Local Impacts of Wind Farms on Property Values: A Spatial Difference-in-Differences Analysis

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Abstract

Today's investment decisions in large-scale onshore wind projects in Germany are no longer determined only by the investment's economic benefit, but also by concerns associated to social acceptance. Despite a mostly positive attitude towards the expansion of wind power, local public concerns often stem from the belief that the proximity to large-scale wind farms may lead to a decrease in property prices. In particular, the change in landscape caused by the construction of a wind farm may have an impact on the view from some properties, and thus may negatively affect their price. To investigate the potential devaluation of properties in Germany due to wind farm investments, we use a quasi-experimental technique and apply a spatial difference-in-differences (DID) approach to various wind farm sites in the federal state of North Rhine-Westphalia. We adopt a quantitative visual impact assessment approach to account for the adverse environmental effects caused by the wind turbines. To properly account for spatial dependence and unobserved variables bias, we incorporate different spatial econometric models into the DID analysis. The estimates indicate that the asking price for properties whose view was strongly affected by the construction of wind turbines decreased by about 10%. In contrast, properties with a medium or minor view on the constructed turbines experienced no devaluation.

Keywords: Wind power, Difference-in-Differences, Visual impact, Spatial dependence

JEL Classification: C31, Q2, Q42, R31

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I. INTRODUCTION

Over the last two decades, fostered by strong financial incentives, wind power in Germany has seen a rapid market diffusion. Guaranteed feed-in tariffs for renewable energies such as wind power often rewarded investors in these technologies with substantial economic returns. However, today's investment decisions in large-scale onshore wind power projects in Germany are no longer determined only by the investment's economic benefit, but also by the mitigation of public concerns and thereby the increase of social acceptance. Despite a mostly positive attitude towards the expansion of wind power, local public concerns often stem from the belief that the proximity to wind turbines diminishes property prices.

The proximity to a wind farm site may lead to various types of locally adverse effects, such as noise, sound pressure, electromagnetic inference, shadow flicker, as well as visual and scenic intrusion (Manwell et al., 2002). While noise, sound pressure, electromagnetic inference, and shadow flicker effects only occur in the immediate proximity to the wind farm (mainly within the first few hundred meters to the site), visual and scenic effects can have strong influences over considerable distances. Generally speaking, among the various locally adverse effects caused by wind farms, landscape and visual effects are considered to be the most dominant and relevant factors triggering public concerns (Andolina et al., 1998; van Beek et al., 1998; Gipe, 2002; Manwell et al., 2002; Benson, 2005; Miller et al., 2005). Wind farms, sited in predominantly rural areas, are usually visible from considerable distances, as these constructions tend to be significantly taller than any other object in the existing landscape (Miller et al., 2005). In addition, the average hub height and rotor diameter of wind turbines have increased tremendously over the last years, causing further changes in the landscape of the affected regions. The current trend of repowering (i.e. substituting older facilities by newer, larger, and more efficient ones) will continue to foster this development.

The visual impact threshold distance, i.e. the maximum distance from which a wind farm is visible, can be up to about 30 to 40 kilometers, depending on the terrain characteristics, landscape background, and weather conditions (Bishop, 2002; Sullivan et al., 2012). However, regarding the determination of thresholds of potential visual wind farm impacts, it is important to note that visibility cannot be regarded as a binary factor (i.e. only indicating if a wind farm is visible or not), but that the significance of the visual impact can vary within a spectrum that ranges from uninformed detection of the wind farm to strong visual disturbance (Bishop, 2002).[1] Therefore, in order to estimate the visual impact of a wind farm for different locations in a specific region, visibility has to be treated as a function of wind farm size and shape in relation to the observer's distance, the view angle to the object, the object's contrast in relation to its background, and atmospheric scattering (Bishop, 2002; Hurtado et al., 2004; Benson, 2005; Möller, 2006; Bishop and Miller, 2007; Molina-Ruiz et al., 2011; Manchado et al., 2013). Even if wind turbines are visible from distances of up to 30 or 40 kilometers under certain circumstances, usually the

[1] Bishop (2002) defines four visibility categories: uninformed detection, uninformed recognition, informed recognition, and informed visual impact. For further information on visual thresholds for detection, recognition, and visual impact, see also Shang and Bishop (2000).

significance of a visual impact can be expected to drop substantially beyond distances in excess of 2 to 3 kilometers (Bishop, 2002; Sullivan et al., 2012). Hence, visual impacts tend to be extremely complex and difficult to estimate quantitatively (Möller, 2006). However, in order to define reasonable threshold values for differentiated visibility levels, the distance to the wind farm and the number of visible turbines can be considered as the most important factors. Nonetheless, the literature on visual impact assessment of wind turbines almost entirely provides qualitative measures, and only very few publications so far focus on the development and application of quantitative measures of visual impacts (Hurtado et al., 2004; Möller, 2006; Torres-Sibille et al., 2009; Manchado et al., 2013; Kokologos et al., 2014).

As location is one of the most important determinants of a property's value, the proximity to environmental amenities and disamenities in the surroundings, and hence the associated preferences of the consumers, are supposed to be indirectly reflected in its value. The assessment and quantification of changes in the locational attributes of a given property (e.g. due to the construction of a wind farm in the proximity) can be implemented by means of the hedonic pricing method, which allows for the extraction of the implicit price of one attribute from the overall price of the property (Rosen, 1974; Parmeter and Pope, 2013).

Applied to the case where the change in the locational attributes of a property is caused by the construction of a wind farm, the extraction of the attributes' implicit price demands for a suitable and differentiated representation of the wind farms' influence on the location of the property. As the impact on landscape and view can be considered as the most dominant wind farm effect, studies aiming at a precise and reliable estimation of potential local impacts of wind farms on property values in the surroundings should rely on an explicit incorporation of visibility effects. Still, most studies only apply simple distance measures as proxies for all kinds of local wind farm effects (see section II), and do not actually account for more precise estimates of actual visibility changes.

The aim of this study is to investigate local visual impacts of wind farms on the development of property prices by explicitly implementing direct visibility estimates in the analysis. Four large-scale wind farm sites located in the immediate vicinity of three medium-sized cities in the federal state of North Rhine-Westphalia (NRW), Germany, are investigated. Within the framework of the hedonic pricing method, we apply a spatial difference-in-differences (DID) model that allows for a comparison of the observed changes in the values of the treated properties against the values of a control group. Applied to the case of wind farm construction, the treatment and control groups are defined according to various wind farm visibility criteria (see section III).

Quasi-experimental approaches, such as the DID approach, are increasingly applied in hedonic pricing analyses. They offer a straightforward way to estimate causal relationships and often ensure better estimates compared to the ones obtained via standard hedonic pricing approaches (Bertrand et al., 2004; Kuminoff et al., 2010).[2] The advantages of applying a quasi-experiment within the framework of the hedonic pricing theory is most evident in relation to empirical deficiencies in traditional hedonic applications, such as the inability to control for endogenous

[2] For further information on advantages of the DID framework over other approaches, see Kuminoff et al. (2010) and Parmeter and Pope (2013).

influences and omitted variable bias (Parmeter and Pope, 2013). The DID framework is particularly well suited for the application to our study case, as it enables us to control for interferences that either exist in the given region prior to the siting of the wind farm, or that affect all properties irrespective of the wind farm construction (Lang et al., 2014).

For the purpose of investigating visual impacts of wind farms, we partially adapt the quantitative visual impact measurement approach proposed by Hurtado et al. (2004) and develop a factor-based 'Visual Impact Level' (*VIL*) ranking incorporating the magnitude of visibility (i.e. the number of visible turbines), the distance to the wind farm, and the view angle from the center of the property. As mentioned above, besides the incorporation of distance, magnitude of visibility, and view angle, visual impact assessments should ideally also consider weather conditions, atmospheric scattering, and background contrasting. However, due to limited data availability and computational issues, accounting for these factors is beyond the scope of this analysis. Nonetheless, thanks to the implementation of a quantitative factor-based approach considering the relation of distance, magnitude of visibility, and view angle, we improve the current practice of applying qualitative-subjective evaluations of visual impacts in hedonic pricing analysis. More specifically, the impact of the different visibility levels on the property values is estimated by means of a Spatial Fixed Effects model, a Spatial Auto-Regressive Lag Model with an Auto-Regressive Error Term (SAC/SARAR)[3], and a Spatial Durbin Error Model (SDEM).

The hedonic pricing literature on wind farm effects is still sparse and only contains a few peer-reviewed, econometrically sound analyses (see section II). The main weaknesses that can be identified in many such studies are related to (1) an insufficient representation of wind farm impacts through simple distance measures that are used as proxies for visual impacts, (2) a rarely systematic and mostly subjective determination of visual impacts (if at all incorporated), and (3) a missing explicit account of spatial dependence by means of spatial econometric methods. We address (1) and (2) through the systematic determination of different *VILs* that explicitly consider the relationship between distance, the degree of visibility, and the view angle. The defined *VILs* are based on viewshed analyses that use high-resolution 3D data with an accuracy of one square meter, and that include, in a digital surface model, all visible elements in the environment, such as heights, slopes, vegetation, and buildings. We approach (3) by applying a Spatial Fixed Effects Model, a SAC/SARAR, and a SDEM in the DID framework (see section IV).

Additionally, while most studies focus on wind farm effects in the US, our research is one of the first comprehensive analyses for Europe and, more specifically, Germany. The insights gained from our analysis may thus be of particular relevance, also in light of differences in the property market conditions and spatial dimensions between Germany and the US, which imply that the results obtained cannot simply be assumed to hold true irrespective of the region considered.

The remainder of this paper is structured as follows. Section II provides an overview of the previous research on wind farm impacts on property values using a hedonic pricing framework.

[3] In the literature, the spatial auto-regressive lag model with an auto-regressive error term is labelled as SAC (LeSage and Pace, 2009) as well as SARAR (Kelejian and Prucha, 1998).

Section III introduces the visual impact assessment, which is then incorporated into the spatial DID framework presented in section IV. Section V presents the results obtained from the different model specifications, and section VI concludes by summarizing the main insights from our analysis.

II. Previous Research

To date, the number of publications that investigate the impact of wind farms on property values by means of hedonic pricing methods is still limited. Despite the limited number of publications, there is considerable variety of approaches regarding the selection of suitable variables (particularly with respect to the choice of the most appropriate proxy for wind farm impacts), estimation techniques (mainly with regard to possible omitted variable biases and spatial dependence), and applications (e.g. in view of single-turbine vs. large-scale wind farm cases). In the following, we highlight the main features of each study, while focusing on how wind farm effects are implemented and also how spatial dependence is accounted for.

Being among the earliest published studies on this topic, Sims and Dent (2007) as well as Sims et al. (2008) investigate the impacts of wind farms on house prices in Cornwall, UK. Sims and Dent (2007) apply a simplistic regression approach that does not control for any spatial effects in the data. Various distance zone dummies are used as proxies for wind farm impacts. Furthermore, the authors consider only property sales between 2000 and 2004 that took place after the construction of the wind farm, which is by far the most problematic issue. Sims et al. (2008), in contrast, consider the problem of spatial relationships in the data by using spatial fixed effects. Furthermore, they incorporate some dummy variables indicating visibility. However, they do so without considering any actual relation to distance or extent of visibility. The data base is again rather small (199 property sales), though it considers a longer time interval (2000-2007). In general, both Sims and Dent (2007) and Sims et al. (2008) could not obtain any significant evidence of the effects investigated, though this outcome might have been strongly influenced by the limitations in the analysis carried out.

Hoen et al. (2009, 2011) and Hoen et al. (2013) analyze wind farm impacts on various sites in the US and provide by far the most comprehensive studies currently available in the literature. In a published article version of their project report (Hoen et al., 2009), Hoen et al. (2011) investigate about 7,500 single-family house sales in the period between 1996 and 2007 in the proximity of 24 large-scale wind farm sites spread across nine US states. In their study, they explicitly focus on visibility effects and develop an ordered qualitative visual impact ranking system that incorporates distance to the turbines, the number of turbines visible, as well as the view angle. To approve the subjectively designed visual impact ranking, they conducted a pre-study survey based on an evaluation of randomly selected site photographs by respondents and checked for correlations between the qualitative ranking and the measured values (i.e. distance, number of turbines visible, view angle) using a regression model. Within a standard hedonic framework, different model specifications were applied, also accounting for spatial autocorrelation via spatial fixed effects and nearest neighbor weights (similar to a spatial lag model). According to the results obtained, no evidence was found for visual impacts or other wind farm-related effects in the considered study areas. Hoen et al. (2013) further improved the two aforementioned studies by applying a DID framework with spatial econometric methods in order to control for spatial dependence. With more than 50,000 property sales from 1996 to 2011 in a 10 miles radius around 67 wind farm sites in nine US states, this report is to date one of the most extensive and well-designed analyses. However, instead of further developing a visual impact ranking based on quantitative measures, rather than only qualitative ones, they simply used distance ranges as proxies for visual influences and other local impacts. Similar to the studies before, they found no statistically significant wind farm construction impacts on property values.

A similar approach was recently adopted in a report by Atkinson-Palombo and Hoen (2014), who investigate potential wind farm impacts on properties in Massachusetts, US. The study specifically focuses on noise and shadow flicker effects within half a mile around the considered properties in more densely populated urban areas. The extensive dataset accounted for 122,000 home sales between 1998 and 2012. Again, a simple distance variable controlled for possible local effects. Spatial relationships in the data were again addressed via spatial fixed effects and nearest neighbor weights. The results obtained did not provide any significant evidence for local wind farm effects caused by the construction or announcement of the projects.

Sunak and Madlener (2012) investigate the impacts of wind farms on property values in Germany by means of different spatial fixed effects specifications and a locally weighted regression model. Besides the estimation of wind farm impacts via a continuous distance variable as well as distance range dummies, visibility is explicitly analyzed in a fixed viewshed effect specification and the locally weighted regression model. The dataset includes 1,405 observations in a period ranging from 1992 to 2010. Overall, some evidence was found for negative impacts on property prices in cause of the wind farm construction.

Heintzelman and Tuttle (2012) provide a wind farm analysis in a standard hedonic framework and apply a spatial fixed effects specification. Wind farm effects are incorporated in the models solely using continuous distance and distance range variables, whereas visibility is not considered. Including about 11,000 property sales occurred in the time period between 2000 and 2009 in northern New York, US, the results indicate statistically significant negative impacts on property prices.

Most recently, Lang et al. (2014) conducted an analysis on the impact of 12 single turbines on property values (48,554 observations) in 10 different sites in the time period between 2000 and 2013 in Rhode Island, US. Applying a DID framework, they incorporate various distance bands around the turbine sites in order to investigate construction and announcement effects. In a further specification of the model, they also apply a qualitative visual impact ranking to examine potential wind farm visibility effects. Spatial relationships in the data are addressed by the implementation of spatial fixed effects, whereas spatial dependence is not considered in their analysis. Although the modeling design and the econometric implementation are elaborate and sound, there are some drawbacks associated to the study objects chosen and the wind farm impact proxies applied. Firstly, in contrast to all other studies that investigate the impacts of large-scale wind farms on surrounding properties, Lang et al. (2014) only focus on single and relatively small turbines. This might affect the significance of their results when compared to studies that consider large-scale farms (e.g. with more than 15 or 20 turbines), which possibly have a stronger impact on landscape and view and thus property prices, *ceteris paribus*. Secondly, even though visual impacts are considered in one model specification, the visual impact classification is solely based on the subjective opinion of one individual that conducted all the field visits. A more systematic approach to rank the data, e.g. relating distance and extent of visibility, would have benefited the study.

Table 1 provides an overview of the studies discussed and their main features.

TABLE 1: Overview of studies discussed and their features

	Study area	***N***	**Time period**	**Object of study**	**Model framework**	**Spatial methods**	**Wind farm effect proxy**	**Impact estimation**
Sims and Dent (2007)	UK	919	2000-2004	Wind farm	Standard hedonic	-	Distance	Negative
Sims et al. (2008)	UK	119	2000-2007	Wind farm	Standard hedonic	SFE	View	None
Hoen et al. (2009, 2011)	US	7,459	1996-2007	Wind farm	Standard hedonic	SFE, Spatial lag	Qual. view ranking	None
Hoen et al. (2013)	US	51,276	1996-2011	Wind farm	DID	SFE, SARAR	Distance	None
Atkinson-Palombo and Hoen (2014)	US	122,198	1998-2012	Wind farm	Standard hedonic	SFE, Spatial lag	Distance	None
Sunak and Madlener (2012)	GER	1,405	1992-2010	Wind farm	Standard hedonic	SFE, LWR	Distance + View	Negative
Heintzelman and Tuttle (2012)	US	11,369	2000-2009	Wind farm	Standard hedonic	SFE	Distance	Negative
Lang et al. (2014)	US	48,554	2000-2013	Single turbines	DID	SFE	Distance + Qual. view ranking	None

III. VISUAL IMPACT ASSESSMENT

Visual Impact Levels

The implementation of a precisely measured and representative proxy for local wind farm effects is crucial for hedonic pricing studies that aim at estimating potential impacts of wind farms on property values. As already indicated above, changes in landscape and view due to the construction of wind farms are the most significant factors and should, therefore, be directly accounted for. Simple distance measures (i.e. grouping property sales according to their distance to the nearest turbine) can only provide a crude representation of local wind farm effects. Likewise, the application of binary visibility variables (i.e., only indicating if a wind turbine is visible or not) may not adequately represent the visual effects caused by wind farm sites. The visual impact of wind farms is rather a function of various factors that affects a specific location, and may include the distance to the nearest turbine, the number and extent of turbines visible, and the observer's view angle.

As described in section II, only two studies adopt qualitative rankings in order to determine the visual impact for each property location. Hoen et al. (2009, 2011) develop a five-categories ranking based on the following wind farm visibility scale from a given property: (1) no view, (2) minor, (3) moderate, (4) substantial, and (5) extreme view. While the classification is not based on values for distance, number of turbines, or view angle, but rather on subjective considerations, at least the ranking is substantiated by a survey and some correlation tests. Lang et al. (2014) also apply a similar approach, yet no quasi-quantitative validation is conducted[4]. Their visual impact assessment is merely based on the individual ratings by a single person who was in charge of conducting all the field visits to properties within two miles around the considered turbine site.

In order to improve the previously applied qualitative approaches to incorporate different levels of visual impact in hedonic pricing studies, we adopt the quantitative, indicator-based visual impact assessment methodology provided by Hurtado et al. (2004), which was further developed by Kokologos et al. (2014). Originally, this approach was proposed to quantify the visual impact of wind farms for site pre-assessment and to evaluate the overall visual impact across whole regions. We apply and adapt the coefficient-based measurements to our study case, hence determining the *VIL* for each considered property in our data set. In addition, we validate the method by considering other proposed approaches and findings in this field (Bishop, 2002; Torres-Sibille et al., 2009; de Vries et al., 2012). The procedure adopted to determine *VIL* for each property is described in the following.

The applied visual impact assessment method is based on five indicators: the visibility of the wind farm from the city area, *a*, the visibility of the city area from the wind farm, *b*, the number of visible turbines in relation to the view angle, *c*, and the distance of the wind farm from the specific location in the city area, *d*. While the indicators *a* and *b* provide a more general characterization of the regional context, and indicate the overall relation of the wind farm to the different cities and city districts, respectively, indicators *c* and *d* measure the exact influence on

[4] The visual impact classes used in their study encompass (1) no view (0%), (2) minor (1-30%), (3) moderate (31-60%), (4) high (61-90%), and (5) extreme (91-100%).

the single property. Even though the main focus lies on the measurement of visual impacts at the single property level (through *c* and *d*), a rather general weighting of different regional effects through indicators *a* and *b* is also important. This needs to be accounted for, as the different cities and city districts in our study area are subject to substantially varying wind farm effects, given that, among other things, the southern part of the study area is affected by about 50 turbines overall and the northern area only by nine (see Figure 1).

The visibility of the wind farm from the city area *a* is given by

$$a = \frac{\sum_{i=1}^{n} \left(\frac{T_i}{WF} \right)}{n}, \tag{1}$$

where *n* is the number of areas inside the city/city district with different views of the wind farm, T_i is the number of visible turbines from this considered area *i*, and *WF* is the total number of turbines in the wind farm.

The visibility of the city area from the wind farm *b* (independent from *a*) is determined by

$$b = \frac{\text{number of properties visible from the wind farm}}{\text{total number of properties in the city district}}. \tag{2}$$

The extent of visibility for each location is specified by

$$c = vt \times va, \tag{3}$$

where *vt* provides the factor for the number of visible turbines and *va* defines the factor for the different view angles to the wind farm (see Table 2 and Table 3, respectively).

TABLE 2: Distribution of factor parameters according to the number of visible turbines

Number of visible turbines	*vt* factor
1-3	0.50
4-10	0.90
11-20	1.00
21-30	1.05
> 30	1.10

Source: Hurtado et al. (2004)

TABLE 3: Distribution of factor parameters according to the view angle to the wind farm

View angle	*va* factor
Frontal	1.00
Diagonal	0.50
Longitudinal	0.20

Source: Hurtado et al. (2004)

Finally, Table 4 provides the coefficients for the distance of the properties to the turbines of the nearest wind farm (indicator *d*).

TABLE 4: Distribution of the coefficients of indicator *d* according to the distance to the nearest turbine

Distance *x* [m]	***d* coefficient**
$x < 500$	1.00
$500 < x < 6000$	$1.05 - 0.0002 \times x$
$x > 6000$ (if turbine is visible)	0.10

Source: Hurtado et al. (2004)

Consolidating the defined indicators for the visual impact assessment, the visual impact *VI* for the different properties in the study area is given by

$$VI = a \times b \times c \times d \text{.}^{5} \qquad [4]$$

By applying the procedure described, a visual impact coefficient between 0 (no impact) and 1 (highest impact) was assigned to each property in the dataset. In order to validate the applied factors and coefficients, we compared them to those used in other visual impact assessment studies in the literature. Overall, we found that the defined factors and their coefficients largely correspond to those applied in other studies. For instance, De Vries et al. (2012) conducted a survey based on photographs of different scenic situations involving the siting of wind farms, where the visual impact depends on distance, the number of turbines, turbine height, and the design of the wind farm. They found that wind turbines located at a distance of 2,500 meters cause about half the impact of turbines located in a 500 meters range. Regarding the coefficients used in Table 4 to determine factor *d*, the decreasing impact in distance coincides with the findings of De Vries et al. (2012) and is consistent with the probabilities of visual impact shown by Bishop (2002) and Sullivan et al. (2012), respecitely. Furthermore, Torres-Sibille et al. (2009) emphasize the importance of the number of turbines visible in relation to the degree of visibility, which in our case is represented by factors *a* and *c*.

[5] In a further step, Hurtado et al (2004) also define an additional factor *e* that indicates the number of people living in the areas affected. As in our case the adaption of the method aims at the determination of impact levels on a single property scale, factor *e* is omitted.

The required data for applying the visual impact assessment to our case study is derived by applying various tools from the ArcGIS software.[6] The measurements of visibility (the areas from where the wind turbines are visible), the distance to the nearest wind farm, and the view angle were estimated on the basis of a high-resolution digital surface model provided upon request by the geodata office of the federal state of NRW (Geobasis Datenportal NRW)[7]. With an accuracy of one square meter (more than 250 million data points), the digital surface model included information about the height level of the terrain, vegetation characteristics, and building types. The use of this digital surface model enables a precise identification of all areas from where the wind farm is visible by means of a viewshed analysis, and which includes all landscape features (e.g. heights, slopes, vegetation, or buildings) that help determine a precise account of the view from a specific location.

In a last step, based on the visual impact assessment for each property, we assigned each property to one of the six *VILs* provided in Table 5. The different steps of the coefficient range that determine the *VILs* are defined based on natural breaks given the number of six levels. The number of the impact levels also corresponds to a large extent to the ranking applied in Hoen et al. (2009, 2011) and Lang et al. (2014), respectively. In addition, Table 5 provides an overview of the number of observations for each level and a percentage value in relation to the total amount of the relevant observations. As visual impact can only be measured after the wind farms are built, the number of relevant observations reduces to 905 out of a total of 2,141 property sales in the dataset. Overall, a substantial visual impact (*VIL VI* and *VIL V*) could be detected for about 22% of the properties considered (197). The developed *VILs* represent the 'wind farm treatment' that is estimated by means of the spatial DID model, as described in section IV.

TABLE 5: 'Visual Impact Levels' and the distribution of observations

VIL	**Visibility**	**Coefficient range** $[a \times b \times c \times d]$	**No. of observations** $[VIL \times PT]$
VI	Extreme	1 – 0.8	63 (7.0%)
V	Dominant	0.8 – 0.6	134 (14.8%)
IV	Medium	0.6 – 0.4	150 (16.6%)
III	Minor	0.4 – 0.2	182 (20.1%)
II	Marginal	0.2 – > 0	122 (13.4%)
I	No view	0	254 (28.1%)
			905 (100%)

Data description

The study area chosen for our analysis has an extent of about 285 km² and is located in the northern part of the federal state of NRW, Germany. This area can be characterized as a relatively

[6] We use ESRI's ArcGIS Spatial Analyst, Spatial Statistics, and 3D Analyst tool in version 10.2.
[7] Further information on the data offered by the Geobasis Datenportal NRW are available online at https://www.geodatenzentrum.nrw.de/ASWeb34_GBDP/ASC_Frame/portal.jsp, accessed June 24, 2014.

flat semi-urban region. In order to investigate potential adverse visual impacts caused by the constructed wind farms in this location, we obtained arm's length property sales data for the three medium-sized cities of Steinfurt, Neuenkirchen, and Rheine. Each of the three cities comprises two city districts: Steinfurt is comprised of Borghorst and Burgsteinfurt, Neuenkirchen consists of Neuenkirchen (city) and St. Arnold, and Rheine's city districts are Mesum and Hauenhorst.[8] The property sales data was provided upon request from the regional Expert Advisory Boards (Gutachterausschüsse) on behalf of the regional administrations. The property sales data contained 2,141 registered sales for the time period between 1992 and 2010. Besides the selling price and selling date for each property, the data also contained the size of the parcels, the address-based location as well as the type and development status of the properties. In order to account for the inflation effect, all sales in the dataset were adjusted according to the German Construction Price Index with 2005 as its base year.[9]

Due to a relatively strict data privacy regulation for address-based property price data in Germany, the regional Expert Advisory Boards granted us access to property prices in terms of prices for parcels of land. The actual house prices could not be disclosed. Even though, according to the German building law, all property sales (homes plus parcels) have to be reported to the respective regional Expert Advisory Board (and are therefore available there), the dataset only consists of land parcel sales, separated from the price of the home, due to the prevailing privacy restrictions. Nevertheless, the obtained property sales data encompass arm's length transactions of parcels for residential utilization only and is, therefore, unconditionally suitable for the study's purpose.[10] Table 6 provides an overview of the distribution of property sales according to the different city districts.

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[8] In the following, we always refer to the city districts.

[9] The German Construction Price Index is published by the German Federal Statistical Office and made available online at https://www.destatis.de/DE/PresseService/Presse/Pressemitteilungen/2013/04/PD13_132_61261.html, accessed April 2, 2014.

[10] The data used only considers properties (i.e. parcels of land) that are assigned for residential utilization according to the regional development plan of the regional administration. We are aware of the problem that wind farms are usually located on land with lower values and that, in this case, using land prices for this type of analysis can lead to biased estimates. This might likely be the case if, for instance, agricultural land prices are considered, as wind farms in Germany are almost entirely sited on agricultural parcels of land. However, a land parcel for residential utilization can, by law, not be utilized for wind farm development in Germany. In the light of the aforesaid, no restraints should be given in order to identify the pure effect of wind farms on property values using residential land price data. Furthermore, as we only consider parcels for residential utilization, the parcels are mostly square-shaped, given that homes have to be built on these parcels. Therefore, differences in prices that may arise from the difference in the shape of the parcels, such as wide or narrow frontage parcels, can be safely neglected.

TABLE 6: Distribution of property sales in the study area between 1992 and 2010

	N
Total number of property sales	**2,141**
Before treatment (*BT*)	1,236
Post treatment (*PT*)	905
Steinfurt	**939**
District Borghorst	561
District Burgsteinfurt	378
Rheine	**603**
District Mesum	406
District Hauenhorst	197
Neuenkirchen	**599**
District Neuenkirchen (city)	466
District St. Arnold	133

Four wind farms of different sizes and configurations are located in the study area. Figure 1 illustrates the location of the wind farm sites as well as the property sales (and their respective *VILs*) in the study area. The construction of the wind farm in the northern part of the area, located near the city districts of Neuenkirchen, St.Arnold, Hauenhorst, and Mesum was announced in the year 2000 and was completed in July 2002. The wind farm consists of nine 1.5 MW turbines with hub heights of 100 meters and rotor sizes of 77 meters. A second site with 19 turbines is located in the proximity of Burgsteinfurt. The turbines built here, each with a capacity of 1.5 MW, have a hub height of 100 meters and rotor diameters of 77 meters (in two cases the rotor diameter reaches a span of 92 meters). The wind farm construction was announced in October 2000 and it has been in operation since December 2001. The smallest wind farm site in the eastern part of the study area near Borghorst has a total capacity of 7.5 MW, thanks to five 1.5 MW turbines with hub heights of 85 meters and rotor diameters of 77 meters. It was announced in October 2000 and finally built in April 2001. Lastly, the largest wind farm site is located in the southern part of the area studied, and consists of 26 turbines, each with an installed capacity between 1 and 1.5 MW, hub heights of 85 to 100 meters, and rotor diameters of 77 to 92 meters. The wind farm construction was first announced in early 2000 and it has been in operation since September 2001.

In the dataset, there are considerable differences with respect to visibility and distance from the properties considered. The number of turbines visible to a single property may range from 0 to 30, while the distance to the nearest wind turbine may vary from a minimum of 726 meters to a maximum of almost 6,000 meters. Thus, the spatial distribution of the properties' *VILs* also varies substantially across the area under study (see Figure 1). Extreme and dominant impact levels are mainly limited to the areas with an unobstructed view in the immediate proximity of wind turbines (e.g. southern Borghorst, northern Burgsteinfrut, and St. Arnold) and at the city limits, where the view is also likely unobstructed (south-western Borghorst). Areas further away from the wind farm, but within the city limits, such as the south-eastern part of Neuenkirchen, still show medium *VILs*. The visual impact mostly appears to fade towards the city centers, as higher building-density increasingly tends to obstruct the view from a given property. In Hauenhorst and

Mesum, mainly due to the long distance and the diagonal angle towards the turbines, the visual impact is mostly minor or even marginal.

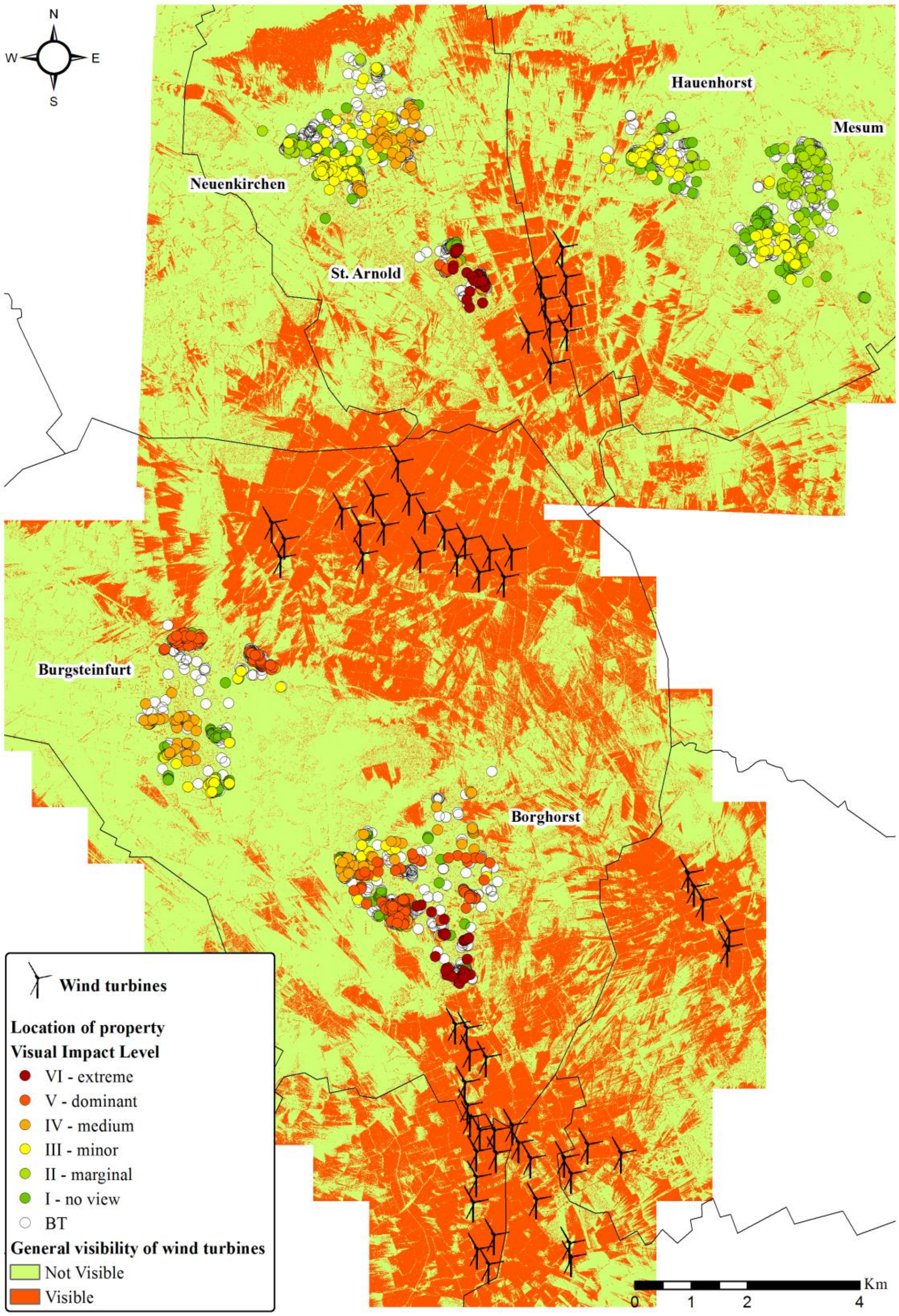

FIGURE 1: Wind farm visibility

Besides the wind farm-related variables of interest, we also included various structural and neighborhood variables that need to be controlled for in hedonic pricing studies. Table 7 provides an overview of descriptive statistics for these variables.

TABLE 7: Descriptive statistics of the structural and neighborhood variables

Variable *	Mean	Std. dev.	Min	Max
ln *p*	10.58	0.70	4.34	12.74
ln *Parcel size*	6.24	0.58	1.10	9.83
Waterfront	0.00	0.07	0	1
Type single-family house	0.62	0.48	0	1
Type duplex house	0.18	0.38	0	1
Type row house	0.02	0.15	0	1
Type multi-family house	0.03	0.17	0	1
ln (*Dist. to CBD*)	-6.82	0.95	-8.28	2.30
ln (*Dist. to Supermarket*)	-6.24	0.58	-7.45	-3.52
ln (*Dist. to Commercial area*)	-6.55	1.25	-8.65	2.30
ln (*Dist. to School*)	-6.33	0.82	-8.01	-4.25
ln (*Dist. to Forestland*)	-5.41	0.87	-6.65	2.30
ln (*Dist. to Major road*)	-5.23	0.89	-6.90	-1.97
ln (*Dist. to Road*)	-2.46	0.40	-4.53	-0.02
Street noise	0.26	0.64	1	5
ln (*Dist to. Railroads*)	-6.83	1.38	-8.91	-3.28
ln (*Dist. to Transmission line*)	-6.73	0.84	-7.72	-2.90
ln (*Dist. to Lake*)	-6.25	0.66	-7.52	-3.23

* *Notes*: The semi-log specification applied has the advantage that it allows for an intuitive interpretation of the results obtained, so that the estimated coefficients of the independent variables can be interpreted as elasticities (Gujarati and Porter, 2009, p.162). The estimated coefficients of the dummy variables can be interpreted as median impacts (Gujarati and Porter, 2009, p.298). Furthermore, the semi-log specification reduces heteroscedasticity (Gujarati and Porter, 2009, p.394). The variables indicating the distance to amenities/disamenities are Euclidean (inverse) distance measures. Using an inverse measure of distance, the measured values increase with decreasing distance. This allows for a direct interpretation of coefficient estimates regarding their signs and magnitude.

It should be mentioned that the set of structural variables includes the property's sales prices, the parcel size, and the development status of the property. The different development status encompass a differentiation between undeveloped/untilled parcels and developed parcels, where the developed ones are again subdivided according to the type of residential building (i.e. single-family house, duplex house, row house, and multi-family house). We estimate the impact of those development statuses relative to the case of an undeveloped parcel. Furthermore, the neighborhood variables mainly comprise distance measures that represent the location of each property. Data on the location of the various amenities and disamenities in the region are obtained from different sources.[11] Based on these, we were able to calculate the Euclidean (inverse) distances by means of tools provided in the ArcGIS toolbox.

[11] The location of the amenities and disamenities are, on the one hand, derived from the geodata obtained from the Geobasis Datenportal NRW, and, on the other hand, provided upon request from the different statistical offices on the state level (federal statistical office of NRW) and regional level (regional/city administrations), respectively.

IV. SPATIAL DIFFERENCE-IN-DIFFERENCES FRAMEWORK

To examine the potential devaluation of properties that have obtained a change in vista in consequence of the construction of a wind farm, we use a quasi-experimental technique and apply a spatial DID approach. The latter allows for a comparison of the observed changes in the values of the treated properties against the values of a control group (Greenstone and Gayer, 2009; Heckert and Mennis, 2012; Parmeter and Pope, 2013).

First, it is necessary to identify the exogenous change (i.e. treatment, e.g. through the introduction of a policy) in one environmental attribute, which is ultimately expected to have an impact on property prices. Importantly, the quasi-experimental approach requires that such exogenous change happens at an unexpected point in time from the viewpoint of the property owner (Parmeter and Pope, 2013). In addition, the development of a quasi-experimental analysis framework requires an understanding of how spatial influences and the timing of the exogenous change are related to the property market (Parmeter and Pope, 2013). Second, in order to investigate this exogenous change when applying a DID framework, data is needed that contain property sales for the areas that are affected by the introduction of the policy (i.e. the exogenous change) as well as data for an unaffected control group. Most importantly, besides the impact of the exogenous change that only occurs in some areas, the properties in the different areas have to be similar, if not identical, regarding their characteristics.

In our model, the treated properties (treatment group) are defined as those with a direct view on the wind farm, while the properties which experienced no treatment (control group) are those without a view on the constructed wind farm. The treatment and control groups are determined by an interaction term that indicates the visual impact and the time of construction of the wind farm. Thus, in the period between 1992 and 2001 (pre-construction phase) all properties can be considered as part of the control group, while after 2001 (post-construction phase) only the group with a direct view on the wind farm is considered to belong to the treatment group.[12] Figure 2 provides an overview of the quasi-experimental approach and the creation of the treatment and control group.

[12] In the literature often also the possible effects of the announcement of a wind farm project are investigated. In our case, there are two reasons not to include the effect of announcement as a treatment. Firstly, as we consider visual impact levels, those are directly related to the physical construction of the wind farm. Therefore, the visual impact cannot be sufficiently predicted before the wind turbines are actually built, even if the wind farm is announced with project plans that indicate the location, size and shape of the future wind farm. Secondly, only very few transactions occurred in the relatively short period between announcement and construction of the wind farms, which in the end do not provide a reliable basis for including the announcement as a treatment.

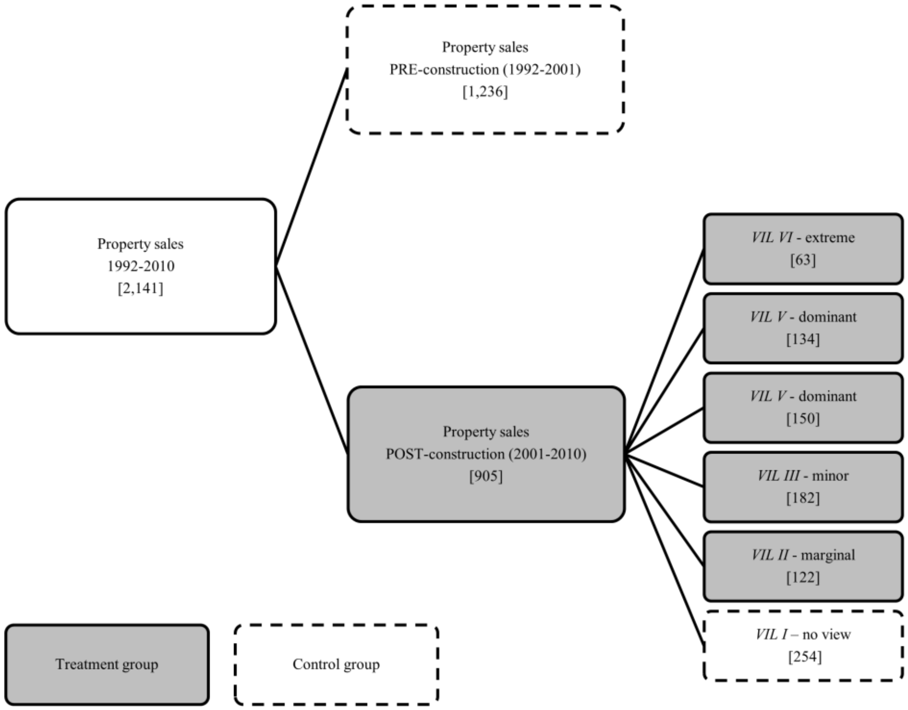

FIGURE 2: Treatment and control group

In order to investigate the impact of different *VILs* on property values in the DID framework proposed, we apply three spatial estimation techniques that differently account for spatial dependence and spatial heterogeneity: (1) a spatial fixed effects model, (2) a SAC/SARAR, and (3) a Spatial Durbin Error Model. In all three models, the coefficients obtained for the interaction between the *VIL* variables and the variable indicating if the transaction occurred post construction are of particular interest (DID estimator: *VIL×PT*).

The first most commonly used standard estimation approach in hedonic pricing studies is the spatial fixed effects model specification. By incorporating dummy variables that indicate, for instance, the city district where the property is located, those spatial fixed effects implicitly pick up any spatially clustered unobserved influences in a given district. The advantage of this specification is its prevention of a misspecification bias due to omitted variables, which explains why this straightforward technique is often applied in hedonic pricing frameworks (see Table 1). A more formal representation of this estimation technique, as applied to our model framework, is the following:

$$\ln\left(p_i\right) = \alpha_i + \delta_i + \sum_{k=5}^{VIL} \beta_1 VIL_{k,i} + \sum_{k=5}^{VIL} \beta_2 PT_i + \sum_{k=5}^{VIL} \beta_3 \left(VIL_{k,i} \times PT_i\right) + \beta_4 X_i + \varepsilon_i, \qquad [5]$$

where $\ln(P_i)$ is the sales price of property i, α_i represents the spatial fixed effects for property i (i.e. the city district), δ_i expresses the temporal fixed effects indicating the time when property i was sold (controlling for annual and monthly variations), $VIL_{k,i}$ indicates the k^{th} level of visual impact for property i, PT_i is a dummy variable equal to unity if property i was sold post wind farm construction, $VIL_{k,i} \times PT_i$ is the already mentioned DID estimator that measures the impact of the $VIL_{k,i}$ in the treatment group (properties that were sold in period PT), X_i a vector containing the set of other structural and neighborhood variables, and ε_i is the error term. The estimates for β_1 can be interpreted as a measure for *ex-ante* treatment differences in property prices for the k^{th} *VIL* relative to *VIL I*, β_2 is the coefficient indicating differences in the control group in the treatment period, β_3 is the coefficient of interest that measures the difference in property prices development for the k^{th} *VIL* relative to *VIL I* as result of the wind farm construction, and β_4 is the coefficient measuring the influence of structural and neighborhood variables on the property price variation.

Although the incorporation of spatial fixed effects mitigates the bias caused by spatially clustered unobserved variables, its ability to sufficiently account for spatial dependence remains empirically spurious (Anselin and Arribas-Bel, 2013). Spatial dependence, not sufficiently controlled for, might lead to biased and/or inefficient estimates (Anselin, 1988; Anselin and Getis, 2010). In order to incorporate spatial dependence, the literature suggests different models that allow for capturing unobserved spatial characteristics by means of the inclusion of spatial lags in the dependent variable, the explanatory variable, and the error term (LeSage and Pace, 2009). From an empirical perspective, strong motivation to apply spatial econometric techniques is provided given the potentially simultaneous presence of spatial dependence and spatially clustered omitted variables (Lerbs and Oberst, 2014). Given the strength of spatial dependence in the dependent variable, the explanatory variables and the error term, the omitted variable bias can be intensified if the included explanatory variables and any omitted spatial effects exhibit a non-zero correlation (Pace and LeSage, 2010). In this context, we estimate the following model specifications that explicitly account for spatial dependence in the dependent variable ($\ln(P_i)$), the explanatory variables ($VIL_{k,i}$, PT_i, X_i), and the error term (ε_i).

Firstly, in order to account for potential spatial dependence in the dependent variable versus the error term, we estimate a spatial auto-regressive lag model with an auto-regressive error term model (SAC/SARAR), which takes the form

$$\begin{aligned}&\ln\left(p_i\right) = \rho W \ln\left(p_i\right) + \delta_i + \sum_{k=5}^{VIL} \beta_1 VIL_{k,i} + \sum_{k=5}^{VIL} \beta_2 PT_i + \sum_{k=5}^{VIL} \beta_3 \left(VIL_{k,i} \times PT_i\right) + \beta_4 X_i + \mu_i \\ &\mu_i = \lambda W \mu_i + \varepsilon_i\end{aligned}, \qquad [6]$$

where all variables and coefficients are equal to those introduced in eq. [5]. The difference compared to eq. [5] lies in the underlying spatial process given by W, which represents an $N \times N$ row-stochastic spatial weight matrix indicating the spatial relationship between the observations. The estimation W is based on the spatial proximity among the properties. Following Tobler's First Law of Geography (Tobler, 1970), we use a spatial weight matrix (W) based on a k-nearest neighbor inverse distance. The latter assumes a decreasing spatial influence as the distance between two properties increases. In the case study applied here, W is calculated for the first 10 nearest neighbors of each observation. Furthermore, ρ and λ are the scalar parameters denoting the spatial dependence in the dependent variable and the error term, respectively. As the

SAC/SARAR simultaneously combines both a Spatial Lag and Spatial Error model, it reduces to a Spatial Error model if ρ=0, and to a Spatial Lag model if λ=0.

Secondly, in the presence of unobserved, spatially dependent local characteristics, the inclusion of spatial lags in the explanatory variables should also be considered (Lerbs and Oberst, 2014). Since the SAC/SARAR does not allow for the inclusion of this type of spatial dependence, the literature suggests the application of a Spatial Durbin Model (SDM) (Pace and LeSage, 2010; Elhorst, 2010). The SDM combines the incorporation of spatial dependence in the explanatory variables, with either a spatial lag in the dependent variable or in the error term. In our case, the SDM is combined with a spatially auto-regressive error term and becomes, therefore, a Spatial Durbin Error Model (SDEM). The SDEM is given by

$$\begin{aligned} &\ln\left(p_i\right)=\delta_i+\sum_{k=5}^{VIL}\beta_1 VIL_{k,i}+\sum_{k=5}^{VIL}\beta_2 PT_i+\sum_{k=5}^{VIL}\beta_3\left(VIL_{k,i}\times PT_i\right)+\beta_4 X_i+W\left(VIL_{k,i}+PT_i+X_i\right)\gamma+\mu_i \\ &\mu_i=\lambda W\mu_i+\varepsilon_i \end{aligned}, \quad [7]$$

where, again, all variables and coefficients as well as W and μ_i are the same as the ones defined in eqs. [5] and [6]. The spatial dependence in the explanatory variables ($VIL_{k,i}$, PT_i, and X_i) is denoted by γ.

V. RESULTS

DID estimations

Table 8 presents the results obtained from the three models. The values of the adjusted R^2 and the Akaike Information Criterion (AIC) are provided at the bottom of the table. The log-likelihood and likelihood ratio are documented for the SAC/SARAR and SDEM in order to indicate the model fit and the significance of the spatial parameters included. Furthermore, the spatial autocorrelation is indicated by Moran's *I* of the estimated residuals and by the Lagrange Multiplier error test for spatial error dependence.

Overall, all three models perform well according to the values obtained for the adjusted R^2 and the AIC. Both indicators report the SDEM to have the highest explanatory power, while the spatial fixed effects model has the lowest. Given the two indicators for the presence of spatial autocorrelation (Moran's *I* and the LM error test), the spatial fixed effects model still suffers from spatial dependence despite the incorporation of city district effects. Both indicators obtain significant values at the 1% level, revealing strong spatial dependence in the error term and the residuals and, therefore, the inability of the spatial fixed effects model to control for spatial dependence. Furthermore, the SAC/SARAR and the SDEM substantially reduce and capture spatial dependence, with the tightest controls in case of the SDEM. In addition, the SDEM outperforms the SAC/SARAR in both the log-likelihood and the likelihood ratio test.

TABLE 8: DID estimates for the three model specifications

Variable	Spatial Fixed Effects Model Coef. (SE)		SAC/SARAR / SE Model Coef. (SE)		SDEM† Coef. (SE)	
Visual Impact Levels relative to *VIL I* (β_1)						
VIL VI	.025	(.040)	.088	(.046)	.107**	(.047)
VIL V	.052*	(.028)	.085***	(.033)	.095***	(.033)
VIL IV	-.005	(.026)	.026	(.028)	.039	(.028)
VIL III	-.006	(.023)	-.010	(.023)	-.000	(.023)
VIL II	.004	(.027)	-.045	(.029)	-.038	(.029)
Time differences relative to *BT* (β_2)						
PT	-.040	(.047)	-.001	(.046)	-.001	(.046)
DID estimates (β_3)						
*VIL VI * PT*	-.068	(.050)	-.094*	(.049)	-.108**	(.048)
*VIL V * PT*	-.128***	(.038)	-.099**	(.037)	-.100***	(.038)
*VIL IV * PT*	-.054	(.038)	-.034	(.037)	-.037	(.037)
*VIL III * PT*	-.012	(.034)	-.007	(.033)	-.008	(.033)
*VIL II * PT*	.108**	(.046)	.081	(.046)	.073	(.046)
Other explanatory variables (β_4)						
ln *Parcel size*	1.036***	(.010)	1.038***	(.010)	1.040***	(.010)
Waterfront	-.004	(.086)	.035	(.084)	.038	(.084)
Type single-family house	.143***	(.018)	.153***	(.018)	.151***	(.018)
Type duplex house	.204***	(.022)	.208***	(.021)	.205***	(.021)
Type row house	.155***	(.042)	.166***	(.040)	.151***	(.041)
Type multi-family house	.161***	(.038)	.154***	(.036)	.169***	(.036)
ln *CBD*	.068***	(.009)	.035***	(.011)	.022*	(.012)
ln *Supermarket*	-.004	(.014)	-.012	(.019)	-.042*	(.022)
ln *Commercial area*	.012	(.010)	.006	(.012)	-.010	(.014)
ln *School*	.035***	(.009)	.035***	(.011)	.030**	(.012)
ln *Forestland*	-.011	(.008)	-.040***	(.010)	-.056***	(.011)
ln *Major road*	-.014*	(.009)	-.010	(.010)	-.012	(.011)
ln *Road*	.058***	(.015)	.065***	(.014)	.064***	(.014)
Street noise	-.002	(.011)	-.006	(.015)	-.002	(.016)
ln *Railroads*	-.001	(.010)	.023	(.014)	.023	(.018)
ln *Transmission line*	-.044***	(.010)	-.101***	(.021)	-.156***	(.030)
ln *Lake*	.001	(.011)	.007	(.019)	.020	(.023)
(*Intercept*)	4.019***	(.199)	3.273***	(.270)	5.143***	(.782)
ρ (dependent variable spatial lag)			.055	(.075)		
λ (spatial error)			.834***	(.030)	.588***	(.057)
Adjusted R^2	.867		.877		.881	
AIC	274.22		163.8		132.8	
Log-likelihood			-21.59		16.62	
Likelihood ratio (LR) test			251.45***		53.13***	
Lagrange multiplier (LM) error test	267.57***		1.324		0.947	
Residuals Moran's *I*	16.15***		1.287*		1.107	

*, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

† Note: The SDEM estimates for the spatial lags in the explanatory variables are provided in Table A1 in the Appendix.

In the SAC/SARAR, the parameter for spatial dependence in the dependent variables ρ is found to be statistically insignificant, while the parameter for spatial dependence in the error term λ is significant. Thus, the SAC/SARAR can be reduced to a Spatial Error model. In our case, this implies that spatial dependence is not present in the form of spatially clustered spillover effects across neighboring properties, but rather in the form of spatial interdependencies among unobserved or poorly observed attributes. Hence, the applied SDEM is based on the spatial dependence-robust Spatial Error model and is further expanded by spatial lags in the explanatory variables (SDM). This outcome can be explained by the characteristics of SDMs in the presence of spatially dependent omitted local effects (Lerbs and Oberst, 2014). The estimated spatial lags for the various explanatory variables of the SDEM are provided in a separate Table A1 in the Appendix.

Across all models, the coefficient estimates can be directly interpreted as the impacts on property prices due to variations in the given attributes. Also in the case of the SDEM, the β coefficients obtained represent direct effects, whereas the coefficients for the spatially lagged explanatory variables correspond to cumulative indirect effects (LeSage and Pace, 2009).[13] Note that estimates for spatial lags of the explanatory variables (provided in Table A1 in the Appendix) usually tend to be higher in their magnitude, as they indicate the cumulative indirect effect of a variation in the given explanatory variable.

Given the comparison of the three models in terms of performance as well as shortcomings, the estimates obtained from the SDEM can be considered to be the most reliable ones. Therefore, the following discussion focusses on the SDEM estimates.

The first set of estimates in Table 8 presents the differences in property values across the various *VIL* relative to *VIL I*. Without considering the construction dates of the wind farms, the estimates indicate if there are any pre-existing differences among the *VIL* groups. Only *VIL VI* and *VIL V* obtain significant coefficients (.107 and .095, respectively), thus indicating a positive premium for these locations (*ex-ante* the ‘wind farm treatment’). These locations were close to, and with an unobstructed view on, the eventual site of the wind turbines. As we only consider residential land within or near urban areas, the common assumption that wind farms are necessarily located near land plots of lower values does not hold for our study area in Germany.

The estimates for β_2 denote the differences in property values of time period *PT* (post-treatment) relative to the period *BT* (before treatment). According to the estimates obtained, no statistical evidence for a significant effect could be found, to some extent also due to the application of temporal fixed effects that enable controlling for annual and monthly variations.

The next set of coefficients, the DID estimates corresponding to β_3, are the key estimates of this analysis, as they measure the impact of the different *VIL* after the wind farms were constructed (*PT*) relative to the control group (properties without view on the constructed wind turbines). Most importantly, negatively significant impacts are found for properties that were

[13] For instance, the inclusion of a spatial lag in the dependent variables would have been more complicated regarding the direct comparison of the coefficients estimated, as in this case the dependent variable are not only directly affected by the locations’ own characteristics, but also indirectly by neighboring locations (Lerbs and Oberst, 2014). For further information on parameter interpretation in spatial models, see LeSage and Pace (2009).

rated having an extreme (*VIL VI*) or dominant (*VIL V*) view of the wind farm *ex-post* construction. Properties with an extreme view on a wind farm site show a decrease in value of 10.8% (at the 5% significance level), and properties that obtained a dominant view dropped in value about 10% (at the 1% significance level). Overall, about 22% of the properties that were affected by the construction of the wind farm experienced property devaluation. These were mainly in close proximity to and with an unobstructed view on wind farms (*VIL* coefficients range between 0.6 - 1, see Table 5 and Figure 1). However, the small number of transactions (63) that occurred in the *VIL VI* group *ex-post* the turbines' construction limits the confidence that can be ascribed to the estimates obtained for this group. Nevertheless, negative impacts on property values for those properties with dominant views are consistent across all three estimated models. In contrast, medium (*VIL IV*) to marginal (*VIL II*) visual impacts are not found to have any significant impact on property prices. In general, according to the coefficients estimated for the different *VILs*, the magnitude of the negative estimates drops as the visual impact decreases.

The set of the remaining explanatory variables shows consistent estimates with respect to their respective coefficient signs and significance levels. Most prominently, as expected, the parcel size and the development statues affect property values positively. Furthermore, short distances to schools, the central business district (CBD), and the road network also have a positive influence on property values. Those distance measure can basically be interpreted as indicators for accessibility and centrality. *Vice versa*, the negative estimate for distance to the next forestland can be interpreted as an indicator for less centrality and remoteness, which is possibly viewed negatively and, ultimately, overcast potential amenity effects due to the proximity to natural reserve area.

One further interesting finding refers to the significantly negative impact of the proximity to electricity transmission lines. A decrease in the distance to the power lines by 1% results in a decrease of property values by .156%. Also here, the significantly negative impact is found to be consistent across all models. The power lines are ramified within the study area and connect the different wind farms with the urban areas, implying a close proximity to the properties in most parts of the area. Due to the widespread, and in rural and semi-urban areas even extensive, siting of energy infrastructure, it might be conceivable that transmission lines affect property values even more than wind farms. Because of their locational coherence, a joint assessment of the (visual) impacts of energy infrastructure (such as wind farms plus associated electricity grid) could be of interest for future research.

Placebo model

In order to test the robustness of the DID framework and the estimates obtained, we performed a series of placebo models on subsets of the dataset. A placebo model basically introduces a placebo treatment that does not exactly correspond to the actual treatment used in the original model, thus performing a procedure that is similar to a sensitivity analysis, which investigates a model's reliability through the variation of some of its key parameters.

Applied to our study case, we included in the placebo group only those properties that were sold before the wind farm construction. In turn, the data used in the placebo setting is reduced to 1,236 property sales taking place in the period between 1992 and 2001. During this time frame no wind farms were constructed in the study area. Apart from that, the treatment group and the control group are based on the same criteria presented. As there were no wind farms constructed in this period of time, the timing of the introduction of the treatment is chosen randomly. We perform different model settings, each assuming a hypothetical introduction of the treatment (wind farm construction) in the years between 1994 and 1999. To verify the robustness of the proposed initial framework, no significant wind farm impact should be measured, as the introduced placebo treatments are chosen arbitrarily.

A representative overview of the placebo estimates for the treatment year 1995 is provided in Table A2 in the Appendix. As the SDEM model yields the most reliable estimates in the DID setting described above, we conducted our analysis in the placebo settings only with the SDEM. Overall, the tested model settings consistently do not find any significant property value changes due to the placebo treatment. Therefore, arbitrarily chosen wind farm construction dates do not have any explanatory power on the variation of the property values. The remaining explanatory variables produced similar results to the ones obtained with the initial DID setting, where the set of structural variables (parcel size and development status) were found to explain most of the variation in property prices. The various distance measures (distance to road network, forestland, and schools) also had a similar influence on properties in the subset regarding their coefficient signs and significance values.

In summary, the series of placebo model settings underline the reliability and statistical evidence of the results obtained. In turn, this supports the application of the suggested DID framework as well as the proxies used for visual wind farm effects.

VI. CONCLUSIONS

We applied a spatial DID approach to investigate the local impacts of wind farms on the development of property prices in the surroundings of a semi-urban region in Germany. In the proposed DID framework, we compared price changes in a treatment group that included properties whose view was affected by the construction of a wind farm, with changes in a control group that consists of properties whose view remained unaltered. The level of the visual impact was assessed by means of a quantitative factor-based approach that incorporated the magnitude of visibility changes for each single property (in terms of the number of visible turbines), its distance to the nearest turbine, the view angle from the given property, as well as an overall visibility effect for the different city districts where each property is located. In addition, three alternative spatial models with different underlying spatial processes were estimated.

Our results indicate that the properties that obtained an extreme or dominant view due to the wind farm construction showed a decrease in price by about 10%. In contrast, medium to marginal changes in the propertiy's views do not cause any statistically measurable adverse effect on its value.

In order to sufficiently capture visual effects caused by wind farms, the definition of valid and reliable proxies is one of the main challenges for this kind of hedonic pricing applications. Applying simple distance variables as proxies for local wind farm impacts can only provide a crude measure and should only be used as a first approximation. The same applies to binary visibility variables that only indicate if the wind farm site is visible or not. Furthermore, due to the subjective and somehow arbitrary nature of qualitative visual impact rankings, the incorporation of quantitative assessments is the preferable strategy. To date, literature that provides quantitative visual impact assessments is still sparse. In addition, most of the proposed methodologies are hard (or even not possible) to implement in hedonic pricing contexts. The approach suggested, and the incorporation of the visual impact assessment (proposed by Hurtado et al., 2004) definitely obtains potential for improvement and extension.

Regarding the estimated models, we find evidence for the application of spatial econometric methodologies that specifically address the problem of spatial dependence in property market data. In our case, the most commonly applied spatial fixed effects specification appears to be less suited due to its inability to capture spatial autocorrelation. Therefore, the application of spatial econometric models, such as the SDEM, is vital for preventing biases caused by the presence of spatial dependence and unobserved spatially clustered effects.

Finally, a further interesting and not yet fully explored potential application for this kind of analyses is the investigation of joint impacts of energy generation facilities and the associated energy infrastructure. In particular, transmission lines (i.e. overhead power cables) are widely spread across entire regions and involve a certain visual impact on the surrounding area. But, in contrast to wind farms, which constitute a large-scale element in the landscape that is limited to a specific location, transmission lines are continuous elements traversing entire landscapes. The investigation of those potentially joint, but yet characteristically different, impacts might yield valuable new insights and thus seems to be another fruitful avenue for future research.

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APPENDIX

TABLE A1: SDEM estimates for the spatial lag of the explanatory variables

Spatially lagged explanatory variables (γ)	Coeff.	(SE)
Spatial lag *VIL VI*	-.188*	(.108)
Spatial lag *VIL V*	-.021	(.091)
Spatial lag *VIL IV*	-.157*	(.092)
Spatial lag *VIL III*	.027	(.104)
Spatial lag *VIL II*	.408***	(.120)
Spatial lag *PT*	.148***	(.056)
Spatial lag ln *Parcel size*	.039	(.088)
Spatial lag *Waterfront*	-.789	(.748)
Spatial lag *Type single-family house*	.221**	(.110)
Spatial lag *Type duplex house*	.270*	(.146)
Spatial lag *Type row house*	-.686**	(.283)
Spatial lag *Type multi-family house*	.842**	(.368)
Spatial lag ln *CBD*	.032	(.028)
Spatial lag ln *Supermarket*	.067	(.052)
Spatial lag ln *Commercial area*	.123***	(.025)
Spatial lag ln *School*	.073**	(.031)
Spatial lag ln *Forestland*	.151***	(.031)
Spatial lag ln *Major road*	-.003	(.038)
Spatial lag ln *Road*	-.058	(.144)
Spatial lag *Street noise*	-.052	(.039)
Spatial lag ln *Railroads*	.001	(.027)
Spatial lag ln *Transmission line*	.138***	(.044)
Spatial lag ln *Lake*	-.053	(.038)

*, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

TABLE A2: SDEM results for the placebo model setting with the introduction of the treatment in 1995

Variable	SDEM† Coef.	(SE)
Visual Impact Levels relative to *VIL I* (β_1)		
VIL VI	-.029	(.071)
VIL V	-.086	(.053)
VIL IV	-.064	(.046)
VIL III	-.057	(.038)
VIL II	-.021	(.046)
Time differences relative to *BT* (β_2)		
PT (1995 – 2001)	.591***	(.047)
DID estimates (β_3)		
*VIL VI * PT*	-.078	(.078)
*VIL V * PT*	-.013	(.050)
*VIL IV * PT*	-.031	(.051)
*VIL III * PT*	.031	(.046)
*VIL II * PT*	-.041	(.052)
Other explanatory variables (β_4)		
ln *Parcel size*	1.044***	(.012)
Waterfront	-.257*	(.129)
Type single-family house	.313***	(.027)
Type duplex house	.361***	(.030)
Type row house	.312***	(.046)
Type multi-family house	.332***	(.046)
ln *CBD*	.009	(.015)
ln *Supermarket*	.002	(.022)
ln *Commercial area*	.006	(.018)
ln *School*	.025*	(.013)
ln *Forestland*	-.034**	(.014)
ln *Major road*	-.018	(.012)
ln *Road*	.051***	(.019)
Street noise	.014	(.018)
ln *Railroads*	.028	(.017)
ln *Transmission line*	-.027	(.028)
ln *Lake*	.053	(.024)
(*Intercept*)	3.859***	(.531)
λ (spatial error)	-.908***	(.253)
Adjusted R^2	.913	
AIC	45.82	
Log-likelihood	53.67	
Likelihood ratio (LR) test	11.17***	
Lagrange multiplier (LM) error test	.180	
Residuals Moran's *I*	-.276	

*, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

† Note: The SDEM estimates for the spatial lags in the explanatory variables are not provided in this table.