The Vindication of Don Quixote: The Impact of Noise and Visual Pollution from Wind Turbines

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ABSTRACT. *In this article we quantify the marginal external effects of nearby land-based wind turbines on property prices. We succeed in separating the effect of noise and visual pollution from wind turbines. This is achieved by using a dataset consisting of 12,640 traded residential properties located within 2,500 meters of a turbine sold in the period 2000–2011. Our results show that wind turbines have a significant negative impact on the price schedule of neighboring residential properties. Visual pollution reduces the residential sales price by up to about 3%, while noise pollution reduces the price between 3% and 7%.* (JEL Q18, Q38)

I. INTRODUCTION

In the sixteenth century, the fictional character Don Quixote thought that windmills were alien to the landscape. Many people have similar views about wind turbines today. The installation of land-based wind turbines is controversial and is often met with opposition from the local community (Wolsink 2000), which often takes the form of a "not in my back yard" argument. The general need to increase renewable energy, and install wind turbines in particular, is acknowledged, but at the same time the location of local wind turbine projects is opposed. Denmark has experienced a massive growth in wind-power capacity. In the mid 1990s less than 2% of the domestic power supply was derived from wind; today 5,000 onshore and offshore turbines make up more than one-fifth of the domestic power supply. The Danish government plans to increase the share of onshore turbines by an additional 1,800 megawatt-hours before 2020. In addition, large offshore wind turbine projects have been initiated. It is expected that offshore projects will dominate the expansion of wind turbine energy production in the coming years.

The noise and visual appearance of wind turbines make them very unattractive neighbors (Devine-Wright 2005). The stated preference literature has shown that people in general have a positive attitude toward wind turbines (Borchers, Duke, and Parsons 2007), while at the same time they are able to put a value on the negative externalities related to noise and visual pollution (Ladenburg 2009; Meyerhoff, Ohl, and Hartje 2010; Ladenburg and Möller 2011). The stated preference results are compelling, but a number of questions follow in their wake. For example, when respondents have to relate to a hypothetical scenario, are they cognitively able to distinguish between their opinions on noise and visual pollution? If not, are conclusions based on hypothetical payments as reliable as results based on observed, actual payments (Diamond and Hausman 1994)?

The externalities related to wind turbines are restricted to local residents, which makes the hedonic house price method the obvious valuation technique to choose. Only a handful of hedonic studies have attempted to estimate the local negative impacts of wind turbines, and only the most recent publications have succeeded (Sims and Dent 2007; Sims, Dent, and Oskrochi 2008; Hoen et al. 2011; Heintzelman and Tuttle 2012). Heintzelman and Tuttle (2012) find that nearby wind facilities

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significantly reduce property values. Their results show that property prices are reduced by between 8.8% and 14.87% at a distance of 0.5 miles to the nearest turbine. They use proximity to wind turbines as a proxy for noise and visual pollution. While both noise and visual pollution from wind turbines are correlated with proximity, they have a dissimilar impact and spatial extent. As such, proximity seems to be a rough generalization of the externalities related to wind turbines, which implies that the result of Heintzelman and Tuttle (2012) should be interpreted with caution.

While only two hedonic studies have demonstrated that wind turbines have an impact—this study included—hedonic house price valuation has been used with success on numerous other externalities, for example, noise pollution from traffic, and having a nice view of, or access to, green spaces (Day, Bateman, and Lake 2007; Sander and Polasky 2009; Zhou et al. 2013). The hedonic literature on road traffic has treated the related externalities much the same way as wind turbines have been treated in this study, by explicitly controlling for both view and noise in the hedonic model. Two examples are studies by Lake et al. (1998) and Bateman et al. (2001). By working with geographical information systems (GISs), the authors were able to estimate the impact of noise and visual pollution for each house in their sample. Their conclusions are broadly similar in that noise and visual pollution from larger roads are reflected in property prices as two different negative impacts.

The main contribution of the present study is the provision of separate estimates of both the noise and visual pollution from wind turbines. We construct viewsheds based on a high-resolution digital surface model (DSM), which enables us to identify properties where wind turbines are visible. Noise pollution is calculated for each wind turbine based on noise level measurements emitted at hub height, distance to the wind turbine, landscape properties, and air absorption under optimal conditions. In total, 12,640 transactions of house sales are included in the model, which ensured a reasonable variation in the variables of interest.

II. METHODS

Modeling Visual Pollution

Visual pollution from wind turbines can be subdivided into several negative effects with different causes, spatial extents, and impacts (Hoen et al. 2011). Wind turbines in the open landscape can make the area appear more developed and less rural or less authentic. The general perception of an area can be degraded, as can a location with a scenic view. In addition, wind turbines add movement to the landscape, which attracts attention and reduces the experience of tranquility and peacefulness that would otherwise be gained from a rural landscape. The rotating wings of a wind turbine reflect the sun, creating flickers of light, which again attracts attention and adds to the nuisance from the movement effect. The last visual effect is shadow-flicker. When the wings rotate, they cast a moving shadow, which in turn causes flickers of shadow in the immediate surroundings of the wind turbines.

In order to experience a visual effect caused by turbines, one needs to be able to see at least a part of a turbine. Properties with a view of one or more turbines were identified by constructing viewsheds for each of the wind turbines in the survey areas at hub height. The viewshed was based on a high-resolution DSM consisting of 1.6×1.6 m cells. The DSM accounts for terrain and obstacles such as buildings, vegetation, forests, and so forth. Houses were identified as having a view of a turbine if at least one of the corners of the building 2 m above terrain was located within the estimated viewshed of a wind turbine. In total, 33% of the houses in the analysis had a view of a wind turbine.

We captured visual pollution in our model by a dummy variable that indicates whether a turbine can be seen from the property, and by an interaction term between the dummy variable and the distance to the nearest wind turbine. The specification implies that having a view of a turbine provides a negative impact and that the impact decreases as distance to the turbine increases. We assume that the combined negative externalities of the visual pollution of wind turbines are captured by this specification.

TABLE 1
The Distribution of Observations across Noise Groups

	< 20 dB	20–29 dB	30–39 dB	40–50 dB
Affected properties (%)	4,077 (32)	7,532 (60)	879 (7)	152 (1)

Noise Pollution

Noise from wind turbines stems from three sources: when the wings pass the tower, when the wings cut through the air, and from the mechanics of the turbine. Noise emitted from a turbine is not constant. Some of the noise is tonal and some is low frequency (Møller, Pedersen, and Staunstrup 2010). The composition of the noise affects how the sound is experienced, which is different from how constant noise sources, such as noise from highways, are experienced.

The noise-level emissions were calculated for each wind turbine based on how much noise a turbine emits in the case of optimal conditions for noise production and noise travel distance. Noise was calculated based on equation [1], which is provided by the Danish legislation in a statute on noise from turbines (Environmental Protection Agency 2011). The equation describes the sound pressure level (SPL) emitted from a wind turbine at a given distance measured in decibels (dB):

$$SPL = L_{\mathrm{wa}} - 10{*}\log(l^2 + h^2) - 11dB + 1.5dB - \Delta L_{\mathrm{a}}, \quad [1]$$

where L_{wa} is the sound pressure from the wind turbine provide by the Windpro database (EMD International A/S 2012), l is the distance to the turbine, h is the hub height, 11 dB is a distance correction constant, and 1.5 dB is a terrain correction constant assuming a rural landscape. The air absorption, ΔL_{a}, is calculated by the following equation:

$$\Delta L_{\mathrm{a}} = \frac{2}{1{,}000}(l^2 + h^2). \quad [2]$$

Noise levels were divided into noise zones (Table 1). Properties located within these noise zones were identified by simple overlay analysis in GIS. No house was found to be located within a noise zone above 50 dB, and the majority of houses in the survey area were located within the noise zone 20–29 dB. Sound below 20 dB is generally perceived as silence (Pedersen and Waya 2004), a whisper is equal to about 30 dB, and a normal conversation is around 60 dB.

Equation [1] does not account for tonal or low-frequency noise, which may affect the perception of experienced noise. Furthermore it does not account for the multiplication effect of noise exposure to several wind turbines. Two turbines emit more noise than one. If a house was affected by more than one wind turbine, the house was assigned the highest noise calculation. In addition, the perception of noise may depend on the background noise. The experience of noise emitted from a turbine in a quiet environment is likely to be perceived differently from turbine noise in an environment with other external noise sources such as highways or railways. The noise calculation does not include other sources of noise. However, such negative externalities are accounted for in the hedonic price model (Table 2).

Theory

The theoretical foundation for the hedonic valuation method stems from Rosen's (1974) seminal paper, which demonstrated that buyers and sellers of houses in a perfectly competitive market will reach a market equilibrium guided by the implicit prices of house characteristics. Rosen argues that household buyers seek to maximize utility by bidding as little as possible for every single house (defined by its characteristics), while household sellers seek to maximize capital rent by offering their house for the highest price possible. The equilibrium price schedule for house characteristics forms where the bid and offer functions meet. In equilibrium, the price, P,

TABLE 2
Overview of Control Variables in the Model

Structural Variables				
Number of floors	Number of rooms	Brick	Tile roof	Renovation 1970s
Basement size	Number of toilets	Flat roof	Cement roof	Renovation 1980s
Size of living area	Number of baths	Age	Fiber Roof	Renovation 1990s
Attic space	Low basement	Detached house	Board roof	Renovation 2000s
Environmental Variables				
Forest	Coastal line	Highway		
Lake	Urban zone	Large road		

of any given house, n, can be modeled as a function of a vector $\mathbf{z}$ that includes all K house characteristics, z_{ik}:

$$P_n = f(z_{n1}, \ldots, z_{nk}, \ldots z_{nK}; \mathbf{\Theta}), \qquad [3]$$

where $\mathbf{\Theta}$ is a set of parameters related to the characteristics and specific to the housing market considered. Note that the characteristics may also include environmental amenities and disamenities obtained by ownership of the house, which here relates to whether the property is exposed to visual or noise pollution from wind turbines. Assuming weak separability with respect to the parameters of interest ensures that the marginal rate of substitution between any two characteristics is independent of the level of all other characteristics. With that assumption in place, the implicit price of a house characteristic, z_k, is its market price and is also a measure of its associated marginal willingness to pay (MWTP) (Palmquist 1991).

At optimum, the household MWTP will equate to the household marginal rate of substitution between the price of the house characteristic z_k and a composite numeraire good, comprising all other goods. Hence, the slope of the hedonic price function for a given house characteristic z_k can be recognized as the MWTP for house characteristic z_k:

$$MWTP_n = \frac{dP_n}{dz_{nk}}. \qquad [4]$$

This allows us to calculate the value of a marginal change in the environmental good also known as the first stage of the hedonic model. From a policy perspective, it can be argued that the value of such a marginal change in amenity values is seldom a crucial piece of information. The reason is that the hedonic price function provides information only on one point on the households' demand function with respect to the environmental good in question—not the demand schedule for that good, which would be the result of undertaking the second stage of the hedonic theory. Nevertheless, results from first-stage models are the most reported results in the hedonic literature (Palmquist 2005). The main problem in reaching the second stage is to come up with appropriate instruments to handle the inherit endogeneity that arises when households at the same time choose both the amount of house characteristics to consume and the house price.

The Model

The hedonic house price model is estimated in two steps. In the first step, the nominal sales prices are detrended using a cross-pooled regression model that allows for different prices across years and municipalities, using 2011 as the reference year. The error term of the cross-pooled regression consists of logged sales prices detrended in time and space. In the second step, the hedonic price model is estimated using a simple nonspatial OLS model and two explicit spatial models based on a generalized method of moments (GMM) estimator developed by Kelejian and Prucha (2010). The spatial models consist of a spatial error model (SEM) and a spatial autoregressive model with a spatial autoregressive error term (SARAR). The two-step approach is required because spatial models are not able to identify highly correlated variables (Panduro and Thorsen 2013) such as the correlation between the interaction term, the municipalities, and the year dummies in equation [5]. Related approaches to time detrending have been applied by Zhou et al. (2013) and Won Kim, Phipps, and Anselin (2003). The detrending procedure assumes that all variables between the two steps are uncorrelated, or that at least all turbine related variables in step two are uncorrelated with all variables in the first step. If this holds the model will yield unbiased estimates for the turbine variables.

The cross-pooled model that corrects for differences in prices over municipalities and years can be written as follows:

$$\ln(P) = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \mathbf{municipality} + \boldsymbol{\beta}_2 \mathbf{year} + \boldsymbol{\beta}_3 \mathbf{year} \times \mathbf{municipality} + \mu, \quad [5]$$

where $\ln(P)$ is logged property prices, $\boldsymbol{\beta}_1$ is a vector of the parameter estimates for the dummy variables referring to municipalities, $\boldsymbol{\beta}_2$ is a vector of the parameter estimates over the 12-year period, and $\boldsymbol{\beta}_3$ is a vector of parameter estimates of the interaction terms between the municipalities and years. Lastly, μ is the model's error term, which essentially is an expression of the logged and detrended price and unexplained noise.

The hedonic house price model is estimated using the logged detrended prices supplied by equation [5]. The full hedonic SARAR model can be written as follows:

$$\mu = \rho \mathbf{W} \mu + \boldsymbol{\theta}_1 \mathbf{Z} + \theta_2 view + view \times \theta_3 dis + \boldsymbol{\theta}_4 noise + \varepsilon, \quad [6]$$

$$\varepsilon = \lambda \mathbf{W} \varepsilon + u, \quad [7]$$

where $\boldsymbol{\theta}_1$ is a vector of coefficient estimates of the control variables presented in Table 2, θ_2 is the coefficient estimate of the dummy variable of having a view, θ_3 is the coefficient estimate of the interaction term between the view and distance to nearest wind turbine, and $\boldsymbol{\theta}_4$ represents the coefficient estimates of being within one of the noise zones, using <20 dB as the reference zone. By using this model specification we hypothesize that the negative impacts of wind turbines are present only if a property is exposed to noise at different levels and to the view of the nearest wind turbine. We further hypothesize that the effect of having a view will decrease over distance. The parameter $\mathbf{W}$ is a row-standardized $N \times N$ spatial weight matrix based on the 10 nearest neighbors. The terms ρ and λ are the spatial autoregressive coefficients, also known as the spatial lag term and the spatial error term, respectively. The hedonic model is estimated using an (nonspatial) OLS model, where both ρ and λ are assumed to be zero; a spatial error model, where ρ is assumed to be zero and λ nonzero; and finally as a SARAR, where ρ and λ are assumed to be nonzero. The objective of the application of the spatial models is to provide consistent and efficient parameter estimates that are robust to model specifications and unobserved spatially correlated variables.

The spatial lag term ρ implies that there is a spillover effect between house prices of neighboring properties. LeSage and Fischer (2008) distinguish between average direct, indirect, and total impacts, depending on whether one looks solely at the estimated coefficient or accounts for neighboring observations. From Won Kim, Phipps, and Anselin (2003), the marginal price of a housing characteristic (total impact) becomes

$$\frac{d\mu}{dz_k} = \boldsymbol{\theta}_k (\mathbf{I} - \rho \mathbf{W})^{-1}, \quad [8]$$

where $\mathbf{I}$ is an identity matrix. The direct effect can be interpreted in the same way as a standard regression coefficient estimate, while the indirect effect depends on the defined neighbors in the spatial weight matrix. The model suggests a marginal change will set off a ripple effect through the housing market, affecting neighbors and their neighbors and so forth.

We believe that the indirect spillover effect represented by the autoregressive lag term ρ can be interpreted as an information effect. If buyers and sellers are unsure of the appropriate value of a property given its characteristics, they may infer the appropriate price by looking at nearby properties with similar characteristics. The information contained in previous transactions in the same area may also allow the household to form expectations about the future evolution of the prices in the area. Alternatively, the lagged dependent variable is likely to be a proxy for unobserved characteristics. In either case, the spillover effect should be disregarded in the interpretation of the MWTP in hedonic house price models, as it does not reflect the preference of buyers.

III. DATA

In total, the analysis contains 12,640 sales of single-family houses sold over the 12-year period from 2000 to 2011. During this period, several turbines were built. Property prices prior to turbine construction were modeled as if the property were not exposed to any externality related to turbines. The anticipated arrival of a turbine before installation will probably be capitalized into the price of the property. However, there will most likely be a large variation from buyer to buyer in knowledge about potential turbines. Therefore we use the time of installation as a cutoff date. This also ensures that it is the actual and experienced noise and view pollution that is evaluated and not the expected pollution.

Data also contain information on the structural characteristics of the property, such as number of rooms, size of the living area, and so forth. This information was extracted from the Danish Registry of Buildings and Housing database (Ministry of Housing, Urban and Rural Affairs 2012). The registry also contains information on the exact coordinates of the location of each house. Proximity variables to environmental externalities were calculated for each property using ArcGIS Desktop 10.1. The proximity measures are proxies for view, accessibility, and so on. To remove possible border problems, all spatial externalities less than 5.5 km from the border of the survey areas were included in the calculation of spatial variables. Spatial data were supplied by the Danish National Survey and Cadastre from the spatial database Kort10 (KMS 2001). A summary of the control variables applied in the model is presented in Table 2.

Data on wind turbines were provided by the Danish Energy Agency (2012) and include the geocoded location of the wind turbines, hub height, total height, and rotor diameter. Noise data for each wind turbine were supplied by the database from the planning program WindPro 2.8, which includes reported noise date from the manufactures (EMD International A/S 2012). The viewshed of each wind turbine was constructed based on a DSM, which consists of 1.6×1.6 m cells. Each cell contains the average height of the surface, which is defined as ground surface including obstacles relevant to the viewshed such as buildings, fences, forest, and so forth. A more detailed description of the properties of the Statistics Denmark data has been provided by Heywood, Cornelius, and Carver (2006). The Statistics Denmark data was supplied by COWI (2009).

Survey Area

The survey consists of 24 spatially detached subsurvey areas, which combined cover 647 km^2, 20 municipalities, and 55,864 houses in Denmark. The subsurvey areas are located in a rural environment characterized by fields, small villages, and towns, which are representative areas for raising wind turbines in Denmark. The main criterion for selection of the survey areas was that they have as many transactions as possible within a primarily 600 m and secondarily a 2,500 m radius of the nearest wind turbine. The selection criterion resulted in a rather dispersed study area, as illustrated in Figure 1. The survey areas were identified using GIS and assessed manually using high-resolution aerial photos. Each survey area consisted of trades within a 2.5 km radius around a given turbine, which ensures that the exposure to the wind turbine externality varies between being exposed and being nonexposed. If two zones overlapped, they were merged. Turbines and other environmental features were modeled within the survey area in a radius of 5.5 km from the border of the survey area.

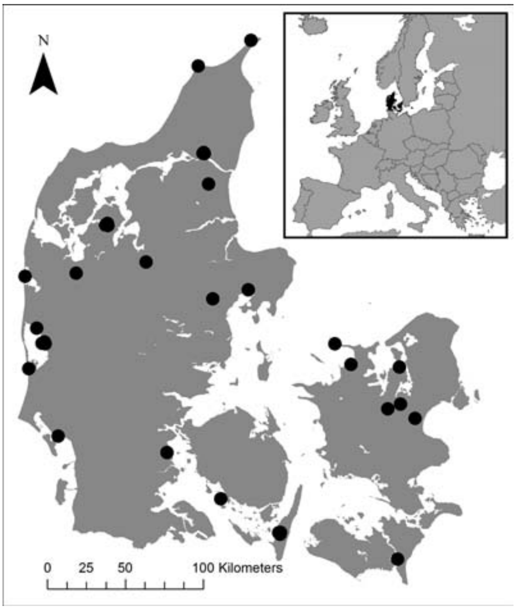

FIGURE 1
Map of Denmark Showing the Spatial Distribution of Study Areas

IV. RESULTS

The results of the model estimations are presented in Table 3 for wind turbine externalities and relevant model tests. The full estimation results can be found in Appendix B. In addition, model estimates using only Euclidian distance to describe the relationship between the wind turbine and sold properties can be found in Appendix B. The estimates of wind turbine externalities vary only marginally between models and are significant at the 5% level except for the view variable in the SEM model and the 39–50 dB noise zone in the OLS model, which are both significant at the 10% level. All three models are robust to heteroskedasticity. The nonspatial model is estimated using OLS with heteroskedasticity-consistent standard errors. The two spatial models are estimated using the GMM with innovations robust to heteroskedasticity; see, for example, Piras (2010) for an elaboration.

Having a view of a wind turbine from the house results in a considerable reduction in the price schedule of the house. The effect of the view of a wind turbine decreases as distance to the turbine increases. The models predict that a house located within one of the noise zones has a discrete impact on the sales price. The negative impact of the noise zone is positively related to the noise level. Comparing this model with a model where distance is used as a proxy for noise and view indicates that changing the specification of the turbine variables has little effect on the control variables. The effects on distance and noise levels are compared in Table 5.

The spatial autoregressive terms in the SEM model and the SARAR model are highly significant, which indicates that the two models adjust for spatial autocorrelation. The adjusted R^2 is calculated for the three models. The SARAR model has a considerably higher adjusted R^2 than either of the other models. This indicates that the lag term in the SARAR model improves model performance.

The global Moran's *I* value is calculated for the residuals for each of the models, based on a row-standardized spatial weight matrix that includes the 10 nearest neighbors. The global Moran's *I* test indicates that all three models suffer from spatial autocorrelation, as the residuals have a significant spatial structure, which is different from a random spatial distribution.

Spatial dependence of the residuals of the OLS models was tested using Lagrangian multiplier (LM) statistics. The term robust in the LM-error and LM-lag (in Table 3) indicates that it tests for one type of dependence under the assumption that the other is present (Anselin et al. 1996). The Lagrangian multiplier tests are significant for both an error term and a lag term. The error term is the more important of the two terms. In the SARAR model, both autoregressive terms are included.

V. MODEL INTERPRETATION

The marginal implicit price of the hedonic price function is presented in Table 3. The price functions are all log-linear, thus the marginal changes represent the relative change in house price. Table 4 contains both a marginal willingness to pay in relative and absolute prices based on the average sales price in 2011 in the survey areas. The table is based on the

TABLE 3
Model Estimation of Turbine Externalities

Variable	OLS	SEM	SARAR
View	− 0.1168† (0.0134)	− 0.0315* (0.0172)	− 0.0398*** (0.0154)
View × Distance	0.00699† (0.0008)	0.00242** (0.0010)	0.00278*** (0.0001)
20–29 dB	− 0.0368† (0.0059)	− 0.0307*** (0.0102)	− 0.0256*** (0.0080)
30–39 dB	− 0.0512† (0.0118)	− 0.0550*** (0.0190)	− 0.0442*** (0.0151)
40–50 dB	− 0.0433* (0.0243)	− 0.0669** (0.0273)	− 0.0509** (0.0243)
λ (error term)		0.6004† (0.0120)	0.4413† (0.0254)
ρ (lag term)			0.2678† (0.0276)
Wald statistics (h_1: $\lambda = \rho = 0$)			1,538.4†
Adjusted R^2	0.3794	0.3704	0.4492
Global Moran's I	0.2553†	0.2776†	0.1367†
LM-error	4,629.275†		
LM-lag	3,220.362†		
Robust LM-error	1,468.492†		
Robust LM-lag	59.576†		

Note: The table is a subset of the full model shown in Appendix B. Here we show only the variables relevant to the wind turbine. N = 12,640, OLS = 12,581 degrees of freedom. Standard errors are in parentheses. LM, Lagrangian multiplier; OLS, ordinary least squares; SARAR, spatial autoregressive model with a spatial autoregressive error term; SEM, spatial error model.
* Significant at 10%; ** significant at 5%; *** significant at 1%; † significant at 0.1%.

TABLE 4
Marginal Implicit Willingness-to-Pay Estimates

Parameter	% Change in the House Price	Average MWTP (€)
View (dummy)	− 3.15	− 6,233
View × Distance (per 100 m)	− 0.24	− 479
20–29 dB (dummy)	− 3.07	− 6,075
30–39 dB (dummy)	− 5.50	− 10,883
40–50 dB (dummy)	− 6.69	− 13,239

Note: The view × distance parameter should be interpreted in relation to the 2,500 m border of the zone. Therefore the effect at 2,500 m equals 0, whereas the effect of a property, e.g., 100 m away from the wind turbine will equal 2,400 × − 0.24. MWTP, marginal willingness to pay.

estimates of the SEM model. The lag term in the SARAR model implies a spillover effect that may be an information effect. Such an effect would be inappropriate to account for in the interpretation of the estimates of the hedonic house price model. Given the ambiguous interpretation of the lag term in the SARAR model, we choose to present and interpret the estimates of the SEM model (see also Section II).

The noise and visual pollution of wind turbines have a considerable impact on local residents. The impact of turbine noise on the immediate surroundings results in a 6.69% reduction in house prices in highly exposed areas. The marginal willingness to pay doubles from the low noise zone of 20–30 dB to the high noise zone of 39–50 dB. The visual pollution of a wind turbine reduces the house price by 3.15%. Starting from the base of the wind turbine, the price increases by 0.24% for each 100 m away from the turbine for those houses with a view of a turbine. The specification of the hedonic model indicates that having a view of a wind turbine is negative. However, the negative visual impact of the turbine reduces with distance.

The results are in line with the findings of the only other hedonic article to identify a negative impact of wind turbines. Heintzelman and Tuttle (2012) find a depression in property price of between 8.80% and 14.49% within a radius of 0.5 miles to the nearest turbine. Our results indicate that prices drop by between − 7.3% and 14% under similar circumstances, depending on the level of noise exposure. Table 5 presents the impact of noise and visual pollution evaluated at the mean

TABLE 5
The Percentage Change in the House Price That Can Be Attributed to Noise and Visual Pollution from Wind Turbines

Distance to Visible Turbine	Noise and Visual Pollution				Distance as Proxy
	<20 dB	20–29 dB	30–39 dB	40–50 dB	
200 m	−8.7	−11.8	−14.2	−15.4	−13.8
400 m	−8.2	−11.3	−13.7	−14.9	−12.6
600 m	−7.7	−10.8	−13.2	−14.4	−11.4
800 m	−7.3	−10.3	−12.8	−14.0	−10.2
1,000 m	−6.8	−9.8	−12.3	−13.5	−9.0
1,200 m	−6.3	−9.4	−11.8	−13.0	−7.8
1,400 m	−5.8	−8.9	−11.3	−12.5	−6.6
1,600 m	−5.3	−8.4	−10.8	−12.0	−5.4

Note: The table is based on the spatial error model (SEM) in Table 3. The column to the far right is based on a SEM using only Euclidian distance to describe the relationship with the wind turbine. The combinations of high sound levels and high distances are calculated according to the model but will in reality not be relevant.

house price for varying levels of distance and noise exposure (see Section II). The impact assessment of the wind turbine is compared with an assessment based on a SEM that uses Euclidian distance between the nearest wind turbine and the sold properties (see Appendix B). The Euclidian distance measure represents a proxy variable of the noise and visual pollution of wind turbines. These estimates are close to the <20 dB noise zone at long distances. At intermediate distances they are closer to the 20–29 dB zone, and at close distances they are closer to the 30–39 dB zone. The distance measure is not able to predict the large variation of impact by wind turbines on neighboring properties driven by the exposure of noise and visual pollution and, therefore, is insufficient as a mean proxy measure. The Euclidian distance measure seems especially inadequate to predict the impact on properties exposed to the high levels of noise.

The effect of lot size as suggested by, for example, Lewis and Acharya (2006) was investigated by interactions with the noise and view variables and showed no appreciable or mixed effects on results, probably due to multicolinarity among the high number of spatial models.

VI. CONCLUSION

In this paper we succeeded in separating and identifying the visual and audible externalities arising from wind turbines. We identified a negative price premium of around 3% of the sales price for having a view of at least one wind turbine. The price premium declines as distance to the turbine increases at a rate of 0.24% of the sales price per 100 m. Furthermore, we find that noise provides an additional negative price premium, which in terms of impact mirrors that of having a view. Approximately 3% to 7% of the change in house prices can be explained by the exposure to noise. The estimates of noise and visual pollution are compared with a simple Euclidian distance measure. From the comparison it is clear that a straight-line relationship between wind turbine and properties is insufficient. The parameter estimate based on the Euclidian distance measure represents a mean expression that will be more or less erroneous depending on which noise zone the property is located in and whether the wind turbine can be seen from the property. In the analyses we do not account for a possible cumulation effect of wind turbines. The effect of having one wind turbine as opposed to having several turbines or an entire wind farm may be different. We account only for the nearest turbine in terms of the visual pollution and the loudest wind turbine in terms of noise pollution. The dataset applied in this analysis was designed in such a way (see Section IV) that it makes it less opportune to study a possible cumulative effect of wind. In addition, information on manufacture and turbine production capacity has been ignored. Such information might have provided further relevant results.

The analysis covers a large number of spatially detached areas. Recall that the hedonic price schedule is assumed to be generated in an equilibrium market. We essentially assume that the supply and preference structures are stable across the spatially detached areas and recognize that this might not be a fully valid assumption. Parameter estimates of noise and view between municipalities in the survey areas were tested by an analysis of variance test. Based on this, we cannot reject that parameter estimates between municipalities are different. Previous hedonic studies on wind turbines have very likely suffered from lack of spatial variation due to a small dataset (Heintzelman and Tuttle 2012). The number of survey areas chosen in this analysis ensures a reasonable variation in the wind turbine variables.

Neither of the model estimations fully resolves the problem of spatial autocorrelation. Both explicit spatial models retain a significant spatial structure in the error term. This indicates that the models still suffer from omitted spatial processes such as misspecification of the functional form, mismeasurement of spatial covariates, or omitted spatial covariates. If the omitted spatial processes are not correlated with the turbine variables, the estimate of the impact of wind turbines remains trustworthy. In addition, the model estimates are robust across models.

The results presented in this article can be applied in cost-benefit analysis, especially because we succeed in modeling view and noise as two separate parameters. Note that the results of the hedonic house price model represent only MWTP and that such results will not usually be used in scenarios with nonmarginal changes. Still, Bartik (1988) argues that the estimates of nonmarginal localized changes based on the hedonic house price model can be used as estimates of benefits or costs, given that the nonmarginal change is restricted to a local area, thus not affecting the global housing market. We regard setting up a wind turbine in the landscape to be both localized and not affecting the global housing market. Based on this assumption, our results are directly applicable in the planning process and could be used to compensate those living close to wind turbines, or as part of a welfare economic cost-benefit analysis that includes the negative effects of noise and visual pollution.

We conclude that noise and visual pollution from wind turbines have a considerable impact on nearby residential properties. When Don Quixote was tilting at windmills, he was fighting imaginary giants. At present, wind turbines are a symbol of sustainable energy, the way of the future; however, local residents who live in close proximity to these sustainable giants experience some very real negative externalities in the form of noise and visual pollution.

APPENDIX A

TABLE A1
Descriptive Statistics for Dummy Variables

Name	Description	Mean	Observations = 1
Brick	House build in bricks	0.9158	13,592
Flat roof	Flat roof	0.0244	362
Cement roof	Cement roof	0.1979	2,937
Fiber roof	Fiber roof	0.4445	6,597
Board roof	Board roof	0.0268	398
Tile roof	Tile roof	0.2778	4,123
Lower basement	Lower basement	0.0912	1,354
Detached house	The property is a detached house	0.8213	12,189
Renovation 1970s	House rebuilt between 1970 and 1979	0.1113	1,652
Renovation 1980s	House rebuilt between 1980 and 1989	0.0703	1,044
Renovation 1990s	House rebuilt between 1990 and 1999	0.0551	817
Renovation 2000s	House rebuilt between 2000 and 2009	0.0701	1,041
<20 dB	Within a zone where a turbine makes noise <20 dB	0.3181	4,721
20–30 dB	Within a zone where a turbine makes noise 20–30 dB	0.5908	8,768
30–39 dB	Within a zone where a turbine makes noise 30–39 dB	0.0756	1,122
39–50 dB	Within a zone where a turbine makes noise 39–50 dB	0.0151	224
View	At least one turbine is visible	0.3547	5,264
Urban zone	House within urban zone or not	0.8117	12,047

TABLE A2
Descriptive Statistics for Nondummy Variables

Variable	Description	Mean	Min.	Max.
Price	Trade price, not corrected for inflation (Danish kroner)	1,329,000	100,000	18,150,000
Age	Age of the house (year built)	1957	1850	2010
Number of baths	Number of bathrooms	1.268	1	4
Size	Size of living area (m^2)	136.5	56	492
Basement size	Size of basement (m^2)	12.19	0	230
Attic size	Size of attic (m^2)	24.43	0	260
Number of rooms	Number of rooms	4.642	1	16
Number of floors	Number of floors	1.03	1	3
Number of toilets	Number of toilets	1.536	1	5
Number of bathrooms	Number of bathrooms	1.268	1	4
Forest	Distance in meters to the nearest forest, zero being within forest; in the model used as dummy variables based on steps of 100 m with reference distance being above 700 m	297.2	0	4,294
Lake	Distance in meters to the nearest lake with a surface greater than 200 m^2; in the model used as dummy variables based on steps of 100 m with reference distance being above 700 m	4,390	0	10,500 (1,903)
Coastline	Distance in meters to the nearest coastline; in the model used as dummy variables based on steps of 100 m with reference distance being above 700 m	4,677	8.022	10,500 (2,348)
Highway	Distance in meters to the nearest highway; in the model used as dummy variables based on steps of 100 m with reference distance being above 1,000 m	8,297	17.94	10,500 (9,606)
Large road	Distance in meters to the nearest road wider than 6 m; in the model used as dummy variables based on steps of 100 m with reference distance being above 400 m	393.9	2.847	5,239
Distance	Distance in meters to the nearest onshore turbine in steps of 100 m	14.89	0.6827	25.00

APPENDIX B

TABLE B1
Full Model for Noise and View

Variable	OLS	SEM	SARAR
Intercept	− 4.8950† (0.1764)	− 5.5474† (0.2479)	− 5.1224† (0.2186)
Brick	0.0686† (0.0095)	0.0632† (0.0103)	0.0605† (0.0097)
Tile roof	0.0155 (0.0168)	− 0.0066 (0.0161)	− 0.0043 (0.0156)
Cement roof	− 0.0267 (0.0172)	− 0.0302* (0.0167)	− 0.0299* (0.0162)
Fiber roof	− 0.1039† (0.0163)	− 0.0940† (0.0153)	− 0.0938† (0.0148)
Board roof	− 0.0391* (0.0222)	− 0.0606*** (0.0226)	− 0.0538** (0.0216)
Flat roof	− 0.1394† (0.0221)	− 0.1324† (0.0208)	− 0.1279† (0.0202)
Age	0.0010† (0.0001)	0.0014† (0.0001)	0.0012† (0.0001)
Detached house	0.0538† (0.0058)	0.0435† (0.0061)	0.0419† (0.0058)
Number of bathrooms	0.0178** (0.0078)	0.0228** (0.0091)	0.0069 (0.0082)
Low basement	0.0179** (0.0088)	0.0230** (0.0092)	0.0269*** (0.0088)
Size (log)	0.5550† (0.0104)	0.5395† (0.0110)	0.5321† (0.0106)
Basement size	0.0007† (0.0001)	0.0007† (0.0001)	0.0008† (0.0001)
Renovation 1970s	− 0.0355† (–0.0080)	− 0.0260† (0.0070)	− 0.0243† (0.0068)
Renovation 1980s	0.0067 (0.0097)	0.0078 (0.0088)	0.0070 (0.0086)
Renovation 1990s	0.0986† (0.0109)	0.0996† (0.0102)	0.1033† (0.0100)
Renovation 2000s	− 0.0958† (0.0102)	− 0.0932† (0.0114)	− 0.0923† (0.0112)
Urban zone	0.0057 (0.0081)	0.0280* (0.0158)	0.0174 (0.0121)
Coast 0–100 m	0.2963† (0.0312)	0.3530† (0.0464)	0.2708† (0.0397)
Coast 101–200 m	0.1762† (0.0207)	0.2252† (0.0344)	0.1549† (0.0277)
Coast 201–300 m	0.1683† (0.0172)	0.2245† (0.0319)	0.1671† (0.0248)
Coast 301–400 m	0.1546† (0.0163)	0.1584† (0.0297)	0.1248† (0.0239)
Coast 401–500 m	0.1780† (0.0159)	0.1474† (0.0288)	0.1302† (0.0232)
Coast 501–600 m	0.1089† (0.0159)	0.1039† (0.0293)	0.0909† (0.0230)
Coast 601–700 m	0.0726† (0.0182)	0.0572** (0.0264)	0.0497** (0.0225)
Highway 0–100 m	− 0.3914† (0.1379)	− 0.3855† (0.0972)	− 0.3900† (0.1013)
Highway 101–200 m	− 0.2173† (0.0881)	− 0.1611* (0.0901)	− 0.1406* (0.0746)
Highway 201–300 m	0.1726** (0.1126)	0.1192* (0.0690)	0.1252** (0.0568)
Highway 301–400 m	− 0.0017 (0.0872)	− 0.0524 (0.0583)	− 0.0591 (0.0530)
Highway 401–500 m	0.1871† (0.0446)	0.1513* (0.0781)	0.1399** (0.0591)
Highway 501–600 m	0.1543† (0.0475)	0.1368*** (0.0432)	0.1185*** (0.0363)
Highway 601–700 m	0.0817*** (0.0281)	0.0646 (0.0435)	0.0467 (0.0335)
Highway 701–800 m	0.1393† (0.0301)	0.1260† (0.0330)	0.1063† (0.0259)
Highway 801–900 m	0.0957† (0.0328)	0.1021*** (0.0319)	0.0789*** (0.0260)
Highway 901–1,000 m	0.1141† (0.0371)	0.0575 (0.0367)	0.0516 (0.0314)
Forest 0–100 m	0.1008† (0.0133)	0.0936† (0.0248)	0.0582*** (0.0191)
Forest 101–200 m	0.0844† (0.0132)	0.0786*** (0.0245)	0.0467** (0.0189)
Forest 201–300 m	0.0841† (0.0133)	0.0807*** (0.0247)	0.0510*** (0.0189)
Forest 301–400 m	0.0943† (0.0137)	0.0979† (0.0251)	0.0657† (0.0193)
Forest 401–500 m	0.1062† (0.0147)	0.0991† (0.0261)	0.0688† (0.0202)
Forest 501–600 m	0.1147† (0.0167)	0.0924† (0.0275)	0.0693*** (0.0216)
Forest 601–700 m	0.0901† (0.0190)	0.0713** (0.0282)	0.0595** (0.0234)
Lake 0–100 m	0.3623† (0.0340)	0.3661† (0.0582)	0.2630† (0.0490)
Lake 101–200 m	0.2021† (0.0219)	0.1988† (0.0395)	0.1169† (0.0317)
Lake 201–300 m	0.0698† (0.0195)	0.0917*** (0.0324)	0.0345 (0.0264)
Lake 301–400 m	0.0310* (0.0191)	0.0519** (0.0256)	0.0229 (0.0214)
Lake 401–500 m	− 0.0394*** (0.0157)	− 0.0321 (0.0232)	− 0.0426** (0.0182)
Lake 501–600 m	− 0.0071 (0.0169)	0.0088 (0.0223)	− 0.0075 (0.0178)
Lake 601–700 m	0.0080 (0.0167)	0.0235 (0.0211)	0.0092 (0.0173)
Large road 0–100 m	− 0.0007 (0.0071)	− 0.0110 (0.0125)	− 0.0038 (0.0094)
Large road 101–200 m	0.0331† 0.0073)	0.0193 (0.0122)	0.0263*** (0.0093)
Large road 201–300 m	0.0253† (0.0077)	0.0011 (0.0123)	0.0086 (0.0097)
Large road 301–400 m	0.0214*** (0.0085)	0.0050 (0.0114)	0.0094 (0.0094)
View	− 0.1168† (0.0134)	− 0.0315* (0.0172)	− 0.0398*** (0.0154)

(table continued on following page)

TABLE B1
Full Model for Noise and View *(continued)*

Variable	OLS	SEM	SARAR
View × Distance	0.00699† (0.0008)	0.00240** (0.0011)	0.0028*** (0.0010)
20–29 dB	−0.0368† (0.0059)	−0.0307*** (0.0102)	−0.0256*** (0.0080)
30–39 dB	−0.0512† (0.0118)	−0.0550*** (0.0190)	−0.0442*** (0.0151)
40–50 dB	−0.0433* (0.0243)	−0.0669** (0.0273)	−0.0509** (0.0243)
Spatial error term (ρ)		0.6004† (0.0120)	0.4413† (0.0254)
Spatial lag term (λ)			0.2678† (0.0276)
Wald statistics (h_1: $\lambda = \rho = 0$)			1,538.4†
R^2	0.3794	0.3704	0.4492

Note: $N = 12{,}640$; OLS = 12,581 degrees of freedom. In parentheses: standard error, R^2 for the OLS adjusted, for SEM and GSM pseudo-R^2. OLS, ordinary least squares; SARAR, spatial autoregressive model with a spatial autoregressive error term; SEM, spatial error model.
* Significant at 10%; ** significant at 5%; *** significant at 1%; † significant at 0.1%.

TABLE B2
Full Model, Distance as Proxy Variable

	OLS	SEM	SARAR
Intercept	−4.9880† (0.1768)	−5.660† (0.2337)	−5.3510† (0.2234)
Brick	0.0667† (0.0095)	0.06262† (0.009776)	0.0609† (0.0097)
Tile roof	0.0137 (0.0168)	−0.0077 (0.0158)	−0.0059 (0.0156)
Cement roof	−0.0267 (0.0173)	−0.0296* (0.0165)	−0.0291* (0.016)
Fiber roof	−0.1035† (0.0164)	−0.09381† (0.0151)	−0.093† (0.0149)
Board roof	−0.0391* (0.0222)	−0.0619*** (0.0221)	−0.0568*** (0.0217)
Flat roof	−0.1403† (0.0221)	−0.1329† (0.0206)	−0.1300† (0.0204)
Age	0.0011† (8.95e–05)	0.0014† (0.0001)	0.0012† (0.0001)
Detached house	0.0542† (0.0058)	0.0432† (0.0057)	0.0422† (0.0058)
Number of bathrooms	0.0146* (0.0078)	0.0211** (0.0089)	0.0095 (0.0084)
Low basement	0.0208** (0.0088)	0.0232*** (0.0088)	0.0262*** (0.0088)
Size (log)	0.5536† (0.0104)	0.5403† (0.0106)	0.5366† (0.01064)
Basement size	0.0007† (9.001e–05)	0.0007† (9.147e–05)	0.0008† (9.105e–05)
Renovation 1970s	−0.0356† (0.0080)	−0.0259† (0.0067)	−0.0248† (0.0067)
Renovation 1980s	0.0048 (0.0097)	0.0076 (0.0085)	0.0068 (0.0085)
Renovation 1990s	0.0947† (0.0109)	0.0995† (0.0098)	0.1023† (0.0099)
Renovation 2000s	−0.0964† (0.0102)	−0.0936† (0.0110)	−0.0933† (0.0111)
Urban zone	0.0081 (0.0081)	0.0213 (0.0154)	0.0158 (0.0129)
Coast 0–100 m	0.2927† (0.0312)	0.3542† (0.0472)	0.2890† (0.0417)
Coast 101–200 m	0.1764† (0.0207)	0.2280† (0.0336)	0.1718† (0.0292)
Coast 201–300 m	0.1640† (0.0172)	0.2267† (0.0303)	0.1805† (0.0261)
Coast 301–400 m	0.1552† (0.0161)	0.1594† (0.0289)	0.1315† (0.0252)
Coast 401–500 m	0.1721† (0.0158)	0.1478† (0.0280)	0.1323† (0.0244)
Coast 501–600 m	0.1080† (0.0159)	0.1055† (0.0281)	0.0945† (0.0244)
Coast 601–700 m	0.0646† (0.01812)	0.05651** (0.0250)	0.0498** (0.0232)
Highway 0–100 m	−0.4113*** (0.1378)	−0.3748† (0.1033)	−0.3856† (0.1049)
Highway 101–200 m	−0.1827** (0.0879)	−0.1517* (0.0896)	−0.1342* (0.0774)
Highway 201–300 m	0.1629 (0.1126)	0.1182 (0.0743)	0.1200** (0.0607)
Highway 301–400 m	−0.0064 (0.0872)	−0.05857 (0.0581)	−0.0639 (0.0524)
Highway 401–500 m	0.1826† (0.0445)	0.1440** (0.0724)	0.1384** (0.0626)
Highway 501–600 m	0.1436*** (0.0475)	0.1306*** (0.0442)	0.1181*** (0.0382)
Highway 601–700 m	0.0712** (0.0280)	0.0575 (0.0427)	0.0446 (0.0358)
Highway 701–800 m	0.1282† (0.0300)	0.1190† (0.0341)	0.1046† (0.0277)
Highway 801–900 m	0.0842** (0.0327)	0.0933*** (0.0316)	0.0774*** (0.0274)
Highway 901–1,000 m	0.1046*** (0.0370)	0.0493 (0.0375)	0.0451 (0.0330)
Forest 0–100 m	0.0990† (0.0133)	0.0882† (0.0248)	0.0623*** (0.0206)
Forest 101–200 m	0.0835† (0.0132)	0.0749*** (0.0246)	0.0511** (0.0203)
Forest 201–300 m	0.0847† (0.0132)	0.0780*** (0.0246)	0.0560*** (0.0204)

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TABLE B2
Full Model, Distance as Proxy Variable *(continued)*

	OLS	SEM	SARAR
Forest 301–400 m	0.0992† (0.0136)	0.0968† (0.0249)	0.0734† (0.0207)
Forest 401–500 m	0.1092† (0.0146)	0.0979† (0.0255)	0.0756† (0.0216)
Forest 501–600 m	0.1187† (0.0166)	0.0914† (0.0262)	0.0750*** (0.0229)
Forest 601–700 m	0.0946† (0.0190)	0.0721*** (0.0263)	0.0642*** (0.0243)
Lake 0–100 m	0.3649† (0.0340)	0.3685† (0.057)	0.2860† (0.0514)
Lake 101–200 m	0.2103† (0.0219)	0.2045† (0.0394)	0.1385† (0.0340)
Lake 201–300 m	0.0882† (0.0195)	0.1025*** (0.0326)	0.0556** (0.0283)
Lake 301–400 m	0.0477** (0.0191)	0.06206** (0.0260)	0.0379* (0.0226)
Lake 401–500 m	−0.0224 (0.0156)	−0.0236 (0.0231)	−0.0331* (0.0193)
Lake 501–600 m	0.0091 (0.0168)	0.0156 (0.0215)	0.0030 (0.0187)
Lake 601–700 m	0.0167 (0.0166)	0.0253 (0.020)	0.0149 (0.018)
Large road 0–100 m	−0.0003 (0.0070)	−0.0111 (0.0123)	−0.0049 (0.0102)
Large road 101–200 m	0.0323† (0.0073)	0.0180 (0.0120)	0.0242** (0.0100)
Large road 201–300 m	0.0252*** (0.0077)	−0.0003 (0.0118)	0.0062 (0.0102)
Large road 301–400 m	0.0242*** (0.0085)	0.0052 (0.0108)	0.0090 (0.0097)
Distance	0.0060† (0.0004)	0.0059† (0.0009)	0.0045† (0.0007)
Spatial lag term (λ)		0.5998† (0.012)	0.2157† (0.0306)
Spatial error term (ρ)			0.4982† (0.0247)

Note: N = 12,640; OLS = 12,585 degrees of freedom. OLS, ordinary least squares; SARAR, spatial autoregressive model with a spatial autoregressive error term; SEM, spatial error model.
* Significant at 10%; ** significant at 5%; *** significant at 1%; † significant at 0.1%.

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