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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 adverse 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 farms, we use a quasi-experimental technique and apply a spatial difference-in-differences 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 biases, we apply augmented spatial econometric models. The estimates indicate that the asking price for properties whose view was strongly affected by the construction of wind turbines decreased by about 10-17%. In contrast, properties with a minor or marginal view on the wind turbines experienced no devaluation.

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

JEL Classification: Q42, Q51, 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 primarily are no longer determined 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 interference, 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; Benson, 2005; Gipe, 2002; Manwell et al., 2002; Miller et al., 2005; van Beek et al., 1998). Wind farms, sited in predominantly rural areas, are usually visible from considerable distances, as these constructions are often 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 (Benson, 2005; Bishop, 2002; Bishop and Miller, 2007; Hurtado et al., 2004; Manchado et al., 2013; Molina-Ruiz et al., 2011; Möller, 2006). Even if wind turbines are visible from distances of up to 30 or 40 kilometers under certain circumstances, usually the significance of a visual impact can be expected to drop substantially beyond distances in excess of two to three kilometers (Bishop, 2002; Sullivan et al., 2012). Hence, visual impacts tend to be extremely complex and difficult to estimate quantitatively (Möller, 2006). Nonetheless, the literature on visual impact assessment

[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).

of wind turbines provides a few studies that focus on the development and application of quantitative measures of visual impacts (Hurtado et al., 2004; Kokologos et al., 2014; Manchado et al., 2013; Möller, 2006; Torres-Sibille et al., 2009).

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 (Parmeter and Pope, 2013; Rosen, 1974). 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, 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 II). To assess the visual impacts of wind farms, we partially adapt the quantitative visual impact measurement approach proposed by Hurtado et al. (2004) and develop a criteria-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.[2] Thanks to the implementation of a quantitative criteria-based approach considering the relation of distance, magnitude of visibility, and view angle, we improve the current common 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).

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 scarcity of

[2] Due to limited data availability and computational issues, accounting for weather conditions, atmospheric scattering, and background contrasting is beyond the scope of this analysis.

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

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) and estimation techniques (mainly with regard to possible omitted variable biases and spatial dependence).

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 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. They do so, however, without considering any actual relation to distance or extent of visibility. The data base is again rather small (199 property sales), though it considers transactions over a longer time interval. Overall, 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 an article distilled from their project report (Hoen et al., 2009), Hoen et al. (2011) investigate about 7,500 single-family house sales 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. Within a standard hedonic framework, different model specifications were applied, also accounting for spatial autocorrelation via spatial fixed effects and nearest neighbor weights. 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, the authors simply used distance ranges as proxies for visual influences and other local impacts. Furthermore, even though spatial econometric techniques were applied, it is not clear how the spatial weight matrix was estimated. 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 the state of 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. Again, a simple distance variable controlled for possible local effects. Spatial relationships in the data were 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 a locally weighted regression model. The dataset includes 1,405 observations. 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 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 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 apply a qualitative visual impact ranking. 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 relevance of their results and conclusions in comparison 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, based on the subjective opinion of one individual that conducted all the field visits, is rather intransparent. 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. In summary, main weaknesses that can be identified in 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 *VIL*s. The defined *VIL*s are based on viewshed analyses that use high-resolution 3D data with an accuracy of one 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 III).

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

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

II. VISUAL IMPACT ASSESSMENT

Visual Impact Levels

As simple distance measures (i.e. grouping property sales according to their distance to the nearest turbine) and binary visibility variables (i.e., only indicating if a wind turbine is visible or not) can only provide a crude representation of visual effects caused by wind turbines, the implementation of a precisely measured and representative proxy for local visibility effects is crucial for hedonic pricing studies that aim at estimating potential impacts of wind farms on property values. [4]

In order to incorporate different levels of visual impact, we adopt the quantitative, criteria-based visual impact assessment methodology originally provided by Hurtado et al. (2004). 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; de Vries et al., 2012; Torres-Sibille et al., 2009). The applied visual impact assessment method is based on four criteria.

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

$$a = \frac{\sum_{i=1}^{n}\left(\frac{x_i}{F}\right)}{n}, \qquad [1]$$

where n is the number of areas inside the city/city district with different views of the wind farm, x_i is the number of visible turbines from this considered area i, and F 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

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

The extent of visibility for each location j is specified by

$$c = x_j \times v_j, \qquad [3]$$

where x_j provides the criterion for the number of turbines visible from location j (i.e. each property), and v_j defines the criterion for the different view angles to the wind farm from location j (see Table 2).

TABLE 2: Distribution of the coefficients for criteria x_j (number of visible turbines) and v_j (view angle)

Coefficients	Number of visible turbines (x_j)	View angle (v_j)
0.20	-	Longitudinal
0.50	1-3	Diagonal
0.90	4-10	-
1.00	11-20	Frontal
1.05	21-30	-
1.10	> 30	-

Source: Hurtado et al (2004)

[4] In this paper, we do not explicitly investigate the impacts of noise, sound pressure, electromagnetic interference, and shadow flicker on property values. As indicated above, the impact of those effects substantially diminishes in excess of about 500 meters to the turbines (Hau, 2006; Rogers et al., 2006) and can therefore be safely neglected, as in our case the minimum distance between a property and a wind turbine is 726 meters.

Finally, Table 3 provides the criterion for the distance of the properties to the turbines of the nearest wind farm (coefficients for criterion *d*).

TABLE 3: Distribution of the coefficients for criterion *d* according to the distance to the nearest turbine

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

Source: Hurtado et al. (2004)

While the criteria *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, criteria *c* and *d* measure the exact influence on 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 criteria *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 2). Consolidating the defined criteria for the visual impact assessment, the visual impact *VI* for the different properties in the study area is given by

$$VI = a \times b \times c \times d \,. \qquad [4]$$

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 criteria and coefficients, we compared them to those used in other visual impact assessment studies in the literature. Overall, we found that the defined criteria 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 3 to determine criterion *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 criteria *a* and *c*.

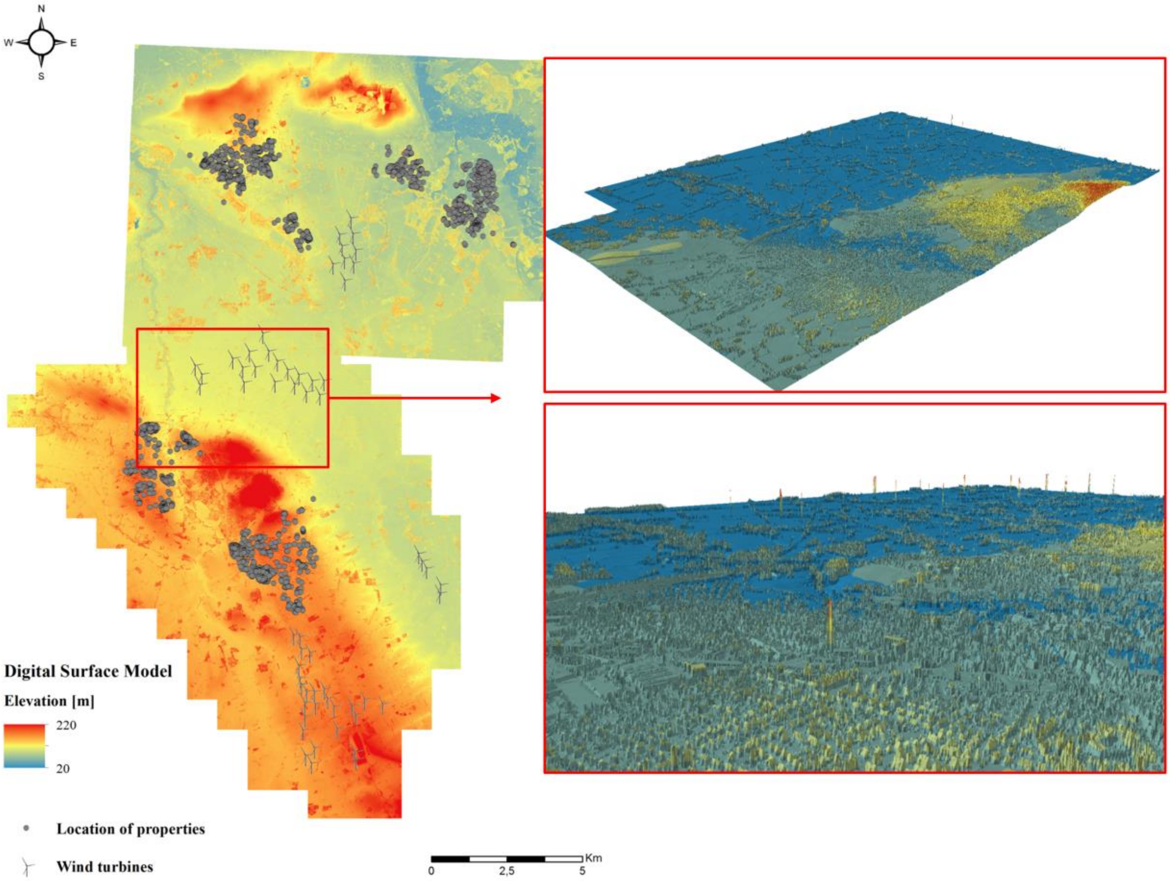

FIGURE 1: Digital Surface Model and Triangulated Irregular Network

The required data for applying the visual impact assessment to our case study is derived by applying various tools from the ArcGIS software.[5] 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 (DSM) provided upon request by the geodata office of the federal state of NRW (Geobasis Datenportal NRW)[6]. With an accuracy of one meter (more than 250 million data points), the DSM included information about the height level of the terrain, vegetation characteristics, and building, and enabled a precise identification of all areas from where the wind farm is visible. The DSM and an excerpt from the Triangulated Irregular Network (TIN), which create the basis for determining the *VIL* for each property, are illustrated in Figure 1.

In a last step, based on the visual impact assessment for each property, we assigned each property to one of the six *VIL*s provided in Table 4. 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 transactions in the dataset. Overall, a substantial visual impact (VIL_6 and VIL_5) could be detected for about 26% of the properties considered (239). Properties both in the VIL_6 and VIL_5 have on average a view on ten turbines, whereas the average distance is 1,190 meters for VIL_6 and 2,297 meters for VIL_5. In the medium level (VIL_4), the property's view is

[5] We use version 10.2 of ESRI's ArcGIS Spatial Analyst, Spatial Statistics, and 3D Analyst tool.
[6] 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, last accessed June 24, 2014.

on average affected by 7 turbines from a distance of 3,087 meters. Minor (VIL_3) and marginal (VIL_2) levels are, on average, characterized by a view on 3 turbines from 3,509 meters distance and 2 turbines from 4,424 meters distance, respectively. The developed *VIL*s represent the 'wind farm treatment' that is estimated by means of the spatial DID model, as described in section III.

TABLE 4: 'Visual Impact Levels' and the distribution of observations

VIL	**Visibility**	**Coefficient range** ($a \times b \times c \times d$)	**No. of observations** (total 905)	**Average number of turbines visible**	**Average distance to nearest turbine** (m)
6	Extreme	1 – 0.8	65 (7.2%)	10	1,190
5	Dominant	0.8 – 0.6	174 (19.2%)	10	2,297
4	Medium	0.6 – 0.4	141 (15.6%)	7	3,087
3	Minor	0.4 – 0.2	168 (18.6%)	3	3,509
2	Marginal	0.2 – > 0	60 (6.6%)	2	4,424
1	No view	0	297 (32.8%)	-	-

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 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 transaction price data for residential land 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 considered are Mesum and Hauenhorst.[7] The property sales data, which is not publicly available, was provided upon request from the regional Expert Advisory Boards (Gutachterausschüsse) on behalf of the regional administrations. The dataset 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 NRW Construction Price Index with 2005 as its base year.[8]

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 only 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 (parcels plus homes) have to be reported to the respective regional Expert Advisory Board, the dataset only consists of residential land parcel sales, separated from the price of the home itself, due to the prevailing privacy restrictions. In Germany, even though a buyer of a given land plot also buys the

[7] In the following, we always refer to the city districts.
[8] The NRW Construction Price Index (*Baupreisindex*) is published by the NRW 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.

associated existing structure on it, if any, the transaction prices for the land and the home can be designated separately.[9]

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, in Germany a land parcel for residential utilization can, by law, not be utilized for wind farm development. 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.[10] Table 5 provides an overview of the distribution of property sales according to the different city districts.[11]

TABLE 5: Distribution of property sales in the study area between 1992 and 2010

	N
Total number of property sales	**2,141**
Before treatment (T^B)	1,236
Post treatment (T^P)	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. Table 6 provides an overview of the wind farm characteristics, and Figure 2 illustrates the location of the wind farm sites as well as the property sales (and their respective *VIL*s) in the study area.

[9] Note that even though the price of residential land might not be the most ideal dependent variable, it is the very best alternative, given the relatively strict data privacy regulation for address-based property price data in Germany. Nevertheless, as the obtained property sales data encompass arm's length transactions of parcels for residential utilization only, we believe that it is unconditionally suitable for the study's purpose.

[10] 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.

[11] Repeat sales were deleted from the dataset, as their low number did not provide a sufficient basis for conducting a repeat sales analysis.

TABLE 6: Wind farm characteristics

Wind farm	Number of turbines	Hub heights [m]	Rotor diameters [m]	Installed capacity [MW]	Announcement	Construction
1	9	100	77	13.5	Jun. 2000	Jul. 2002
2	19	100	77-92	28.5	Oct. 2000	Dec. 2001
3	5	85	77	7.5	Oct. 2000	Apr. 2001
4	26	100	77-92	27.8	Mar. 2000	Sept. 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.[12] Thus, the spatial distribution of the properties' *VIL*s also varies substantially across the area under study (see Figure 2). 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 *VIL*s. 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 anyway. 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.

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 in order to capture the key determinants of residential land value. Those variables essentially should indicate the structural character and the level of accessibility to economic activities as well as (dis)amenities (Brigham, 1965; Cheshire and Sheppard, 1995). Table 7 provides an overview of descriptive statistics for the included variables.

[12] Note that, by law, in Germany a minimum distance of 650 meters to residential land has to be kept.

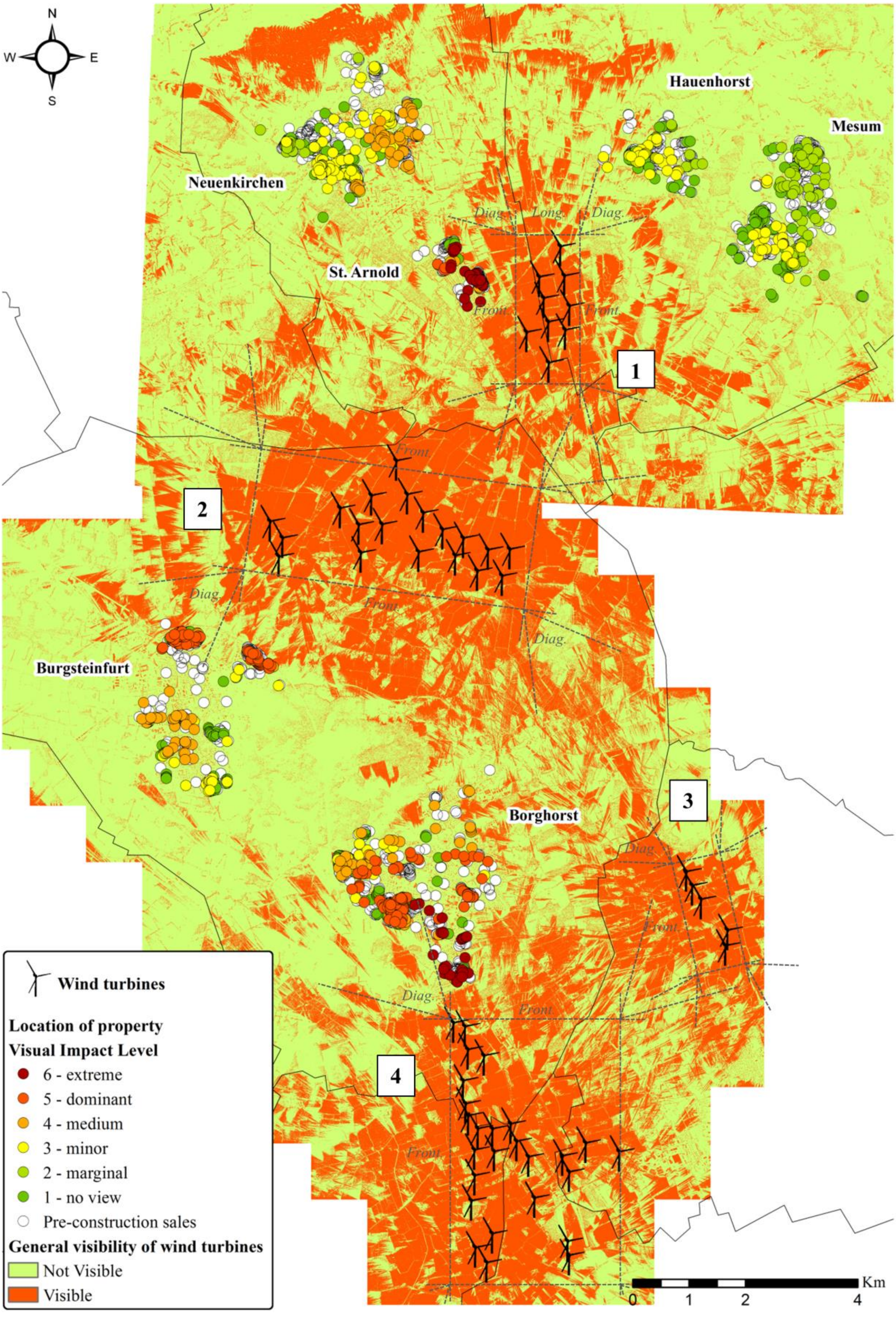

FIGURE 2: Wind farm visibility

TABLE 7: Descriptive statistics for the dependent and explanatory variables

Variable	Mean	Std. dev.	Min	Max
ln (p)	10.58	0.70	4.34	12.74
VIL_6	0.68	0.25	0	1
VIL_5	0.18	0.38	0	1
VIL_4	0.16	0.37	0	1
VIL_3	0.21	0.41	0	1
VIL_2	0.10	0.30	0	1
T^P	0.42	0.49	0	1
ln (*Parcel size*)	6.24	0.58	1.10	9.83
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 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 transmission line*)	-6.73	0.84	-7.72	-2.90

The set of structural variables essentially includes the parcel size and the development status of the property. The development status is included in order to control for variations in land values if those are developed or undeveloped, i.e. if it is still an untilled parcel or if a specific house type has been already built on the parcel. The different development statuses 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.

The neighborhood variables mainly comprise distance measures that represent the location of each property.[13] The variables indicating accessibility and distances to (dis)amenities 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. Data on the location was obtained from different sources.[14] Based on these, we were able to calculate the Euclidean (inverse) distances by means of tools provided in the ArcGIS toolbox.

III. 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

[13] We are aware of correlation problems that may occur using too many distance variables. Therefore, we tested for autocorrelation, multicollinearity, and heteroskedasticity by applying the Durbin-Watson test, variance inflation factor (VIF), and the White test, respectively, and selected according to that the variables entering the model.

[14] 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.

Gayer, 2009; Heckert and Mennis, 2012; Parmeter and Pope, 2013). The DID approach offers 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). 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 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).

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.[15] Figure 3 provides an overview of the quasi-experimental approach and the creation of the treatment and control group.

[15] In the literature the possible effects of the announcement of a wind farm project are often also 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 as well.

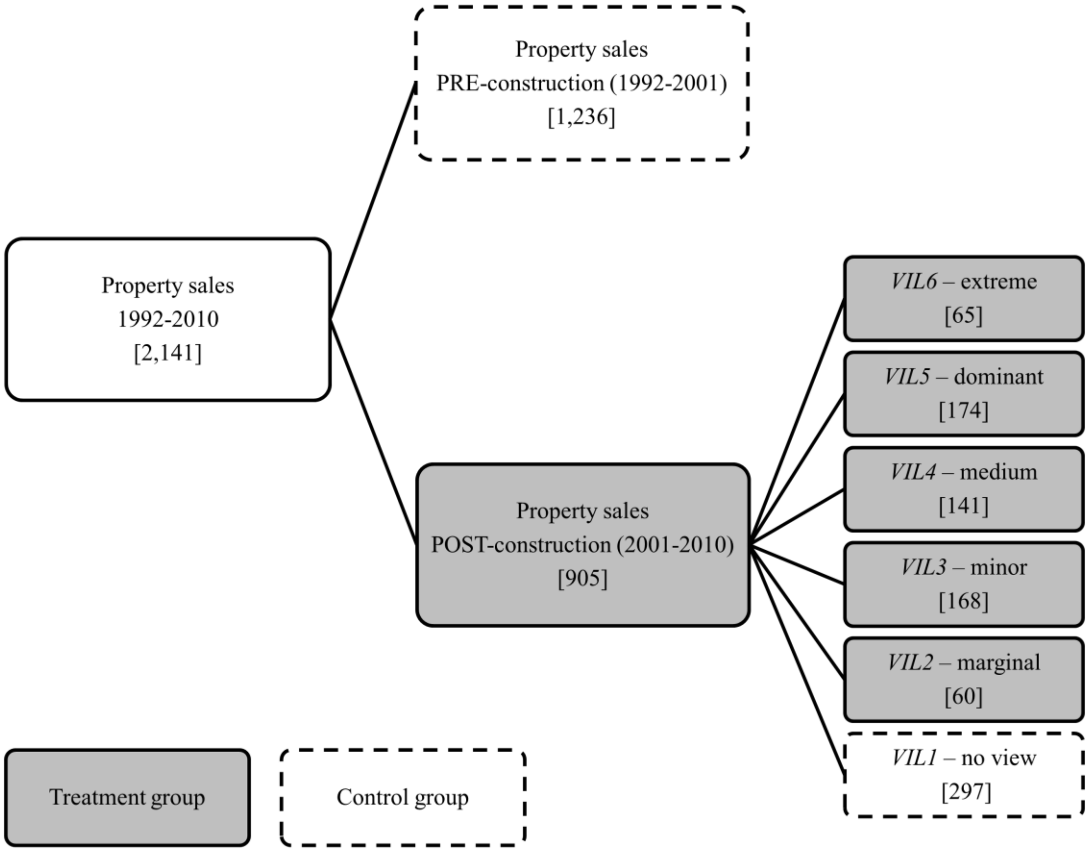

FIGURE 3: Treatment and control group

In order to investigate the impact of different *VIL*s on property values in the DID framework proposed, we apply three spatial estimation techniques that differently account for spatial dependence and spatially clustered unobserved influences: (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: $VIL \times T^P$).

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 in our model framework, is the following:

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

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, $T^P{}_i$ is a dummy variable equal to unity if property i was sold post wind farm construction[16], $VIL_{k,i} \times T^P{}_i$ is the DID estimator that measures the impact of the $VIL_{k,i}$ in the treatment group (properties that were sold in period T^P), 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_1, 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_1 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 variables, 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 ($VIL_{k,i}$, $T^P{}_i$, 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

$$\ln\left(p_i\right) = \rho W \ln\left(p_i\right) + \delta_i + \sum_{k=5}^{VIL} \beta_1 VIL_{k,i} + \sum_{k=5}^{VIL} \beta_2 T_i^P + \sum_{k=5}^{VIL} \beta_3 \left(VIL_{k,i} \times T_i^P\right) + \beta_4 X_i + \mu_i, \qquad [6]$$

where $\mu_i = \lambda W \mu_i + \varepsilon_i$ and 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, i.e. specifying 'neighborhood sets' for each observation (Anselin, 2002). 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

[16] $T^P{}_i$ indicates 'post treatment', $T^B{}_i$ denotes the 'before treatment' phase.

study applied here, **W** is calculated for the first five nearest neighbors of each observation.[17] 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) (Elhorst, 2010; Pace and LeSage, 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

$$\ln\left(p_i\right) = \delta_i + \sum_{k=5}^{VIL} \beta_1 VIL_{k,i} + \sum_{k=5}^{VIL} \beta_2 T_i^P + \sum_{k=5}^{VIL} \beta_3 \left(VIL_{k,i} \times T_i^P\right) + \beta_4 X_i + W\left(VIL_{k,i} + T_i^P + X_i\right)\gamma + \mu_i , \quad [7]$$

where, again, all variables and coefficients as well as **W** and μ_i ($\mu_i = \lambda W \mu_i + \varepsilon_i$) are the same as the ones defined in eqs. [5] and [6]. The spatial dependence in the explanatory variables ($VIL_{k,i}$, $T^P{}_i$, and X_i) is denoted by γ.

IV. 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

[17] Among the various possibilities to specify **W**, e.g. based on contiguity, fixed or inverse distances, nearest neighbors, or spatial interaction, we believe that a combination of distance and nearest neighbors is the most appropriate alternative for addressing spatial spillovers in a property market. In this way, we can account for varying spatial densities of neighbors in different locations. After testing various alternative *k*'s to determine the most efficient set of influential neighbors for each observation, we assume that the five nearest neighbors capture potential locational spillover effects most sufficiently. Overall, the results turned out to be relatively insensitive to different weight matrices. Nonetheless, the underlying structure of **W** remains the strongest assumption in spatial models, where the appropriateness in a given situation is an empirical matter (Anselin, 2002).

control for spatial dependence. Furthermore, the SAC/SARAR and the SDEM substantially reduce and capture spatial dependence. 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 Coeff.	(SE)	SAC/SARAR / SE Model Coeff.	(SE)	SDEM[†] Coeff.	(SE)
Pre-differences in *VIL*s relative to $VIL_1 (\beta_1)$						
VIL_6	.016	(.039)	.028	(.042)	.054	(.046)
VIL_5	.053*	(.028)	.144***	(.031)	.125***	(.034)
VIL_4	-.009	(.026)	.063**	(.028)	.065**	(.029)
VIL_3	-.011	(.023)	.016	(.024)	.013	(.024)
VIL_2	-.000	(.027)	-.067**	(.030)	-.060**	(.030)
Time differences relative to T^B (β_2)						
T^P	-.045	(.048)	.047	(.048)	.047	(.047)
DID estimates (β_3)						
$VIL_6 \times T^P$	-.063	(.050)	-.104*	(.054)	-.098*	(.054)
$VIL_5 \times T^P$	-.128***	(.037)	-.157***	(.040)	-.155***	(.040)
$VIL_4 \times T^P$	-.059	(.037)	-.089**	(.039)	-.091**	(.038)
$VIL_3 \times T^P$	-.011	(.034)	-.049	(.033)	-.045	(.033)
$VIL_2 \times T^P$	.107**	(.045)	.073	(.047)	.071	(.047)
Other explanatory variables (β_4)						
ln (*Parcel size*)	1.032***	(.010)	1.012***	(.010)	1.011***	(.010)
Type single-family house	.148***	(.018)	.153***	(.018)	.160***	(.018)
Type duplex house	.207***	(.022)	.186***	(.021)	.188***	(.022)
Type row house	.156***	(.042)	.181***	(.044)	.203***	(.044)
Type multi-family house	.156***	(.038)	.140***	(.036)	.161***	(.037)
ln (*Dist. to CBD*)	.069***	(.009)	.056***	(.010)	.052***	(.016)
ln (*Dist. to supermarket*)	-.003	(.013)	.020	(.020)	.009	(.043)
ln (*Dist. to school*)	.034***	(.008)	.030***	(.011)	.026*	(.013)
ln (*Dist. to forestland*)	-.014*	(.008)	-.038***	(.011)	-.062***	(.021)
ln (*Dist. to major road*)	-.020***	(.008)	-.024**	(.011)	-.064***	(.017)
ln (*Dist. to transmission line*)	-.041***	(.010)	-.005	(.013)	-.209***	(.068)
(*Intercept*)	3.784***	(.154)	3.615***	(.296)	4.111***	(.274)
ρ (dependent variable spatial lag)			.029	(.020)		
λ (spatial error)			.503***	(.025)	.501***	(.021)
Adjusted R^2	.866		.878		.881	
AIC	278.53		139.08		119.85	
Log-likelihood			-14.54		-11.07	
Likelihood ratio (LR) test			424.61***		384.17***	
Lagrange multiplier (LM) error test	268.32***		.088		.145	
Residuals Moran's *I*	16.48***		.330		.414	

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

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

[‡] The coefficients can be interpreted as elasticities in the case of a log-log form and as semi-elasticities in the case of a log-level form (Gujarati and Porter, 2009). In order to correctly interpret dummy variables in semilogarithmic models, the coefficients have to be transformed according to Halvorsen and Palmquist (1980). In the table above we report the estimated coefficients, the transformed, relative effects are indicated in the discussion of the results.

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).[18]

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 efficient ones. Therefore, the following discussion focuses on the SDEM estimates.

The first set of estimates in Table 8 presents the differences in property values across the various *VIL*s relative to VIL_1. Without considering the construction dates of the wind farms, the estimates indicate if there are any pre-existing differences among the *VIL* groups. VIL_5 and VIL_4 obtain significant coefficients (.125 (relative effect .133) and .065 (relative effect .067), respectively), thus indicating a positive premium for these locations (*ex-ante* the 'wind farm treatment'). These locations were partly close to, and/or 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. Properties in the group VIL_2 had lower values prior to the treatment.

The estimates for β_2 denote the differences in property values of time period T^P (post-treatment) relative to the period T^B (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*s after the wind farms were constructed (T^P) relative to the control group (properties without view on the constructed wind turbines). Most importantly, negatively significant impacts are found for properties that were rated having an extreme (VIL_6), dominant (VIL_5), and medium (VIL_4) view of the wind farm *ex-post* construction. Properties with an extreme view on a wind farm site show a decrease in value of 10.3% (at the 10% significance level). Properties that obtained a dominant view dropped in value by about 16.8% (at the 1% significance level). Also properties with a medium impact level (VIL_4) decreased in price by about 9.5% (at the 5%

[18] 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).

significance level) in consequence of the wind farm construction.[19] Overall, about 42% of the properties that were affected by the construction of the wind farm experienced property devaluation. According to Table 4, these are located, on average, within the first three kilometers to the nearest turbine and have an average unobstructed view on seven to ten turbines. However, the small number of transactions (65) that occurred in the VIL_6 group *ex-post* the turbines' construction limits the confidence that can be ascribed to the estimates obtained for this group, whereas it must be assumed that the negative effects of this *VIL* might be underestimated. Nevertheless, negative impacts on property values for those properties with dominant views are consistent across all three estimated models. The negative impacts on properties with a medium view on the wind farm are significant at the 5% level in the SARAR and SDEM. In contrast, minor (VIL_3) and marginal (VIL_2) visual impacts are not found to have any significant impact on property prices. Thus, a view that is on average affected by three turbines (or less) visible from a distance of 3.5 kilometers (or more) does not diminish property values. In general, according to the coefficients estimated for the different *VIL*s, the magnitude of the negative estimates tends to drop as the visual impact decreases.

The set of the remaining explanatory variables shows consistent estimates with respect to their corresponding coefficient signs and significance levels. Most prominently, as expected, the parcel size and the development status affect property values positively. Furthermore, short distances to the central business district (CBD) and schools also have a positive influence on property values. Those distance measures 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. The proximity to major roads (e.g. freeway or highway) has a negative impact on property prices, likely due to a higher noise level in their surroundings.

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 in property value by .209%. 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.

[19] The relative effect of -10.3% corresponds to a coefficient of -.098 (VIL_6), an effect of -16.8% to a coefficient of -.155 (VIL_5), and the effect of -9.5% to an estimated coefficient of -.091 (VIL_4) (see Table 8).

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 1,131 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 CBD, major road, 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.

V. CONCLUSIONS

In this paper 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 criteria-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 to medium view due to the wind farm construction showed a decrease in price by about 10-17%. In contrast, minor and marginal changes in the property’s views do not cause any statistically measurable adverse effect on its value. In this context, the relationship between the number of visible turbines and the distance from where those are visible plays a key role regarding the local impact of wind farms on their surroundings.

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 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_6	-.068	(.057)
Spatial lag VIL_5	.027	(.040)
Spatial lag VIL_4	-.049	(.038)
Spatial lag VIL_3	.000	(.034)
Spatial lag VIL_2	-.041	(.045)
Spatial lag T^P	.066***	(.025)
Spatial lag ln (*Parcel size*)	.016	(.023)
Spatial lag *Type single-family house*	.098***	(.037)
Spatial lag *Type duplex house*	.174***	(.044)
Spatial lag *Type row house*	.032	(.087)
Spatial lag *Type multi-family house*	.137	(.087)
Spatial lag ln (*Dist. to CBD*)	.013	(.022)
Spatial lag ln (*Dist. to supermarket*)	.006	(.049)
Spatial lag ln (*Dist. to school*)	.020	(.018)
Spatial lag ln (*Dist. to forestland*)	.047*	(.024)
Spatial lag ln (*Dist. to major road*)	.052**	(.023)
Spatial lag ln (*Dist. to transmission line*)	.215***	(.070)

*, ** 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† Coeff. (SE)	
Pre-differences in *VIL*s relative to VIL_1 (β_1)		
VIL_6	-.023	(.079)
VIL_5	.052	(.055)
VIL_4	-.004	(.047)
VIL_3	-.052	(.040)
VIL_2	-.027	(.048)
Time differences relative to T^B (β_2)		
T^P (1995 – 2001)	.588***	(.050)
DID estimates (β_3)		
$VIL_6 \times T^P$	-.046	(.078)
$VIL_5 \times T^P$	-.054	(.054)
$VIL_4 \times T^P$	-.018	(.054)
$VIL_3 \times T^P$	.058	(.048)
$VIL_2 \times T^P$	-.052	(.056)
Other explanatory variables (β_4)		
ln (*Parcel size*)	1.027***	(.013)
Type single-family house	.266***	(.027)
Type duplex house	.311***	(.031)
Type row house	.305***	(.050)
Type multi-family house	.268***	(.047)
ln (*Dist. to CBD*)	.077***	(.020)
ln (*Dist. to supermarket*)	-.008	(.049)
ln (*Dist. to school*)	.026*	(.016)
ln (*Dist. to forestland*)	-.011	(.025)
ln (*Dist. to major road*)	-.075***	(.020)
ln (*Dist. to transmission line*)	-.174**	(.073)
(*Intercept*)	4.136***	(.343)
λ (spatial error)	-.512***	(.028)
Adjusted R^2	.908	
AIC	79.56	
Log-likelihood	-20.22	
Likelihood ratio (LR) test	220.47***	
Lagrange multiplier (LM) error test	.047	
Residuals Moran's *I*	-.175	

*, ** 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

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