analyses for policy and planning by using geodata to map out approximate marginal gains (costs) in terms of property value increases when a turbine was removed from (added to) existing turbine sites. We show how two main drivers affect these results, namely, the number of wind turbines already placed in an area and the value and density of properties in the proximity.

2. Case areas and data

2.1. On-shore wind turbines

The first research question of this paper focuses on the relationship between on-shore wind turbines and the property prices of residential and vacation homes. We obtained data on on-shore wind turbines' longitudinal and latitudinal coordinates and other technical specifications (ENS, 2016), the prices of detached residential housing, and vacation homes (OIS, 2016). Properties traded following bankruptcies, sales within the family and similar circumstances were excluded from the dataset. The dataset includes structural data on each property, including the number of bedrooms, the living area and lot size, roofing type, etc. Using geographical information about land use and information on the surroundings of each property, we calculated a number of other variables representing the spatial attributes of each property in the dataset. These included variables describing the number of wind turbines within various distances and the distance to each wind turbine from the individual property. To illustrate, Tables 1, 2 include selected descriptive statistics for the traded properties (residential and vacation homes, respectively) and the wind turbines in their surroundings for the region of Central and Western Zealand in Fig. 1. Approximately half of the two samples from Zealand have at least one turbine within 3 km, ranging from 1 to 15, as shown in Tables 1, 2. The corresponding descriptive statistics on properties and wind turbines for the remaining regional markets are provided in the appendix to this paper.

Wind turbines are not evenly distributed across the Danish landscape, and at the same time, property markets may also show spatial variation in the pricing of a number of property characteristics, potentially among them the effect of nearby wind turbines on property prices. To account for this possibility, we undertook several spatial analyses in order to define and select a suitable set of spatially distinct areas for our purposes. We selected areas that had sufficiently coherent and active property markets in the sense that we had enough property trades within the considered time period and that property prices were described well by a single hedonic function with little or no systematic spatial variation in residuals. Furthermore, the areas should have a suitable number of wind turbines of varying types affecting a sufficiently large set of properties to allow for a reliable estimation. This approach resulted in the selection of areas shown in Fig. 1, and we estimated separate models for single residential and vacation homes in these areas. The five areas cover a total of 17,788 km^2, which is more than 40% of Denmark's total area.

2.2. Off-shore wind turbines

The second main research question of this paper focuses on whether the view of an off-shore wind farm affects the price of residential housing. We use the same data sources in the analysis on off-shore turbines as we did in the analysis of onshore turbines. In order to statistically identify an effect, we need a sufficient number of properties that can see a wind farm either from the home or nearby beach. We selected two farms, Nysted and Rødsand II, which were constructed at two different times but placed rather close to each other several kilometers apart on the southern coast of the Danish island of Lolland. The wind turbines at Nysted and Rødsand II are placed between 9.5 and 3.5 km off the coast. Nysted was completed and in use by 2003 and contains 72 wind turbines with a hub height of 72 m. Rødsand II was completed and in use by 2010 and contains 90 wind turbines with a hub height of approximately 80 m, cf. Fig. 2. A selected set of descriptive statistics is shown in Table 3.

2.3. The wind turbine variables

The negative impact of wind turbines on sales prices of neighboring properties are often attributed to noise and visual pollution (Jensen et al., 2014). In this paper, we specifically focus on the cumulative impact of the number wind turbines in an area. The relationship between property sales prices and wind turbines were captured in two variables. The first is a simple count of the turbines within a 3-kilometer radius of each property. The second variable is denoted *weighted density* and accounts for both the number and the proximity of wind turbines around each property. It is calculated as follows: for each home i, we recorded the number of turbines within 3 km, call it n_i, and the Euclidian distance in km between each turbine j and each property i denoted $distance_j$. Then, we calculated a weighted density d_i for each property in the sample and took the natural log of this measure:

$$\ln(d_i) = \ln\left(\sum_{j=1}^{n_i} \max(0; 3 - distance_j)\right)$$

The max function is used to ensure that a turbine 4 km away will add 0 to d_i and hence not be counted, whereas a turbine 2.4 km away will add 0.6 km to the index. We tested a number of distances and functional specifications before arriving at this choice. For all trades in the sample, we calculated the Euclidian distance between each property in the dataset and each turbine within 10 km of it. We then tested

Table 1
Descriptive statistics for selected variables describing primary homes and wind turbines in the landscape in Central and Western Zealand.

	Wind turbines			Properties				Log(Weighted density)
	Capacity (kW)	Total height (m)	Year build	Property price (1000 DKK)	Living area (m^2)	Distance to nearest wind turbine (m)	# of mills within 3 km (where > 0)	
Min	11	22	1980	100	50	36	1	0
Max	3000	140	2013	7500	400	8853	15	9.904
Mean	658	61	1997	1451	140	2977	4	7.572
Median	600	60	1998	1300	135	2627	3	6.330
# of wind turbines	381	381	381					
Properties traded				8865	8865	8865	4932	

different specifications for this variable and the simple number of turbines variable, and by evaluating model fit, we found the best version of the variables to account for wind turbines up to a 3-km radius from each property. We return to why we use this distance in the following section. We note that the best function form specification for the weighted density variable was found to be the natural log, and hence, we use the natural log of this measure in our models. The weighted density measure captures the cumulative effect of the relationship between the aggregate distance to the turbines and the number of turbines. As this number increases, the “weight” of wind turbines around the property increases.

3. Econometric approach

Lancaster (1966) was the first to put forth the theory that the value of a good to the consumer is composed of the value of the attributes of that good. Rosen (1974) showed that in a well-functioning housing market, buyers will look for a house, where the combination of housing attributes results in the highest value to them relative to the housing price. Likewise, sellers will look for buyers who place the highest value on the exact combination of attributes inherent in their house. As a result, the price of a traded property is a function of the property's attributes as the market agents value them. Formally, the relationship can be formulated as

$$P_n = f(z_{1n}, \dots, z_{In}; \theta) \tag{1}$$

The P of the n'th house is a function of the I attributes of z and depends on the functional form of f, where θ is a vector of parameters. The attributes of z may include structural variables describing the house as, e.g., the number of bedrooms, the type of roofing, and the year built and traded, as well as geographical attributes describing the location of the house, e.g., distance to the coast, forest areas, larger roads, and train stations. The geographical attributes may also include variables describing proximity to, a view of, or noise from wind turbines. Theory provides no general guidance on the form of f, and hence, the modeler will need to make informed and transparent choices that secure a statistically valid and efficient description of the relation between P and z.

3.1. Identification for onshore turbines

We pursue a strategy similar to Heintzelman and Tuttle (2012) and Jensen et al. (2014) by applying cross-sectional models with components accounting for omitted spatial effects, as suggested in the literature (Greenstone and Gayer, 2009; Kuminoff et al., 2010), to handle omitted variable endogeneity issues. We also investigated the options for a difference-in-differences identification strategy, which would be a strong additional identification (see, e.g., Hoen et al., 2016; Sunak and Madlener, 2016) and proved sensitive to data availability; however, as in Denmark, the on-shore expansion took place from 1990 to 2000 but has since almost halted (Gavard, 2016). Spatial data from before 2000 are not of sufficient quality, and few new mills were put into place during the period that our data span. Using the limited data available for difference-in-differences models showed the expected poor inference, but nevertheless, the sign and size of parameters were in accordance with results of the present paper. In particular, there was no indication that house prices were lower in areas where wind turbines were placed prior to the installation, further reducing concerns about endogeneity bias. Thus, we progress with the cross-sectional, spatial fixed effects approach.

An additional challenging aspect of this type of model is the role of spatial autocorrelation in the error terms of any model, possibly reflecting spatial correlations in unobserved omitted variables of potential relevance. To reduce the possible biases arising from such patterns, we applied a spatial semi-parametric Generalized Additive Model (GAM), which allows for a smoothing component in addition to the spatial fixed effect of our model. This approach is stronger than the spatial fixed effect alone because it allows for both a non-parametric and data-driven analysis, as well as a parametric and hypothesis-driven control for omitted spatial variables. The GAM makes fewer *a priori* assumptions about the structure of the possible spatial autocorrelation (Wood, 2006; von Graevenitz and Panduro, 2015). In GAM, the spatial autocorrelation is modeled using a non-parametric function of the spatial (x, y) coordinates of the longitudinal and latitudinal location of each house using a number of splines. Thus, the only decision needed by the modeler is how detailed a fit the resulting spatial autocorrelation plane needs to be as determined by the k splines used. Thus, this is a purely data-driven approach to account for spatial autocorrelation.

Table 2
Descriptive statistics for selected variables describing secondary homes and wind turbines in the landscape in Central and Western Zealand.

	Wind turbines			Properties				Log(Weighted density)
	Capacity (kW)	Total height (m)	Year build	Property price (1.000 DKK)	Living area (m^2)	Distance to nearest wind turbine (m)	# of mills within 3 km (no., where no ≥ 1)	
Min	11	22	1980	50	16	328	1	0
Max	3000	140	2013	4000	293	8964	15	9.965
Mean	658	61	1997	957	71	3140	2	6.944
Median	600	60	1998	800	67	3102	2	0
# of wind turbines	381	381	381					
Properties traded				5488	5488	5488	2648	

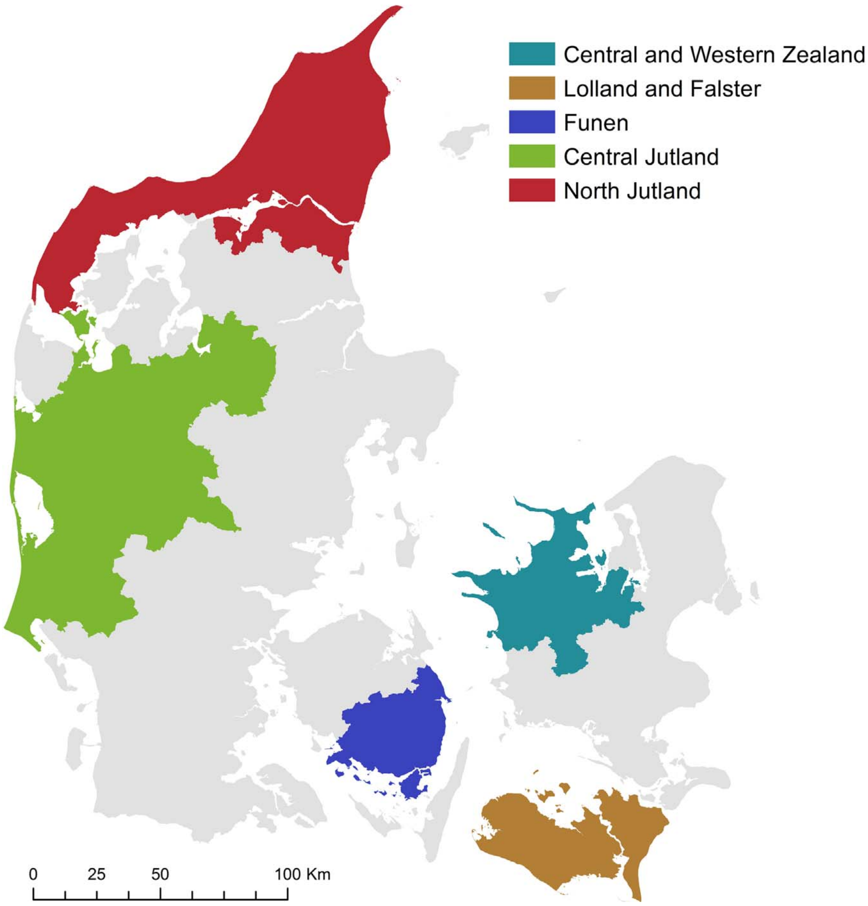

Fig. 1. The selected areas used to analyze the effect of land-based wind turbines on property prices.

Fig. 2. The position of the Nysted and Rødsand II wind turbine farms.

Table 3
Descriptive statistics for the two wind turbine farms.

	Nysted	Rødsand II
Year of completed construction	2003	2010
Number of wind turbines	72	90
Hub height (m)	69	80
Wind turbines shortest distance to the coast of Lolland (m)	9500	3500
Primary homes		
Traded homes	1611	703
Homes with a direct view	275	91
Traded after the turbine farm	822	387
Homes with a view and traded after the turbine farm	162	49
Number of homes with ≥1 landbased turbine within 3 km	195	73
Secondary homes		
Total number of secondary homes in models	2712	1316
Number of secondary homes with a direct view	43	9
Traded after the turbine farm	1386	802
Homes with a view and traded after the turbine farm	29	4
Number of homes with ≥1 landbased turbine within 3 km	582	345

Our resulting GAM is

$$Ln(P_i) = \theta z_i + \alpha n_i + \beta ln(d_i) + g(x_i, y_i; k) + \varepsilon_i \quad (2)$$

Where again, P is the price of the i'th house and the natural log of P is a linear additive function of the attributes of the house z, which may also include spatial fixed effects. The wind-turbine-related attributes account for the number, n, of turbines within 3000 m and the log to the weighted density, d, respectively. The last term describes the non-parametric part of the model where k is the number of splines used across space (x, y). The error term is ε and assumed i. i. d. The parameters to be estimated are the vector θ describing the relationship between the housing attributes and the sales price, and the wind-turbine-specific attributes α and β.

The exact functional form and choice of variables to include in Eq. (2) are determined through the evaluation of model performances across the different spatial housing markets for residential and vacation homes.[1] We generated a range of different variables in order to determine how wind turbines in the landscape are perceived by households in the housing market. These variables included the number of wind turbines from 0.5 to 5 km, the number of wind turbines from 0.5 to 5 km of different heights, the shortest distance to a wind turbine and the average distance to wind turbines from 0.5 to 5 km. Based on model performance, we found a clear impact on price from wind turbines of up to 3 km away. This is an average and a result of the wind turbine composition within Denmark. The results, however, do not deviate much from the findings of other studies. Dröes and Koster (2016), a Dutch study, find the effect to be negligible beyond 2 km, and Gibbons (2015) find a negative price premium of 5–6% at 2 km in the UK. Given that we do not model the actual disamenities (view and noise, as in Jensen et al., 2014) but use distance and numbers as a proxy, the spatial extent may very well increase as the average size of wind turbines increases over time.

3.2. Identification for off-shore wind farms

The off-shore wind farm case is particular challenging. The above identification strategy for on-shore wind turbines relies on considerable variation in the distribution of wind turbines relative to the distribution of residential and vacation homes in the landscape. With off-shore wind farms, however, we find very little variation in the direction of, e.g., views from the houses to the mills and little variation in distance from houses to wind farms. This finding is simply because our data contain only two wind farms situated in demarcated areas at sea, and all houses are located in and around a few small towns on the coast. In addition, while there may be an effect of a direct view from a house to the wind farms, there may also be an effect of a view from the nearby beach to the wind farms, as proximity to the coast and attractive beaches may be a valuable attribute of these houses. Again, this is an attribute shared among many houses and hence has little variation. This kind of spatial pattern in the location of wind turbines makes it challenging to identify an effect of views to the wind farms, whether from houses or from the beach.

To allow for identification, we instead turn to the use of the difference-in-differences method, as have related recent studies (e.g., Hoen et al., 2016; Sunak and Madlener, 2016). Specifically, we use variation across time and treatment to identify an effect of living in an area with a view of the wind farms from residential and vacation homes and/or from the beach nearest to the property. We use the fact that the two wind farms were completed in 2003 and 2010, respectively, leaving us with three time periods: before the first wind farm was completed, between the establishment of the first and the second wind farms and after 2010, and in the presence of both wind farms. As a treatment difference, we used data on either residential or vacation homes from villages in the area without a view of the wind farms from the homes nor nearby beaches as the "no treatment" sample, and villages and areas with a view of the wind farms from the homes and/or from a nearby beach as the treatment samples. These samples were found in and around the villages of Marielyst, Stubberup and Nysted. Time and treatment variables were modeled using simple dummies¸ D, for the event, E, of a wind farm being completed, and for the treatment, T, of having a view from the house and/or beach.

The technical formulation of this model becomes

$$ln(P_i) = \beta_0 + \beta_1 D_i^E + \beta_2 D_i^T + \beta_x X_i^E + \varepsilon_i \quad (3)$$

Here, P, as before, is the price of the i'th house, β are parameters to be estimated, X a vector of control variables accounting for numerous other relevant attributes of the house and its location, including a spatial fixed effect on postal codes. Finally, ε is an i.i.d. error term. The model is estimated for both residential and vacation homes. The experimental design thus results in eight different models to be estimated; a model before and after for the years 2003 and 2010, with a view of the wind farms from the house or from the beach (both against the basis of a new view from the house or beach) and, finally, for both types of housing.

4. Results

We present three sets of results, namely, the effect of on-shore wind turbines on the prices of residential homes across the five markets, the effect on the prices of vacation homes across the five markets and the effect of off-shore wind turbines on the price of both types of homes in Southern Denmark.

4.1. Impact of on-shore wind turbines on the price of residential and vacation homes

A subset of the pricing function for residential homes is presented in Table 4. Full estimation results are presented in the appendix. The model includes more than 40 control variables. We find the signs and significance in accordance with expectations, e.g., the parameter for the area of the house is positive and the distance to the center of town is negative. We find that both the variables measuring the number of wind turbines and the density measures of the wind turbines around residential homes reflect negatively on property prices. The parameters imply that adding another wind turbine within 3 km decreases prices between 0.2% and 1.1%. The log transformations imply a marginal

[1] The functional form choices in the model estimation were based on parametric functional form ranking following the procedure outlined by Panduro and Jensen (2016).

Table 4
The effect of onshore wind turbines on the prices of primary homes.

	Central and western Zealand	Lolland and Falster	Funen	Central Jutland	North Jutland
Wind turbines within 3 km	−0.007**	−0.006**	−0.011**	−0.006***	−0.002**
	(0.003)	(0.003)	(0.005)	(0.001)	(0.001)
Log(weighted density)	−0.004**	−0.006*	−0.0005	−0.003**	−0.004***
	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)
Constant	11.770***	9.841***	11.590***	10.709***	10.584***
	(0.280)	(0.135)	(0.710)	(0.075)	(0.102)
Observations	8865	6137	7593	21,185	25,301
Adjusted R2	0.515	0.467	0.486	0.423	0.503
Log Likelihood	−129,022	−86,903	−110,508	−307,422	−367,150
UBRE	0.165	0.252	0.192	0.198	0.201

1% (***), 5% (**), 10% (*).

Table 5
The effect of onshore wind turbines on the price of secondary homes.

	Central and western Zealand	Lolland and Falster	Funen	Central Jutland	North Jutland
Log(weighted density)	−0.0001	−0.021***	0.011	−0.008***	−0.006**
	(0.003)	(0.003)	(0.007)	(0.002)	(0.002)
Constant	11.979***	13.224***	14.055***	12.460***	12.272***
	(0.137)	(0.317)	(0.445)	(0.123)	(0.119)
Observations	5488	2198	408	4904	5337
Adjusted R2	0.428	0.446	0.282	0.572	0.393
Log Likelihood	−78,005	−30,916	−5981	−70,448	−76,555
UBRE	0.199	0.172	0.214	0.139	0.171

1% (***), 5% (**), 10% (*).

decreasing cost of placing another wind turbine within 3 km of the house in focus. The logged measure of weighted density also implies that placing a wind turbine nearby is worse than placing it further away, and the marginal cost of another wind turbine is decreasing in the number of wind turbines already within the 3 km range.

We find similar results for vacation homes, but they are not as strong. A subset of the pricing function for summer cottages is presented in Table 5, and full estimation results are in the appendix. We observe fewer summer cottages, which are also reflected in the number of control variables. We include more than 10 control variables, and in addition to the smoothing on coordinates, we introduce a fixed effect on postal codes. We find the signs and significance in accordance with our expectations, e.g., the parameter for the area of the house is positive and the distance to the coast is negative, indicating that proximity to the coast is valuable.

We find a significant wind turbine effect in three vacation home markets. We tested different specifications and found the weighted density to best explain the relation. It should be noted that the number of wind turbines is indirectly reflected by the weighted density measure. The reason why we do not see a significant effect for both weighted density and the number of wind turbines could be that the dataset on vacation homes is smaller and the properties are more heterogeneous. leaving more noise in the data and hence lower efficiency in inferences. Another reason for not finding an effect could be the spatial dispersion of vacation homes in Denmark. The majority of vacation homes are clustered, e.g., along the coast. In contrast, residential homes are both clustered in the cities and more dispersed across the countryside. This means that, for the vacation homes compared to the residential homes, there are stronger correlations between being closest to the wind turbine and a range of other amenity values, which again reduce efficiency in inferences.

4.2. Impact of off-shore wind turbines on the price of residential and vacation homes

Table 6 shows the main results of the effects of installing off-shore wind farms (Nysted and Rødsand II) on the prices of residential and vacation homes on the coastline of Lolland Island. The results show that for neither of the wind farm installations do we find a significant effect of having a view across the sea including wind farms relative to a view across the sea without a visible wind farm. There is no difference between the two regardless of whether the variable measures the view from each property or the view from the beach nearest to the property.

Table 6
The effect of a visible off-shore wind turbine farm on the prices of primary and secondary homes.

	Nysted		Rødsand II	
	Secondary home	Primary home	Secondary home	Primary home
Traded after the installation	1.210***	−0.203**	−0.157***	0.086*
	(0.262)	(0.097)	(0.056)	(0.052)
View	−0.596***	0.058	−0.045	−0.113
	(0.166)	(0.181)	(0.060)	(0.161)
View and after the installation	0.144	−0.005	−0.039	−0.035
	(0.203)	(0.242)	(0.072)	(0.165)
Wind turbines within 3 km	0.220***	−0.013	−0.003	−0.041**
	(0.057)	(0.036)	(0.020)	(0.018)
Constant	13.395***	10.116***	9.913***	10.530***
	(1.607)	(0.451)	(0.334)	(0.296)
Observations	703	1611	1316	2712
Adjusted R2	0.919	0.407	0.288	0.715
Log Likelihood	−10,529	−23,768	−18,671	−37,987
UBRE	601,558,277,726	382,008,229,794	0.277	85,821,726,96

1% (***), 5% (**), 10% (*).

We note that the models have a reasonable to very good technical fit, and we note that in the relevant cases, we found effects of nearby on-shore wind turbines just as we did in the above on-shore analysis. Thus, with the proposed difference-in-differences approach, we are unable to identify significant robust effects of the off-shore wind farms analyzed here.

4.3. The implication of the results for future decisions

The density of homes and the value of these homes are drivers of the welfare economic impact of wind turbines on neighboring communities in any given area. In the following, we simulate the welfare economic impact of removing a wind turbine for existing wind turbine sites. Six simulations were conducted. Each simulation was distinctly different from the others i) by accounting for the presence and spatial distribution of existing turbines or overlooking the presence, ii) by accounting for the spatial distribution of homes in the landscape or not accounting for it and iii) by accounting for the specific value of these homes or not accounting for these values of houses. The six simulations were all based on the model estimates for residential homes in the Lolland Falster housing market. Note that the model estimates of wind turbine impacts on housing prices represent a measure of the marginal price of this impact, which can be interpreted as a percentage of the value of a house, which means that all houses are affected equally in a relative sense, the absolute price impact will differ depending on the sales price of the house.

In 2015, a total of 366 onshore wind turbines delivered power to the net from their position on the islands of Lolland and Falster. This simulation area was divided into raster cells of 100 × 100 m. All data were aggregated to this cell level, i.e., the number of wind turbines, the number of residential homes and the median trading price of these homes.

The intuition behind the simulations is to estimate the welfare economic impact – a gain – of removing in turn an existing wind turbine from each cell containing wind turbines. This exercise is much in line with the challenges that energy planners currently face in Denmark. According to the Danish energy strategy from 2012,[2] Danish onshore wind turbine capacity will increase by approximately 30% from 2012 to 2020, but with technology development, the Danish government expects to reduce the number of onshore wind turbines from approximately 5000 to 3400 wind turbines. Hence, when an old wind turbine is scrapped, it is not necessarily replaced by a new wind turbine. Thus, a new task is to identify which wind turbines to replace and which to permanently remove. Of course, the results could also be interpreted as the impact of adding another wind turbine to the existing turbines in each cell, provided that the new turbine is of a similar type as those in the underlying model.

Similarly, Fig. 3 shows that the numbers and values of residential homes are spatially clustered. Specifically, the spatial dispersion of the median trading prices and the number of residential homes per hectare is shown in Fig. 3. The calculations were all conducted in a 100 × 100 m resolution but are shown here in 1000 × 1000 m resolution for illustrative purposes. Comparing the panels in Fig. 3, we see a strong correlation between mean trading prices and the population density measured as the density of residential homes.

Using the spatial information depicted in Fig. 3 and our estimated model, we can simulate the different value components of removing (adding) a wind turbine from (to) an area. The results of these simulations are shown in Fig. 4. By definition, the simulation covers only existing wind turbines sites, and areas in Fig. 4 with no color are areas with no wind turbines present within 3000 m of residential homes. The simulations are presented both accounting for the current 2016 dispersion of wind turbines (left panel of Fig. 4) and ignoring pre-existing wind turbines (right panel of Fig. 4).

The first row in Fig. 4 shows the impacts including both the spatial variation in the trading prices of residential homes and the spatial density of homes. We find that the distribution of existing wind turbines drive results very little when accounting for spatial variation in prices and the density of residential homes. In the second row of Fig. 4, we include only spatial variation in trading prices but keep residential home density fixed. These results are very similar to those in the first row due to the high correlation between the trading price of residential homes and the density of residential homes. In the last row, we removed spatial heterogeneity in both trading prices and the density of residential homes and estimated the benefit (cost) of removing (placing) another wind turbine, given only one house within each hectare at a constant price but allowing for spatial variation in the density of wind turbines, which allows the impact of variation in the distribution of wind turbines to stand out, and we see that the cheapest locations are those in which the density of existing wind turbines is high. Finally, in the bottom-right panel, we see that when we remove the spatial variation in wind turbine density and in the prices and density of homes, we also remove the variation in the impacts of adding or removing another wind turbine.

The results presented in Fig. 4 show that the density and the value of homes are the most important factors to consider in an impact assessment of where to remove or add wind turbines in the landscape. Furthermore, the results clearly show that choice of location matters for the economic impacts of the decision. In Table 7, the impact of removing or adding a turbine is shown for the different simulation scenarios. The differences in impact across wind turbine sites vary with a factor of 100.

The model estimates presented in Tables 4, 5 show the marginal declining cost of additional wind turbines in an area. However, the "marginal declining cost" effect does not contribute as much to the absolute impact of adding or removing wind turbines from the different sites as the spatial variation in density and prices of homes. In the stylized case, where housing density and housing value are kept constant, i.e., columns 3 and 6 in Table 7, the gain of removing a wind turbine is more than halved for 75% of the sites. The marginal declining cost of the last wind turbine obviously has an effect on the distribution of impacts but is easily dominated.

5. Concluding discussion

5.1. Our main findings

In this study, we have provided further evidence on the impact of on-shore wind turbines on nearby property prices. We add to the literature by presenting the first results to distinguish between residential and vacation homes. Our results across several spatially distinct housing markets show unequivocally that significant negative effect of wind turbines exist if placed up to as much as 3 km away from a property, which is partly a result of the existing stock of turbines in the analyzed areas. Interestingly, however, the size of the effects we find are very similar to those in other studies in other areas. Recent research documents effects on the stated well-being of people living in close proximity to wind farms find an effect of up to as much as 4000 m (Krekel and Zerrahn, 2017) from one or more wind turbines. Heintzelman and Tuttle (2012) find that property prices decrease by between 8.8% and 14.87% at a distance of 0.5 miles (equal to approx. 800 m) to the nearest wind turbine in the State of New York, USA. Jensen et al. (2014) document a significant effect of noise and visual pollution from wind turbines of a similar size in Denmark.

The results also show that there is a declining marginal effect of the number of turbines within 3 km of affected properties. These are important findings of clear relevance to resolve the question of where to best place new on-shore wind farms or replace existing ones in the

[2] Available in Danish only at https://ens.dk/sites/ens.dk/files/Energibesparelser/aftale_22-03–2012_final_ren.doc.pdf.

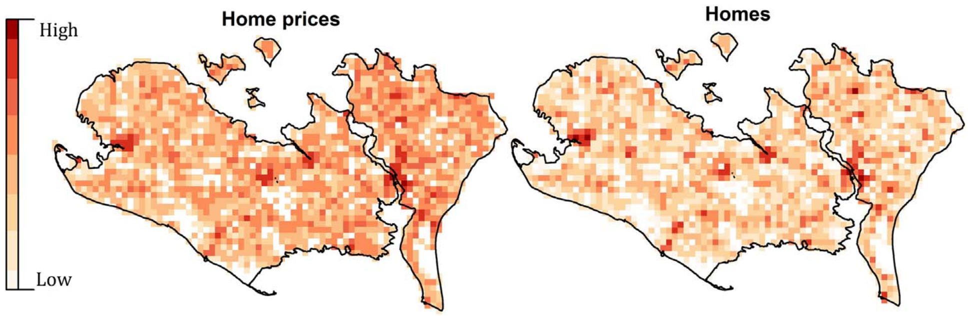

Fig. 3. The median trading prices of residential homes and the number of residential homes per hectare; aggregated at 1 km2 level.

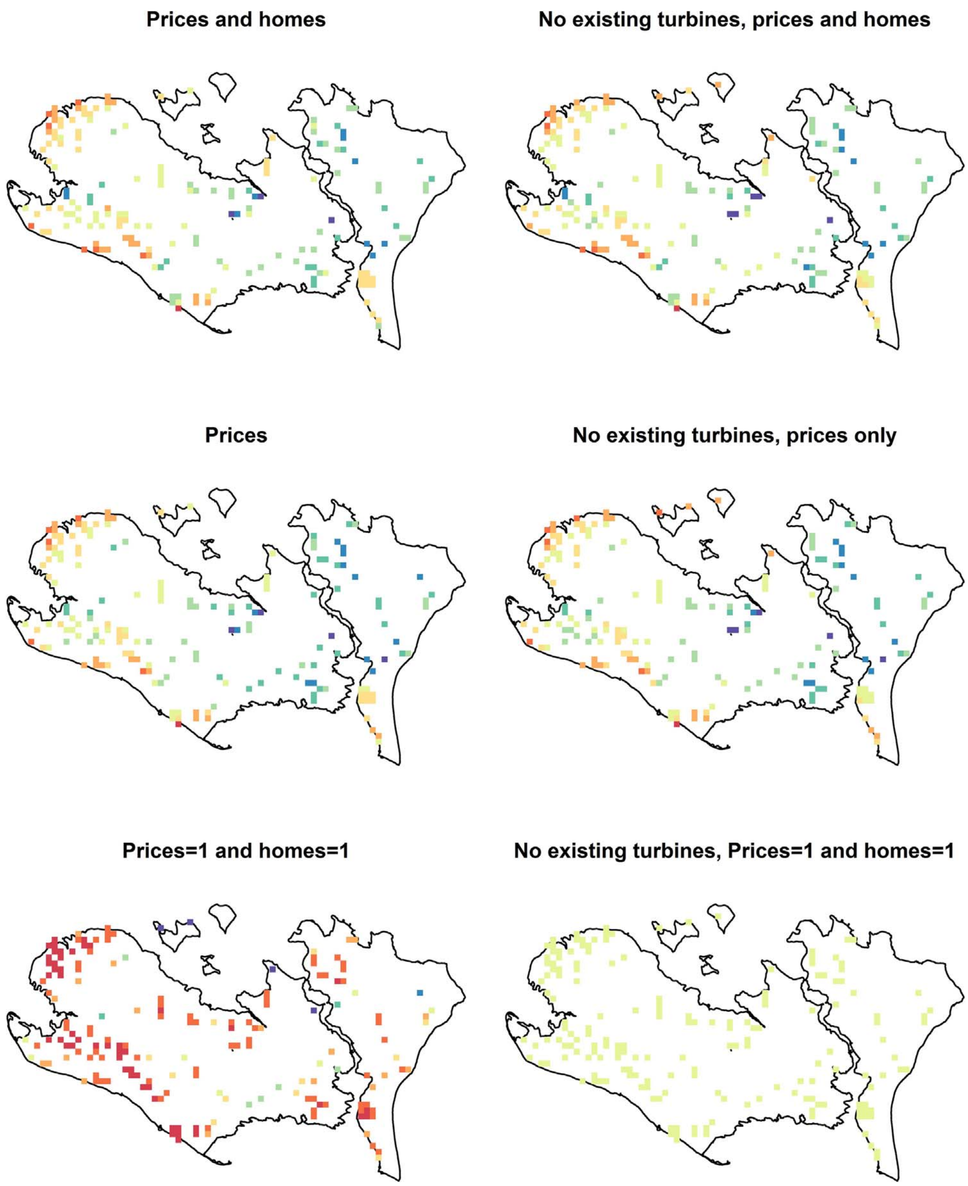

Fig. 4. Spatial variation in the relative impacts in terms of the benefit (costs) of removing (placing) another wind turbine in an area, when accounting for spatial variation in the distribution of existing wind turbines, spatial variation in the prices of residential homes and density of residential homes. The right-hand figures ignore spatial variation in wind turbine density. First-row figures include spatial variation in price and the number of residential homes. Second-row figures include spatial variation in residential home prices only. Third-row figures ignore spatial variation in prices and the density of residential homes.

landscape, taking into account the impacts on the value of nearby properties.

Furthermore, to our knowledge, this study is also the first to address the impact of off-shore wind turbines on property prices. We outline the challenges with the identification of such effects and we apply a difference-in-differences design to a case study of two wind farms placed approximately 9 km off the coast of an island in southern Denmark. We do not find a significant effect of these wind farms on the price of properties with a view of the wind farms from the house itself or from nearby beaches. We note that this may not be surprising because the effect of on-shore mills only reach 3 km in our data. Nevertheless, the public debate about off-shore wind farms includes the perceived aesthetic effects even of farms as far from the coast as those analyzed here, as do stated preference studies (Ladenburg, 2009). Our results suggest that the effects of farms this far off the coast are likely to be negligible for people living in the area and using the beaches. Our results, however, say nothing about off-shore wind farms closer to the coast.

Table 7
Distribution of absolute costs (benefits) of placing (removing) another wind turbine in the landscape when accounting for density of existing wind turbines or not. Calculations correspond to the different panels of Fig. 4 (units are EUR per wind turbine site).

	Existing wind turbines			No existing wind turbines		
	Prices and houses	Only prices	Prices = 1 and houses = 1	Prices and houses	Only prices	Prices = 1 and houses = 1
Min	167,966	155,770	21	366,953	344,234	48
1st quantile	611,126	372,995	21	1,269,489	805,877	48
Median	1,242,035	604,451	22	2,590,305	1,274,391	48
Mean	2,096,778	823,096	23	4,093,380	1,662,059	48
3rd quantile	2,447,104	198,607	23	4,738,831	2,218,193	48
Max	16,251,670	3,258,602	47	25,906,037	6,226,380	48

5.2. Caveats

Of course, our findings rely on the data on existing wind turbine installations. Wind turbine technology is constantly evolving, which may affect the longevity of our findings. In particular, the size and height of wind turbines is increasing for both on-shore and off-shore wind turbines. Thus, future wind turbines on average may be visible still further away (Jensen et al., 2014) and loom larger when close by than do wind turbines in our data. It is likely that this may push impacts of the individual wind turbine upwards and outwards.

Furthermore, the analysis is cross-sectional, relying on a state-of-the art spatially explicit model to account for systematic and unobserved differences between homes with and without turbines, but even so, it does not allow us to rule out that such differences still exist. Unfortunately, the data did not allow us to estimate a sound difference-in-differences model because very few new wind turbines have been installed over the period. The fairly weak models we did estimate, however, suggested no basis for the concern that wind turbines were systematically placed in areas with lower property prices. Thus, we have no reason to believe that such a systematic difference exists. We note that our models take account of regional differences, the housing quality in Denmark is very diverse on a local level, and around half of the homes in each sample are affected by at least one turbine. Even so, we note that results based on a hedonic cross-sectional model are a sum of both possible pre-existing differences and the effects caused by turbines.

Our results for the off-shore wind farms are limited by the data material, including two wind farms in the same area and located fairly far out from the coast. For that reason, the number of property trades in the data is also much lower than that in the large on-shore case. The difference-in-differences method is usually a strong identification tool, and we note that the model behaves as expected, including finding the effect of the on-shore wind turbines in the area. Thus, in spite of the caveats, we believe that the results for the case are robust.

5.3. Policy perspectives and further work needed

With our policy simulation, we find large spatial variation in the impacts of adding or removing wind turbines in the landscape. The main welfare economic drivers of amenity costs are the density of housing and the value of these houses. Our results suggest that if an energy planner has to choose between different sites to place one or more entirely new wind farms, the spatial distribution of homes and the their value are important factors to consider. However, once the site has been chosen, the marginal declining effect of wind turbines in a wind farm implies that from a welfare economic perspective, it is better to establish fewer and larger wind turbine farms than more and smaller farms in terms of wind turbines at each site. In other words, the main policy recommendation is to "build wind turbine farms in remote areas and make them large".

Our results are based on the existing combination of turbines that affects homes traded in each market. Thus, if the planner wants to install a turbine that deviates from the existing turbine population, our results may be a conservative estimate of the effect because new turbines are usually significantly larger. The vast majority of the wind turbines within the area are at least 15 years old; more than 30 were connected to the grid before 1990, and these are smaller than the average wind turbine within the sample. Our results show the change in the costs of removing or adding a marginal average wind turbine within the area at existing wind turbine sites. In recent time, however, wind turbines have been placed in bulks and installed as wind turbine farms. They will most likely also be scrapped in bulk, which calls for an analysis that evaluates wind turbine locations in bulks as well.

Finally, turning to our results for the off-shore cases. we note that much more work is needed using several different cases, including cases with wind turbines closer to the shore, if possible. That work will likely have to solve the identification issues addressed in our study, but this should be possible, provided suitable geographical distribution of properties with and without a view of wind turbines.

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