The effect of wind turbines on property values
A meta-regression analysis

Alexandra Allard[a,b,c] and Mats A. Nilsson[b]

[a] Örebro University
[b] Södertörn University
[c] Research Institute of Industrial Economics (IFN)

Draft, 28 February 2025

Abstract

Wind power must expand to meet the increasing electricity demand while tackling the ongoing climate issue. However, there has been an increase in local opposition, leading to an intensified discussion of the magnitude of the external effects. In this study, we conduct a meta-analysis, relying on 169 property value estimates presented in 20 studies, to examine whether, and to what extent, property prices are affected by the distance to wind turbines. We also test how this relationship is affected by the construction or announcement year as well as the population density in the studied area. We find no significant effect of construction year but find that studies with one more inhabitant per square kilometer find a more negative effect of 0.01 percentage points. Regarding distance, we find a negative and significant effect when distance bands of 1 km each are used. Further, the negative effect size generally decreases the further away the property is from a wind turbine.

Keywords: Wind Turbines; Property Values; Meta-Regression Analysis
JEL-codes: C8; Q42

1. Introduction

Wind power met 17% of the EU electricity demand in 2022. Even so, it is argued that the installed capacity of wind power must increase as part of the solution to the ongoing climate issue (Barthelmie & Pryor, 2021). If we define a good site for wind power as sites where there are good wind conditions and small impact on humans, we could argue that many of the best sites for wind power have been exploited. Thus, we should expect an increase in suggested sites where the external effects of wind power are more visible, and where new projects are ever more contested. This can be seen in the increased local opposition (e.g., Niskanen et al., 2024; Reusswig et al., 2016; Susskind et al., 2022). It is likely that we will get an intensified discussion of the magnitude of the external effects. One way to measure these effects is by analyzing the effect of wind power turbines on real estate values in adjacent properties. In this study, we conduct a meta-analysis to examine previous findings on how the distance to the nearest wind turbine affects real estate values. We use distance as a measurement of disturbance from wind turbines as it is assumed to incorporate effects on view, noise, and flicker from the wind turbine.

Earlier literature does not present a unified picture of the impact on property values. North American studies tend to be inconclusive (Castleberry & Greene, 2018; Hoen et al., 2011, 2015; Lang et al., 2014) with a few showing negative or mixed effects on property values (Heintzelman & Tuttle, 2012; Vyn, 2018). European studies on the other hand tend to show negative effects (Dröes & Koster, 2016, 2021; Gibbons, 2015; Jensen et al., 2014, 2018; Sunak & Madlener, 2016, 2017).

We think the choice of studying the impact of wind power development on property values is motivated by the facts that: (a) it can be seen as a direct valuation of the external effects; and (b) the empirical literature is large enough to draw conclusions. The econometric analysis in the paper relies on 169 property value estimates presented in 20 studies conducted during the time period 2011–2021. These studies are in turn employing data over the period 1985–2020.

Schütt (2024) published a comprehensive meta-analysis on the effect of wind turbines on property values. This is to our knowledge the only meta-analysis previously conducted on this subject, with the exception of a mini meta-analysis included in a literature review by Parsons and Heintzelman (2022), in which 18 observations are used to calculate the mean effect. We contribute to this literature by estimating the effect for different distance bands, instead of, like Schütt (2024), including the mean distance in our estimations. Further, Schütt (2024) thoroughly examines the effect of data and model specifications, such as whether the exact wind turbine or property coordinates are used, whether a difference-in-difference model is used, and whether the regression includes control variables for amenities and other disseminates, while we take a more policy related approach. As compensation for residents affected by wind power has become a more debated issue, it is crucial to also look at factors that might affect the relationship between wind turbines and property values, but usually are not included in the literature, such as population density.

To account for study-specific effects, we use fixed-effect models with clustered standard errors. As we only include estimates from one full sample regression and sub-sample regressions, when such are included, from each paper, there is no within-study variation for model specifications. Instead, we focus on the effect of wind turbines on property values for properties within different distance bands from the turbines.

In the initial part of our meta-analysis, we see that later studies generally find more of a negative impact. Thus, studies with data from earlier periods may have less negative impact than later studies. To control for this, we include a variable for mean announcement or construction effect, depending on whether it is the effect of announcing or constructing a wind turbine that is being studied. Additionally, we control for the population density in the studied area. Thus, we can explicitly test the hypothesis that earlier wind power developments avoided areas with other competing (to wind power production) values by comparing the different time periods studied in the studied literature. In addition, we can test whether population density impacts the empirical estimates.

2. The impact of wind power

Apart from the production of electricity, wind power electricity generation can broadly be said to have two positive values. First, the electricity generation is renewable, and as such it fits well in a future circular economy. This is a value not explicitly renumerated in many countries but can be said to be part of the reason for subsidizing wind where that is the practice. Secondly, wind power is climate-friendly as no climate gases are emitted during electricity generation. The climate effect is however priced via the EU emissions trading which raises electricity prices. So that effect is included in the wind power economic calculations.

Wind power also has negative values. Most commonly cited are the impacts on fauna and the landscape view (Dai et al., 2015; Wang & Wang, 2015). Latter external effects discussed are for example infra-noise and negative effects on reindeer herding. In our case, the most important issues would be the changing landscape and noise/light issues. These could both impact the values of adjacent properties in a negative way.

2.1. Property values and hedonic pricing

Hedonic pricing is one of the main methods used to value non-market goods. Fundamentally it presumes that an individual's decision to purchase goods or services depends on the features or attributes of those goods (Hanley et al., 1997). The hedonic pricing method is often used when investigating property markets (e.g., Khoshnoud et al., 2023). Environmental effects such as aesthetic degradation of the landscape view, noise, and light flicker associated with wind farm installation are likely affecting housing values.

We can typically divide the characteristics into three groups (Khoshnoud et al., 2023; Kong et al., 2007; Skenteris et al., 2019). First, we have physical attributes such as those mentioned above. Second, we have neighborhood characteristics such as good schools, transportation infrastructure, closeness to services, etc. Finally, we have environmental characteristics such as views, noise, air pollution, and proximity to lakes and forests. Assembling data on such characteristics we can use econometrics to derive a value on different characteristics for the value of housing.

3. Literature review

In an early study, Sims and Dent (2007) find that property values in the UK located within a mile of a wind farm were affected. These results contradicted interviews conducted with estate agents from the area, which revealed no negative attitudes toward wind farms upon the purchase of nearby houses. By analyzing over 11,000 sales transactions in the USA, Heintzelman and Tuttle (2012) study the impact of wind power on property values. Their results also conclude that closer proximity to wind farms results in a reduction in property values. This result was again confirmed by Sunak and Madlener (2016) in a study covering North Rhine-Westphalia, Germany. Jensen et al. (2018) use hedonic pricing models to investigate how onshore and offshore wind turbines affect property values in Denmark, and find that the price of properties within a distance of three kilometers from an onshore wind farm is negatively affected. Their results were mixed as they find no impact of offshore wind turbines on property values. The results of negative impacts are confirmed by Skenteris et al. (2019) studying Greece, Dröes & Koster (2021) and Eichholtz et al. (2023), both studying the Netherlands, (Jarvis, 2021) studying the UK but got mixed results, Joly and De Jaeger (2021) Belgium and Westlund and Wilhelmsson (2021) studying Sweden.

In a later study, Heintzelman et al. (2017) find decreasing values in New York, USA. On the other hand, no negative impacts were identified on properties in Ontario, Canada. There are several studies that report that property values are not affected by nearby wind farms, in the UK (Sims et al., 2008), USA (Carter, 2011; Castleberry & Greene, 2018; Hoen et al., 2011; Lang et al., 2014; Laposa & Mueller, 2010), and in Ashhurst, New Zealand (McCarthy & Balli, 2014).

Our study will explicitly test for the impact of population density on the property value change when wind farms are announced or built. We believe this to be one possible explanation of the differences in the previous literature. We will also test the hypothesis that earlier wind power developments used land where the impacts on the population would be smaller. If that is true, and developers are now using land that has a higher opportunity cost, this could be traceable in our data set.

4. Meta-regression analysis

We use a meta-regression analysis to examine which variables are of importance when estimating the effect of wind power plants on property values. A meta-regression analysis is a statistical method that combines the results of related studies to investigate study-to-study variation (Stanley, 2001). Consequently, meta-analysis has become a conventional tool to summarize existing evidence in a research field while providing crucial information to calibrate key parameters (Havránek et al., 2020).

4.1. Data

For the meta-analysis, we collected information from 20 studies, which provided 169 estimates of the effect of distance to wind turbines, in the form of distance bands, on property values. We conducted a literature search through the search engine Google Scholar using the following search terms: Wind power, property values, and real estate. To ensure that no relevant studies were excluded, we went through a literature review by Parsons and Heintzelman (2022) and used backward snowballing, where we looked at the reference lists of the included papers to identify additional studies. This increases our sample with four studies.

We used a number of selection criteria to ensure comparability between included studies. Firstly, we only included studies that used hedonic price models with semi-logarithmic functional form. Secondly, the sample was restricted to studies examining the effect on actual, and not perceived, property values. This led to the exclusion of one study. Thirdly, we want to restrict our sample to one measurement for wind turbine disturbance. Distance is the most common measurement, as it is expected to incorporate other disturbance effects, such as noise, view, and flicker. Thus, it is favorable to use distance bands, instead of inverse distance, as it allows us to estimate the effect at different distances and when the effect, if any, increases or diminishes. By only including studies using distance bands as measurements for wind turbine disturbance, five studies were excluded.

The included studies are summarized in Table 1, which shows the studied county, time period, sample size, and general findings of each study. Number of estimates from each study that are included in our meta-analysis is also presented in Table 1, where we differentiate between estimates based on full sample observations, under “Full”, and estimates based on sub-samples, under “Sub”.

Table 1: Studies included in the meta-analysis

Study	Country	Years	Sample size	General finding	Incl. estimates Full	Incl. estimates Sub
Carter (2011)	US	1998–2010	1,298	∅	3	3
Hoen et al. (2011)	US	1996–2007	7,459	∅	16	
Heintzelman & Tuttle (2012)	US	2000–2009	11,331[1]	↓,∅		20
Lang et al. (2014)	US	2000–2013	48,557	∅	8	
Vyn & McCullough (2014)	Canada	2002–2010	7,004[2]	∅	3	
Gibbons (2015)	England & Wales	2000–2012	1,710,293	↓	12	
Hoen et al. (2015)	US	1996–2012	51,276[3]	∅	4	
Dröes & Koster (2016)	Netherlands	1985–2011	2,219,088[4]	↓	1	
Hoen & Atkinson-Palombo (2016)	US	1998–2012	122,198	↓	2	
Sunak & Madlener (2016)	Germany	1992–2010	2,141	↓	5	
Sunak & Madlener (2017)	Germany	1992–2010	1,405	∅	5	
Jensen et al. (2018)	Denmark	2003–2010	93,757[5]	↓,∅		7
Vyn (2018)	Canada	2002–2013	22,159[6]	↓,∅	12	24
Skenteris et al. (2019)	Greece	2006–2016	1,816[7]	↓,∅		4
Sampson et al. (2020)	US	2001–2017	13,196	∅	3	
Dröes & Koster (2021)	Netherlands	1985–2019	3,389,780	↓	1	
Jarvis (2021)	UK	1995–2020	8,100,000	↓,∅	5	
Joly & De Jaeger (2021)	Belgium	2004–2016	207,776[8]	↓	6	12
Westlund & Wilhelmsson (2021)	Sweden	2013–2018	97,229	↓	9	
Eichholtz et al. (2023)	Netherlands	1985–2015	~2,300,000[9]	↓	4	

Note: Where ∅ and ↓ specify the general findings: ∅ indicate no effect and ↓ indicate a price decline.

As shown in Table 1, the included studies were published between 2011 and 2021 and use data from 1985 to 2020. Looking at the general findings, the included studies either find a negative effect or no effect on residential prices. One interesting pattern is that recent studies more often find a negative effect, potentially since wind turbines are often built closer and closer to residential areas as wind power production expands or because more recent wind turbines are higher and have larger blades, thus leading to higher visual and noise disturbances within the same distance. Further, data and methodological choices could also affect the change in general findings.

[1] 11,331 is the total number of observations used in Heintzelman and Tuttle (2012). However, their sample is divided into three markets: Clinton County, 6,142 observations, Franklin County, 3,251 observations, and Lewis County, 1,938 observations.
[2] The authors divided these into two sub-samples: rural residential houses, 5,414 observations, and farmland, 1,590 observations. In this paper, we include the estimates for residential properties.
[3] Out of these, 38,407 observations are included in the relevant model, which is a spatial error model (SEM).
[4] 357,745 of these are used for their baseline estimate.
[5] The study divides the observations into onshore, 87,415, and offshore, 6,342, observations. Further, of the onshore observations, 69,083 are primary homes, while 18,332 are secondary. For the offshore observations, 4,323 are primary homes and 2,019 are secondary.
[6] 19,683 sales are in areas opposed to wind farms, while 2,476 sales are in unopposed areas.
[7] Out of these, 400 properties are in Evia and 1,416 in Kefalonia.
[8] 83,241 in West Flanders and 124,535 in East Flanders.
[9] 1,196,458 of these are included in the relevant model.

The effect size estimates of each study are summarized in the boxplot in Figure 1. The sample mean is shown by the (gray) vertical line. The boxes denote the interquartile range (P75–P25), while dots reflect outlying observations within a study.

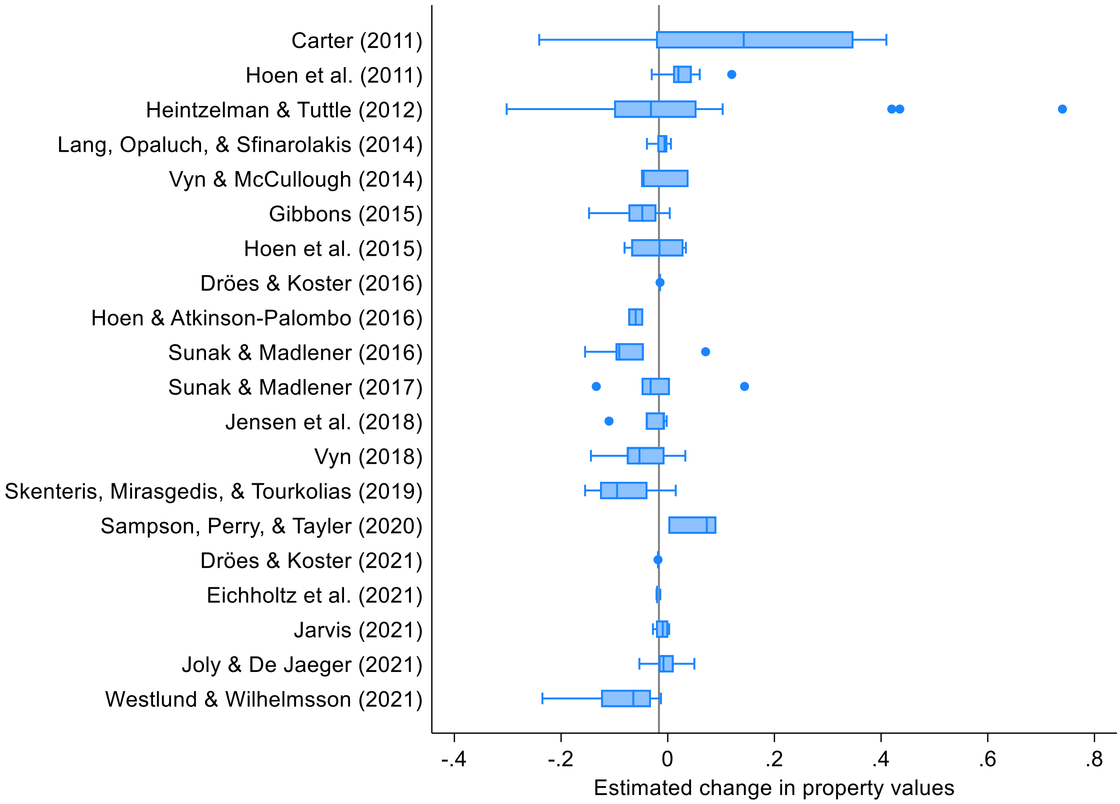

Figure 1: Boxplots of the estimated effect of wind turbines on property values

Note: The sample mean is shown by the (gray) vertical line. The boxes denote the interquartile range (P75–P25), while dots reflect outlying observations within a study.

As shown in Figure 1, the estimates vary both within and between studies. Even though Table 1 shows that the more recent studies generally find a more negative effect, it is not as distinctly shown in Figure 1. One reason can be, that even though we can find positive estimates in recent studies, the positive estimates generally are less significant than the negative. One evident trend is that the confidence intervals become narrower over time, which can indicate better data is available or that more refined methodical choices are made (Parsons & Heintzelman, 2022; Schütt, 2024).

4.2. Effect size measures

In this meta-analysis, the included studies use semi-logarithmic regression equations with distance bands to capture whether, and to what degree, wind turbines affect property prices. As distance bands are dummy variables, the estimated coefficient cannot be interpreted as the percentage change. Halvorsen and Palmquist (1980) explain that as dummy variables are dichotomous variables, their coefficient measures the dichotomous effect of a factor's existence, operationalized by the dummy variable, on the dependent variable.[10] The coefficient of a dummy variable, c, can be interpreted as $\ln{(1+g)}$, where g is the relative effect on the dependent variable. Thus, the relative effect is $g = e^c - 1$, and the percentage effect is:

$$100 * (e^c - 1) \tag{1}$$

where c denotes the coefficient estimate.

We apply the calculation in Equation 1 to adjust the estimates of the included studies. However, for onshore wind farms, Jensen et al. (2018) estimate the effect of the number of turbines within a distance band.[11] Similarly, Jarvis (2024) estimates the effect of added capacity within different distance bands. Thus, they use continuous, and not dichotomous, variables. Instead of using the adjustment in Equation 1, these estimates are multiplied by 100. As the main effect measured in these estimates is the number of turbines or added capacity, rather than the distance, they might have a distorted effect on our results. Nevertheless, these 10 estimates, which are based on continuous variables, either have distance bands that cover 2 or 3 km each, and will thus only be included in our sensitivity analysis. There are also other studies measuring the effect view and/or number of turbines while simultaneously measuring the distance effect, using interaction terms.

4.3. Publication bias

One factor that might influence published estimates, except for the choice of data, methodological choices, and model specifications, is publication bias. Publication bias occurs when researchers or journals reject findings based on the effect's direction, magnitude, or statistical precision, resulting in a skewed representation of reality in the literature. The presence of publication bias can be tested in a funnel plot. A funnel plot is a scattered diagram, where the effect size is measured against its precision, such as the inverse of the standard errors. If no publication bias is present, the true effect should be mirrored by the most precise estimates. Moving down the figure, the less precise estimates should be more spread out but should still be symmetrically distributed around the true mean, creating an image of an inverted funnel.

Figure 2 shows the funnel plot for the included estimates in this study. However, to make the funnel plot clearer, one outlier with a percentage change exceeding 100% is excluded. The funnel plot also includes two vertical gray lines; the solid line indicates the mean percentage change in the included estimates while the dashed line shows at which point no effect occurs, i.e., where the percentage change is equal to zero.

[10] Where a semi-logarithmic regression equation with a single dummy variable, i.e., $\ln Y = a + \sum_i b_i X_i + cD$, can be written as $y = (1+g)^D \exp(a + \sum_i b_i X_i)$ (Halvorsen & Palmquist, 1980).

[11] However, for offshore wind farms, Jensen et al. (2018) estimate the effect of distance bands, without including the amount of wind farms.

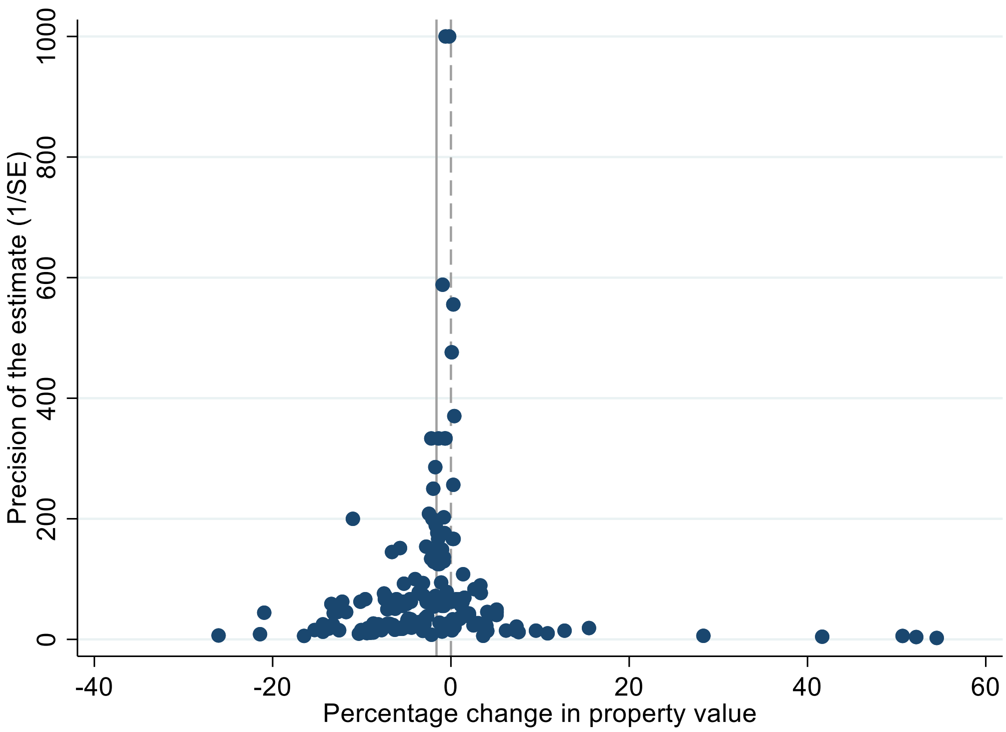

Figure 2: Funnel plot

Note: the solid gray line indicates the mean percentage change in the included estimates, while the dashed gray line shows at which point no effect occurs, i.e., where the percentage change is equal to zero.

Figure 2 shows that the estimate with the most and next to most precision lies between the sample mean and no effect, followed by three estimates around zero, two of which are slightly positive. Looking at the less precise estimates, from around 200 and down, an inverted funnel is created around the mean, but it is a bit more scattered to the left. However, the largest outliers are to the right, with the highest above 100%, which have been excluded in the funnel plot. The funnel plot indicates that there likely is a publication bias towards publishing negative estimates.

4.4. Moderator variables

In the meta-analysis, our dependent variable is the estimated percentage price change, as it facilitates a clearer understanding of how proximity to wind power plants is associated with variations in property values, compared to the estimated coefficient. To understand study-to-study variation we include explanatory variables for (1) distance, using distance bands; (2) whether the estimate measures the construction or announcement effect; (3) population density; (4) mean year for construction or announcement, depending on which effect being measured; and (5) whether the estimate is significant at 10% level. Table 2 summarizes the definitions and basic descriptive statistics for our dependent and independent variables. The variable definitions and descriptive statistics are included in Table 2.

Table 2: Variable definitions and descriptive statistics

Variables	Definition	Mean	Std. dev.	Min	Max	Obs
est	Estimated price change	-0.017	0.111	-0.302	0.74	169
$\Delta Price$	Percentage price change	-0.963	13.401	-26.067	109.594	169
0-1 km	Distance band, 0-1 km	0.142	0.35	0	1	169
1-2 km	Distance band, 1-2 km	0.082	0.276	0	1	169
2-3 km	Distance band, 2-3 km	0.083	0.276	0	1	169
3-4 km	Distance band, 3-4 km	0.053	0.225	0	1	169
> 4 km	Distance band, > 4 km	0.266	0.443	0	1	169
$PostCon$	Dummy, 1 if the observation measures construction, and not announcement, effects	0.657	0.476	0	1	169
$Year$	Construction or announcement year	2007.537	4.146	1997	2015.133	169
$PopDens$	Population density	169.92	182.499	5.047	533.436	169
$Sig10$	Dummy, 1 if the estimate is significant at a 10% level	0.45	0.498	0	1	169

Our dependent variable is $\Delta Price$, which is the percentage price change in property values, which is a transformed version of the estimate, est, in accordance with equation (1).

Our main explanatory variables are the distance bands. In our main model, the distance bands are 0–1 km, 1–2 km, 2–3 km, 3–4 km, and more than 4km, as we want to use distance bands that are short enough to capture changes in the estimated effect while being long enough to include a sufficient number of estimates. Using distance bands at 1 km each gives us enough distance bands to examine how the effect changes while including the majority of all estimates in our regression. However, not all observations are included in these distance bands as some of the included studies use larger distance bands, such as 0–2 km or 0–3 km (e.g., Gibbons, 2015; Sampson et al., 2020). Because of this, we also use larger distance bands in our sensitivity analysis.

As the included observations either examine the announcement effect or the construction effect, we include a dummy for post-construction, called $PostCon$. As shown by Table 3, about 67 percent of the included observations examine the post-construction, i.e., construction effect, while the remaining 29 percent examines the post-announcement and pre-construction period, i.e., announcement effect.

We include the variable $Year$ to account for the period in which the price change was estimated. As each of our estimations is the mean price change within a specific area, we use the mean announcement or construction year for that area. When sub-samples are used the mean announcement or construction year is calculated for that sub-sample, and otherwise, it is calculated for the whole sample. We primarily collect information on announcement and construction year from each study. However, when this information is not included in a study, the variable is estimated based on available information on wind turbines in the area.

Population density ($PopDens$) is used to examine whether differences in the included study's findings can be accounted for by differences in population density, and thus if the effect of wind turbines is higher in densely populated areas. Hence, it also helps us control for noise in the data. Similarly to $Year$, we primarily use information from the included studies. However, if a study does not provide information on the population density in the study area, we collect this information for the announcement or construction year, depending on the effect being studied. Lastly, $Sig10$ accounts for whether the estimate, which we include as an observation, is significant. As shown in Table 3, this is true for almost half of our sample.

4.5. Econometric specification

As there are small varieties between the distance bands used in the included studies, it is possible that multiple observations from one study can be included in the same distance band. Estimates from the same source might be correlated, and when several observations from the same paper are used for the same variable, heteroscedasticity might occur. If an OLS model is used, this heteroscedasticity might lead to biased and inefficient estimates. Nevertheless, we employ a fixed effect model and treat the study effects as a unit-specific constant effect. Thus, we specify the following meta-analysis fixed-effect regression model, with robust standard errors:

$$\begin{aligned}\Delta Price_{ij} = \mu_j + \sum_{k=1}^{K} \beta_k DistBands_{kij} + \beta_{K+1} PostCon + \beta_{K+2} PopDens_{ij} \\ + \beta_{K+3} Year_{ij} + \beta_{K+4} Sig10_{ij} + \varepsilon_{ij}\end{aligned} \quad (2)$$

where i indexes each included estimate and j indexes the individual study. $\Delta Price_{ij}$ is the percentage change in property prices, with respect to a set of K distance bands, $DistBands_{kij}$. We include four distance bands in the main model: 0–1 km, 1–2 km, 2–3 km, and 3–4 km, which are estimated relative to the excluded dummy >4 km. The model also includes a set of control variables, $PostCon$ if it is the construction, and not announcement, effect that is estimated, $PopDens_{ij}$ is the population density in the studied area, $Year_{ij}$ is mean construction, or announcement, year, and $Sig10_{ij}$ indicates whether the estimate is significant at, at least, 10 % level. Lastly, μ_j is the group effect, and ε_{ij} is the classical error term.

5. Empirical results

Table 3 presents the results from our fixed-effects model, where our dependent variable is the percentage change in property prices. We include both full and sub-sample estimates in our main estimation, in order to account for within-study variations for construction/announcement year and population density.

Table 3: FE model, percentage change, estimates based on full and sub-samples

	(1)	(2)	(3)	(4)	(5)
0–1 km	-8.554***	-8.554***	-8.545***	-8.589***	-7.898***
	(1.957)	(1.967)	(1.984)	(2.022)	(1.820)
1–2 km	-6.506***	-6.506***	-6.501***	-6.526***	-5.566***
	(0.685)	(0.688)	(0.697)	(0.705)	(0.862)
2–3 km	-4.602*	-4.602*	-4.596*	-4.622*	-3.662
	(2.201)	(2.213)	(2.225)	(2.234)	(2.337)
3–4 km	-5.378***	-5.378***	-5.374***	-5.394***	-4.878***
	(0.797)	(0.801)	(0.806)	(0.810)	(0.980)
PostCon		-0.349	-0.348	-0.480	-0.073
		(1.121)	(1.127)	(1.209)	(1.158)
PopDens			-0.011***	-0.011***	-0.012***
			(0.001)	(0.001)	(0.001)
Year				0.381	0.213
				(0.638)	(0.662)
Sig10					-2.303*
					(1.141)
Constant	0.830	1.046	3.124**	-761.682	-424.249
	(0.592)	(1.150)	(1.138)	(1,280.680)	(1,328.927)
Observations	105	105	105	105	105
Adjusted R^2	0.274	0.267	0.264	0.258	0.297

Note: ***, **, and * indicate significant p-values at the 1 %, 5 %, and 10 % level, respectively. Standard errors are presented in parentheses.

As shown in Table 3, there is a significant and negative effect for all distance bands, relative to properties more than 4 km away from wind turbines. For properties within 0–1 km from a wind turbine, there is a more negative effect size of about 7.9–8.6 percentage points, compared to properties further than 4 km from a wind turbine. For the remaining distance bands, the negative size effect is 6.5 percentage points for properties within 1–2 km, 3.6–4.6 percentage points for properties within 2–3 km, and 4.9–5.4 percentage points for properties within 3–4 km. So, generally, the impact is greater the closer the property is to the wind turbine. Further, there is a decrease in significance for the 2–3 km distance band and the effect seems to be larger for properties within a distance of 3–4 km from a wind turbine. This might be explained by the fact that there are fewer observations for the 3–4 km distance band, as shown by the mean in Table 2, and thus it is based on estimates from a smaller set of studies.

Table 3 also shows a negative and significant effect of higher population density. Put more precisely, in study areas with one more inhabitant per km, a more negative effect of 0.01 percentage points is found. This finding is in line with our hypothesis, that population density impacts the effect of wind turbines. For our other hypothesis, that wind power development avoids areas with other competing values, we do not find a significant effect. If anything, there is a positive effect on construction or announcement year. However, the variable is based on the mean announcement or construction year. For short time periods or for an area with very few wind turbines the mean year might be a good indication of announcement or construction year. However, for studies examining the effect in entire countries or for a very long period, it might not be an as strong indication.

Studies analyzing the construction effect, compared to the announcement effect seem to find a slightly more negative effect on property prices. However, this effect is not significant. So, the announcement of a wind turbine being constructed in the future seems to affect property prices to the same degree as the wind turbine being constructed.

Lastly, significant estimates also find a more negative effect of about 2.3 percentage points, as shown in Table 3. As the general effect seems to be more negative for significant estimates, we want to know the effect size for different distance bands. Thus, we estimate the effect of wind turbines on property prices using only significant estimates in Table 4.

Table 4: FE model, percentage change, significant estimates:

	(1)	(2)	(3)	(4)
0–1 km	-12.214***	-12.067***	-12.600***	-12.715***
	(2.054)	(2.730)	(2.407)	(2.487)
1–2 km	-7.663***	-7.545***	-7.424***	-7.512***
	(0.313)	(0.690)	(0.851)	(0.874)
2–3 km	-6.173**	-6.006**	-5.940**	-6.065**
	(2.089)	(1.973)	(1.958)	(1.940)
3–4 km	-6.488***	-6.345***	-6.471***	-6.579***
	(0.377)	(0.857)	(0.776)	(0.819)
PostCon		0.285	0.029	-0.187
		(2.020)	(1.850)	(1.914)
PopDens			-0.044***	-0.045***
			(0.009)	(0.009)
Year				0.953
				(0.646)
Constant	0.703***	0.403	9.129**	-1,905.810
	(0.041)	(2.131)	(3.205)	(1,295.073)
Observations	49	49	49	49
Adjusted R^2	0.336	0.321	0.364	0.353

Note: ***, **, and * indicate significant p-values at the 1 %, 5 %, and 10 % level, respectively. Standard errors are presented in parentheses.

The effect size is more negative of 12–12.7 percentage points for properties within 0–1 km, 7.4–7.7 percentage points for properties within 1–2 km, 5.9–6.2 within 2–3 km, and 6.3–6.6 within 3–4 km, relative to properties more than 4 km from a wind turbine, as shown in Table 4. Thus, when significant estimates are used, the effect size is more negative for the four distance bands compared to when all estimates are included in Table 3, which finds a negative effect size of 7.9–8.6, 6.5, 3.6–4.6, and 4.9–5.4 percentage points, respectively.

Similar results are found for population density, which remains negative and significant when only significant estimates are included. There is also a more negative effect size of 0.044–0.045 percentage points, as shown in Table 4, compared to 0.011 in Table 3. The year variable is still insignificant, with a more positive effect. Lastly, there is still no significant effect of measuring construction year, compared to announcement year, and this variable is positive before year is controlled for, when it becomes negative.

5.1. Sensitivity analysis

To test the robustness of our estimations we conduct two sensitivity analyses. Firstly, we estimate our model based on full sample observations, in Table 5. By only using full sample estimates we decrease the risk that a few studies, with more observation within each distance band skew the observations. However, by only including full sample observations we decrease the within-study effects for the remaining variables, especially population density and construction/announcement year. Secondly, we test the effect of different distance bands in Table 6.

Table 5: FE model, percentage change, estimates based on full samples

	(1)	(2)	(3)	(4)	(6)
0–1 km	-10.528***	-10.528***	-10.528***	-10.528***	-9.777***
	(2.060)	(2.078)	(2.097)	(2.117)	(2.712)
1–2 km	-7.945***	-7.945***	-7.945***	-7.945***	-7.416***
	(1.079)	(1.088)	(1.098)	(1.109)	(1.183)
2–3 km	-4.047	-4.047	-4.047	-4.047	-3.296
	(4.335)	(4.374)	(4.414)	(4.456)	(4.350)
3–4 km	-7.332***	-7.332***	-7.332***	-7.332***	-6.928***
	(1.174)	(1.184)	(1.195)	(1.207)	(1.233)
PostCon		0.070	-0.002	-0.713	-0.453
		(0.840)	(0.833)	(0.602)	(0.743)
PopDens			2.305**	0.930	0.983
			(0.766)	(1.460)	(1.422)
Year				0.995**	0.884**
				(0.340)	(0.385)
Sig10					-1.335
					(2.195)
Constant	1.539*	1.485	-500.985**	-2,198.039***	-1,988.071***
	(0.752)	(1.193)	(166.406)	(526.212)	(634.874)
Observations	61	61	61	61	61
Adjusted R^2	0.295	0.282	0.272	0.267	0.263

Note: ***, **, and * indicate significant p-values at the 1 %, 5 %, and 10 % level, respectively. Standard errors are presented in parentheses.

When only full sample estimates are included, three out of four distance bands remain significant, as shown in Table 5. There is a negative size effect of 9.8–10.5 percentage points for properties within 0–1 km, 7.4–7.9 percentage points for properties within 1–2 km, and 6.9–7.3 within 3–4 km, and an insignificant effect of 3.3–4 percentage points within 2–3 km, relative to properties more than 4 km from a wind turbine. These size effects for properties within 1–2 and 3–4 km are similar to those when only significant estimates are included, in Table 4, while the effect on properties within 0–1 km from wind turbines are somewhere in-between previous results, in Table 3 and Table 4.

The post-construction variable is still insignificant and negative in most estimations. Population density, however, is now positive and significant before controlling for year. Mean construction/announcement year becomes significant when only full sample estimates are included and have a positive effect size of almost 1 percentage point. One reason for deviating results might be that when sub-samples are excluded, we do not get as much within-study variation. For example, when sub-samples are included, population density is compared between different areas. However, when sub-samples are excluded, the only variation is between years, if the study measures announcement as well as construction effects, which is fairly stable.

We estimate the effect for different distance bands in Table 6. Columns (1) and (2) include the distance bands 0–2 km, 2–4 km, and 4–6 km, relative to properties more than 6 km away from a wind turbine. Columns (3) and (4) include distance bands for 0–3 km and 3–5 km, relative to more than 5 km, and columns (5) and (6) include distance bands for 0–4 km and 4–8 km, relative to more than 8 km. Lastly, columns (7) and (8) include the distance band 0–5 km, relative to more than 5 km to the nearest wind turbine. In order to decrease the number of estimations, we only include distance bands in column (1), (3), (5), and (7), and include all variables in column (2), (4), (6), and (8).

In Table 6, it is evident that distance bands lose significance when larger distance bands are applied. The coefficients are still negative for the lower distance bands, e.g., 0–2 km and 2–4 km in columns (1) and (2) and 0–4 km in columns (5) and (6). Looking at the other variable, post-construction is insignificant and positive, while construction/announcement year is omitted. Population density is negative in most estimations and significant in one. In column (4), where population density has a significant effect, the negative effect size is similar to the effect size found in our main model, of 0.01 percentage points. Lastly, significant estimates are negative and significant, indicating that a more negative effect of 2.1–3.8 percentage points is found for significant estimates.

Table 6: FE model, percentage change, different distance bands, and estimates based on full and sub-samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0–2 km	-4.2666	-4.0468						
	(3.3849)	(3.2468)						
2–4 km	-1.1620	-1.1752						
	(3.2256)	(3.0804)						
4–6 km	2.4696	1.7658						
	(3.9388)	(3.8447)						
0–3 km			-3.3511	-2.6754				
			(2.2205)	(2.0139)				
3–5 km			-0.8347	-0.8778				
			(1.9287)	(1.8677)				
0–4 km					-3.9580	-3.6288		
					(3.0445)	(2.7364)		
4–8 km					0.5697	-0.4388		
					(3.0813)	(2.8180)		
0–5 km							-3.0054	-2.3635
							(1.7654)	(1.4484)
PostCon		0.5670		0.6483		0.7941		0.2094
		(1.2615)		(1.1059)		(1.2149)		(1.3111)
PopDens		-0.0080		-0.0100***		-0.0052		0.1091
		(0.0046)		(0.0033)		(0.0096)		(0.0747)
Year		-		-		-		-
Sig10		-2.1010*		-3.4855**		-3.8460**		-3.8510
		(1.0472)		(1.2913)		(1.5705)		(2.2445)
Constant	-0.7701	1.3947	-0.8255	1.7788	-0.2203	2.0153	-0.9936	-12.3582
	(2.7725)	(3.1473)	(1.5320)	(1.7465)	(2.6209)	(2.7682)	(0.7519)	(7.7524)
Observations	121	121	137	137	137	137	54	54
Adjusted R^2	0.162	0.171	0.0564	0.119	0.0759	0.140	0.0471	0.116

Note: ***, **, and * indicate significant p-values at the 1 %, 5 %, and 10 % level, respectively. Standard errors are presented in parentheses. Columns (1) and (2) include the distance bands 0–2 km, 2–4 km, and 4–6 km, relative to properties more than 6 km away from a wind turbine. Columns (3) and (4) include distance bands for 0–3 km and 3–5 km, relative to more than 5 km, columns (5) and (6) include distance bands for 0–4 km and 4–8 km, relative to more than 8 km, and columns (7) and (8) include the distance band 0–5 km, relative to more than 5 km to the nearest wind turbine. Columns (1), (3), (5), and (7) only include distance bands in column, while all variables are included in columns (2), (4), (6), and (8).

6. Conclusion

In this paper, we use a meta-analysis to examine the effect of wind turbines on property values found in previous research, using distance bands. In our main regressions, we include distance bands for properties within 0–1 km, 1–2 km, 2–3 km, and 3–4 km from a wind turbine, relative to properties more than 4 km from the nearest wind turbine and find negative effect sizes for all distance bands. The negative effect size generally decreases the further away the property is from the wind turbine and the distance band for properties within 3–4 km becomes insignificant in some estimations.

We find negative effect sizes of 7.4–12.7 percentage points for properties within the 0–1 km distance band, 6.5–7.9 percentage points for 1–2 km, 3.3–6.2 percentage points for 2–3 km, and 4.9–7.3 percentage points for properties between 3 and 4 km from a wind turbine, relative to more than 4 km. When larger distance bands are used, in our sensitivity analysis, we no longer find any significant effect on property values, indicating that the distance bands should not be larger than 1 km each when estimating whether, and to what degree, property prices are affected by wind turbines.

We also test for two hypotheses: (1) the effect on property prices should be larger for later construction and announcement year, as earlier wind power developments avoided areas with other competing values; (2) the effect on property prices should be higher in more populated areas. We find no support for our first hypothesis, as there is no significant effect of mean announcement/construction year. Regarding the second hypothesis, however, we find that studies conducted in more populated areas find more negative effects on property prices. Put more precisely, in study areas with one more inhabitant per km, a more negative effect of 0.01 percentage points is found.

Our findings have important implications for both future research and policy. Firstly, our results highlight the need for further investigation into how population density moderates the relationship between wind turbines and property values. Secondly, while our meta-analysis explicitly examines wind turbine disturbance through distance bands, the effect of other potential disturbance measurements are not analyzed. Thus, future meta-analyses should consider incorporating alternative measures, such as view or number of turbines, to provide a more comprehensive understanding of how wind turbines influence property values.

From a policy perspective, our findings suggest that if compensation schemes are implemented for property owners near newly announced or constructed wind, both distance and population density should be taken into account. Given that we observe more negative effects in study areas with higher population density, policymakers may need to design compensation structures that reflect not only proximity to turbines but also the characteristics of the surrounding area.

References

Barthelmie, R. J., & Pryor, S. C. (2021). Climate change mitigation potential of wind energy. *Climate*, *9*(9), 136.

Carter, J. (2011). The effect of wind farms on residential property values in Lee County, Illinois. *Illinois State University*.

Castleberry, B., & Greene, J. S. (2018). Wind power and real estate prices in Oklahoma. *International Journal of Housing Markets and Analysis*, *11*(5), 808–827. https://doi.org/10.1108/IJHMA-02-2018-0010

Dai, K., Bergot, A., Liang, C., Xiang, W.-N., & Huang, Z. (2015). Environmental issues associated with wind energy–A review. *Renewable Energy*, *75*, 911–921.

Dröes, M. I., & Koster, H. R. (2016). Renewable energy and negative externalities: The effect of wind turbines on house prices. *Journal of Urban Economics*, *96*, 121–141. https://doi.org/10.1016/j.jue.2016.09.001

Dröes, M. I., & Koster, H. R. (2021). Wind turbines, solar farms, and house prices. *Energy Policy*, *155*, 112327-. https://doi.org/10.1016/j.enpol.2021.112327

Eichholtz, P., Kok, N., Langen, M., & Van Vulpen, D. (2023). Clean Electricity, Dirty Electricity: The Effect on Local House Prices. *The Journal of Real Estate Finance and Economics*, *66*(4), 743–777. https://doi.org/10.1007/s11146-021-09878-6

Gibbons, S. (2015). Gone with the wind: Valuing the visual impacts of wind turbines through house prices. *Journal of Environmental Economics and Management*, *72*, 177–196. https://doi.org/10.1016/j.jeem.2015.04.006

Halvorsen, R., & Palmquist, R. (1980). The interpretation of dummy variables in semilogarithmic equations. *American Economic Review*, *70*(3). https://search.ebscohost.com/login.aspx?direct=true&profile=ehost&scope=site&authtype=crawler&jrnl=00028282&asa=N&AN=4503529&h=glaHC127bkicpU6%2FOYwtgpdAipaX1r%2BCn1JsJH9ORhl54SD0qT%2Bau6etSTGtbr6UyyoZ7xmV8SRILzZWMNT4vg%3D%3D&crl=c

Hanley, N., Shogren, J. F., & White, B. (1997). *Environmental Economics in Theory and Practice*. Macmillan.

Havránek, T., Stanley, T. D., Doucouliagos, H., Bom, P., Geyer-Klingeberg, J., Iwasaki, I., Reed, W. R., Rost, K., & van Aert, R. C. M. (2020). Reporting Guidelines for Meta-Analysis in Economics. *Journal of Economic Surveys*, *34*(3), 469–475. https://doi.org/10.1111/joes.12363

Heintzelman, M. D., & Tuttle, C. M. (2012). Values in the Wind: A Hedonic Analysis of Wind Power Facilities. *Land Economics*, *88*(3), 571–588.

Heintzelman, M. D., Vyn, R. J., & Guth, S. (2017). Understanding the Amenity Impacts of Wind Development on an International Border. *Ecological Economics*, *137*, 195–206. https://doi.org/10.1016/j.ecolecon.2017.03.008

Hoen, B., & Atkinson-Palombo, C. (2016). Wind Turbines, Amenities and Disamenities: A Study of Home Value Impacts in Densely Populated Massachusetts. *The Journal of Real Estate Research*, *38*(4), 473–504.

Hoen, B., Brown, J. P., Jackson, T., Thayer, M. A., Wiser, R., & Cappers, P. (2015). Spatial Hedonic Analysis of the Effects of US Wind Energy Facilities on Surrounding Property

Values. *The Journal of Real Estate Finance and Economics*, *51*(1), 22–51. https://doi.org/10.1007/s11146-014-9477-9

Hoen, B., Wiser, R., Cappers, P., Thayer, M., & Sethi, G. (2011). Wind Energy Facilities and Residential Properties: The Effect of Proximity and View on Sales Prices. *The Journal of Real Estate Research*, *33*(3), 279–316. https://doi.org/10.1080/10835547.2011.12091307

Jarvis, S. (2021). The Economic Costs of NIMBYism: Evidence from Renewable Energy Projects. *Energy Institute at Haas*, *Energy Institute WP 311*.

Jensen, C. U., Panduro, T. E., & Lundhede, T. H. (2014). The Vindication of Don Quixote: The Impact of Noise and Visual Pollution from Wind Turbines. *Land Economics, 90*(4), 668–682.

Jensen, C. U., Panduro, T. E., Lundhede, T. H., Nielsen, A. S. E., Dalsgaard, M., & Thorsen, B. J. (2018). The impact of on-shore and off-shore wind turbine farms on property prices. *Energy Policy*, *116*, 50–59. https://doi.org/10.1016/j.enpol.2018.01.046

Joly, M., & De Jaeger, S. (2021). Not in my backyard: A hedonic approach to the construction timeline of wind turbines in Flanders, Belgium. *Land Use Policy*, *108*, 105527.

Khoshnoud, M., Sirmans, G. S., & Zietz, E. N. (2023). The Evolution of Hedonic Pricing Models. *Journal of Real Estate Literature*, *31*(1), 1–47. https://doi.org/10.1080/09277544.2023.2201020

Kong, F., Yin, H., & Nakagoshi, N. (2007). Using GIS and landscape metrics in the hedonic price modeling of the amenity value of urban green space: A case study in Jinan City, China. *Landscape and Urban Planning*, *79*(3), 240–252. https://doi.org/10.1016/j.landurbplan.2006.02.013

Lang, C., Opaluch, J. J., & Sfinarolakis, G. (2014). The windy city: Property value impacts of wind turbines in an urban setting. *Energy Economics*, *44*, 413–421. https://doi.org/10.1016/j.eneco.2014.05.010

Laposa, S., & Mueller, A. (2010). Wind Farm Announcements and Rural Home Prices: Maxwell Ranch and Rural Northern Colorado. *Journal of Sustainable Real Estate*, *2*(1), 383–402. https://doi.org/10.1080/10835547.2010.12091798

McCarthy, I., & Balli, H. O. (2014). Windfarms and residential property values. *International Journal of Strategic Property Management*, *18*(2), 116–124. https://doi.org/10.3846/1648715X.2014.889770

Niskanen, J., Anshelm, J., & Haikola, S. (2024). A multi-level discourse analysis of Swedish wind power resistance, 2009–2022. *Political Geography*, *108*, 103017.

Parsons, G., & Heintzelman, M. D. (2022). The Effect of Wind Power Projects on Property Values: A Decade (2011–2021) of Hedonic Price Analysis. *International Review of Environmental and Resource Economics*, *16*(1), 93–170. https://doi.org/10.1561/101.00000132

Reusswig, F., Braun, F., Heger, I., Ludewig, T., Eichenauer, E., & Lass, W. (2016). Against the wind: Local opposition to the German Energiewende. *Utilities Policy*, *41*, 214–227.

Sampson, G. S., Perry, E. D., & Taylor, M. R. (2020). The on-farm and near-farm effects of wind turbines on agricultural land values. *Journal of Agricultural and Resource Economics, 45*(3), 410–427.

Schütt, M. (2024). Wind Turbines and Property Values: A Meta-Regression Analysis. *Environmental & Resource Economics*, *87*(1), 1–43. https://doi.org/10.1007/s10640-023-00809-y

Sims, S., & Dent, P. (2007). Property stigma: Wind farms are just the latest fashion. *Journal of Property Investment & Finance*, *25*(6), 626–651.

Sims, S., Dent, P., & Oskrochi, G. R. (2008). MODELLING THE IMPACT OF WIND FARMS ON HOUSE PRICES IN THE UK. *International Journal of Strategic Property Management*, *12*(4), 251–269. https://doi.org/10.3846/1648-715X.2008.12.251-269

Skenteris, K., Mirasgedis, S., & Tourkolias, C. (2019). Implementing hedonic pricing models for valuing the visual impact of wind farms in Greece. *Economic Analysis and Policy*, *64*, 248–258. https://doi.org/10.1016/j.eap.2019.09.004

Stanley, T. D. (2001). Wheat From Chaff: Meta-Analysis As Quantitative Literature Review. *Journal of Economic Perspectives*, *15*(3), 131–150. https://doi.org/10.1257/jep.15.3.131

Sunak, Y., & Madlener, R. (2016). The impact of wind farm visibility on property values: A spatial difference-in-differences analysis. *Energy Economics*, *55*, 79–91. https://doi.org/10.1016/j.eneco.2015.12.025

Sunak, Y., & Madlener, R. (2017). The impact of wind farms on property values: A locally weighted hedonic pricing model. *Papers in Regional Science*, *96*(2), 423–444. https://doi.org/10.1111/pirs.12197

Susskind, L., Chun, J., Gant, A., Hodgkins, C., Cohen, J., & Lohmar, S. (2022). Sources of opposition to renewable energy projects in the United States. *Energy Policy*, *165*, 112922.

Vyn, R. J. (2018). Property Value Impacts of Wind Turbines and the Influence of Attitudes toward Wind Energy. *Land Economics*, *94*(4), 496–516. https://doi.org/10.3368/le.94.4.496

Vyn, R. J., & McCullough, R. M. (2014). The Effects of Wind Turbines on Property Values in Ontario: Does Public Perception Match Empirical Evidence? *Canadian Journal of Agricultural Economics/Revue Canadienne d'agroeconomie*, *62*(3), 365–392. https://doi.org/10.1111/cjag.12030

Wang, S., & Wang, S. (2015). Impacts of wind energy on environment: A review. *Renewable and Sustainable Energy Reviews*, *49*, 437–443.

Westlund, H., & Wilhelmsson, M. (2021). The socio-economic cost of wind turbines: A Swedish case study. *Sustainability*, *13*(12), 6892.