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The effect of wind power on residential property values in Norway

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A B S T R A C T

This paper analyses, for the first time in Norway, the effects of onshore wind farms on residential property prices by using a hedonic price model in combination with difference-in-differences analysis and spatial fixed effects to estimate homeowners' preferences for (avoiding) living near a wind farm. The analysis utilizes data on all 60 concessioned wind farms in Norway and over 160,000 observations of property transactions in the period 2010–22. We find that residential property prices decline in proximity to operating wind farms. The magnitude and spatial extent of the estimated price effects are uncertain and vary across model specifications, from −4 to −14 % for properties within 2 km. The effect diminishes with distance and converges to zero at 3–7 km. An event study analysis indicates that property prices are primarily affected after wind farms become operational, with some impact during the construction phase. We find no evidence of price adjustments over time consistent with adaptation or diminishing sensitivity. Heterogeneity analyses indicate that price reductions may be larger near wind farms with more turbines. Within 2 km, a substantial share of the effect appears to be driven by turbine visibility: using a digital elevation model combined with data on forest and vegetation cover, we isolate visibility from proximity through a difference-in-differences-in-differences design. The paper contributes to a surging literature on hedonic analysis of renewable energy infrastructure and the ongoing discussions on trade-offs between climate benefits and local disamenity costs.

1. Introduction

Onshore wind power has evolved from a nearly insignificant energy source in the early 2000s to Norway's second largest, surpassed only by hydropower. In 2025, onshore wind power produced 15.9 TWh in Norway (NVE, 2025a). Onshore wind power is the production technology with the lowest production cost per kWh and the fastest implementation time in Norway (NOU, 2023:3; NVE, 2025b). Hence, onshore wind power may be essential for the green transition, to cover potential future power deficits in 2040, and to reduce electricity prices (Ueland et al., 2021). Onshore wind power appears as Norway's most favourable solution to today's and future power challenges, also due to substantial unexploited wind resources.

However, the development of wind power in Norway has been subject to extensive debate due to local environmental disamenities and challenges, such as the loss of nature and wildlife, and the depreciation of ecosystem services that natural areas provide (Grimsrud et al., 2024; Dugstad et al., 2023; 2024). It is a classic example of how climate and environmental considerations may conflict. Further,

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the development is characterised by NIMBY-effects[1] where the local population typically opposes development in their areas (Dugstad et al., 2020).

This resistance—particularly from residents living near wind farms, due to the limited consideration of local externalities—led to a complete halt in the licensing process for all new onshore wind power projects during 2019–2022 (Ministry of Energy ED, 2022). While some recent stated preference studies have assessed local (and national) preferences for avoiding new wind power in Norway (Dugstad et al., 2020, 2023, 2024), there is a lack of revealed preference studies. This article presents the first hedonic analysis of Norwegian residents' preferences for onshore wind power, measured through the impact of wind farm development on neighbouring property values. We conduct a comprehensive state-of-the-art analysis of how both the distance to and the visibility of wind turbines affect residential property prices, examining announcement and anticipation effects, as well as price development in the years following the start of operations.

Studies have shown that wind farms have negative externalities on local residents (Zerrahn, 2017) through noise pollution (Jensen et al., 2014; Aasvang and Krog, 2022), shadow flicker (Andersen and Hener, 2025), and visual disamenities (Guo 2024; Dong et al., 2024; Mei et al., 2024; Gibbons, 2015; Sunak and Madlener, 2016; Zimmer et al., 2018). Living near wind farms is also associated with a higher risk of disturbed sleep (Onakpoya et al., 2015) and with lower subjective well-being more generally (Krekel and Zerrahn, 2017).

There is a growing international literature on property price effects and revealed preferences for wind farms, especially from the USA and Europe. Parsons and Heintzelman (2022) review the literature over the last decade and identify 10 studies from Europe and 8 from North America. The meta-analysis by Schütt (2024) identifies estimates from 25 studies. Some of the hedonic analyses reveal significant negative effects on property prices due to the proximity to wind farms (Heintzelman and Tuttle, 2012; Heintzelman et al., 2017; Jensen et al., 2014; 2018; Dröes and Koster, 2016; 2021; Brunner et al., 2024), whereas others find no such impact (Hoen et al., 2011; 2015; Lang et al., 2014). Outside the USA and Europe, Mei et al. (2024) found price depreciation of land parcels located within 1–3 km of wind farms in China. The hedonic valuation literature presents divergent findings regarding the existence of negative preferences for living in proximity to wind farms, with effects varying across areas. There is a need for further investigation into the impact, particularly in countries that have not yet been studied, using newer and better data, according to Parsons and Heintzelman (2022).

In Norway, there is still a critical lack of knowledge about the value of the impacts of onshore wind power on nature, local populations, and the surrounding environment, as pointed out by e.g., Grimsrud et al. (2024). Recently, there has been some research on people's stated preferences to avoid some of the negative effects of onshore wind power in Norway (for example, Dugstad et al., 2023; 2024) and how to better incorporate such considerations into energy system modelling and siting of facilities (Grimsrud et al., 2021; 2024). However, revealed preference studies to estimate welfare loss from wind farms in Norway are scarce, and no hedonic studies have been carried out to date.[2]

In their review of hedonic studies of wind power, Parsons and Heintzelman (2022) conclude by recommending more comprehensive robustness checks, such as varying the boundaries for spatial fixed effects models, performing heterogeneity analyses on turbine counts, and more thoroughly investigating announcement and anticipation effects by delineating the impacts both pre- and post-construction, which have been given limited consideration in previous studies. Both Schütt (2024) and Parsons and Heintzelman (2022) underscore the importance of not relying solely on spatial fixed effects methods in new studies but also leveraging difference-in-differences (DiD) analysis as a strategic approach for identification. This method ensures that spatial factors and other confounding variables in pre-existing price differentials are distinguished from the effects attributed to the proximity of wind farms.

In this paper, we expand the existing literature by incorporating these considerations for new data. We implement a series of robustness tests, including variations in spatial fixed effects, model boundaries, and control groups, in conjunction with DiD estimation. To explore the possibility of premature treatment effects arising from announcement and anticipation, we assess the extent to which price effects occur before or during the construction phase of wind farms. Furthermore, we investigate price changes over time due to adaptation effects and diminishing sensitivity among the local residents.

We also investigate the effect of wind farm visibility. Visibility or viewshed is determined using a digital elevation model (DEM) in combination with data on forest cover and vegetation to account for potential visual obstructions caused by nearby trees and vegetation. As a result, we can estimate the likelihood that each property has a view of a wind turbine, given terrain features such as hills, mountains, and surrounding forests. We then estimate the effect of visibility on residential property prices, using a difference-in-difference-in-differences (DiDiD) approach to distinguish the impact of visibility from the effect of proximity. The former primarily captures the visual (aesthetic) disamenity, while the latter likely serves as a more accurate indicator of turbine-related noise pollution.

We utilize data on all onshore wind farms in Norway simultaneously in a staggered research design to estimate the pooled market effect on residential property prices in the country. This approach also results in a larger number of affected properties in our dataset compared to an analysis conducted at the individual wind farm case level.

To extend our understanding of the factors driving price effects, we conduct heterogeneity analyses to determine whether wind farms with higher turbine counts exert a greater impact on prices.

[1] "Not in my backyard".

[2] Kipperberg et al. (2019) investigate how the development of wind power may affect recreational behaviour and costs, and consumer surplus, in Rogaland County, by using a combined travel cost method and contingent behaviour method.

2. Data

This analysis uses data from Finn.no[3] on over 160,000 property transactions for residential properties located within 20 km of an onshore wind farm. The data covers residential properties across Norway sold in the period from 2010 to 2022. Residential property transactions in major cities such as Oslo and Bergen are excluded, as these areas are more than 20 km from the nearest wind farm. The data include actual sales prices and precise coordinates of the properties, along with a range of structural attributes such as area, number of rooms, construction year, garage space, property type, etc., which can be used to define the hedonic price function.

The property data are combined with data from the Norwegian Water Resources and Energy Directorate (NVE) on the 60 operational wind farms in Norway.[4] See Fig. 1 for an overview of all the wind farms in Norway. This data includes coordinates for all turbines in all wind farms, enabling calculation of the shortest distance from each property to the nearest wind turbine in the nearest wind farm. In addition, we have data on the number of turbines in each wind farm and their height. An immediate challenge with this analysis is that there are likely to be few residential properties very close to wind farms, as they are often built in non-central locations, such as mountains or coastal areas. By using all wind farms in Norway, however, it is possible to increase the number of affected properties while estimating pooled effects across the country.

2.1. *Explanatory variables*

The data source includes various structural variables that can be used in the analysis to explain the property price, including size, number of bedrooms, construction year, etc. Descriptions of these variables, their modelling, and the expected effects on residential property prices, based on theory and previous studies, are shown in Table A1 in Appendix A.

2.2. *Observations close to wind farms and removal of outliers*

An outlier analysis was conducted with the aim of cleaning the dataset for outliers and observations of highly unusual property transactions. This includes, among others, properties with very high or very low prices, unlikely observations due to errors in real estate agents' reporting, and possible duplicates. This reduces the dataset by around 5500 observations of property transactions to the total of 166,934 transactions that are used in the analysis. Descriptive statistics over variables of interest are presented in Table A2 in Appendix A. Since the number of observations of properties near wind farms is central to the analysis, we have included an overview of the number of residential property observations in each distance interval up to 10 km in Table A3 in Appendix A.

3. Method

We apply the hedonic price model (HPM)[5] combined with a difference-in-differences (DiD) approach to analyse the causal impact of establishing wind farms on residential property prices. This method exploits spatial and temporal variation in transactions of residential properties in proximity to wind farm installations across the country. The model estimates the average change in property prices for homes affected by a wind farm—either through proximity or by being within its viewshed—when the wind farm becomes operational, relative to properties in the same area that are not affected by the installation. This is a powerful and commonly used model to estimate causal inference of onshore wind deployment on property prices, where deployment of multiple wind farms is observed in a staggered design. Many previous studies examining the effect of wind farms on residential property prices employ similar models, combining HPM with DiD approaches (e.g., Westlund and Wilhelmsson, 2025; Guo et al., 2024; Dong and Lang, 2022; Dong et al., 2023; 2024; Mei et al., 2024, Dröes and Koster, 2016; 2021; Hoen et al., 2015; Vyn, 2018; Lang et al., 2014, among others).

The staggered treatment introduces additional challenges if wind farms are close enough to each other, such that properties may fall into the treatment groups of multiple wind farms. Although this could present a potential weakness in the dataset and methodology, the wind farms are generally spaced sufficiently apart all over Norway, so it does not pose a problem for the analysis. We also estimate a model that restricts the study area to a 10 km radius around the wind farms for robustness.

A key challenge in research designs with staggered treatment is the potential mixing of treatment and control groups when treatment occurs across time and space, which could lead to biased estimates (de Chaisemartin and D'Haultfœuille, 2020). However, by including wind farm-specific fixed effects, we isolate the treatment and control groups for each individual wind farm, separating them from those associated with other wind farms established at different points in time. The wind farm-specific fixed effects also capture spatial heterogeneity in prices, allowing us to control for differential price trends across locations through interactions with time fixed effects. We conduct an event study as a robustness test of the staggered DiD design by including leads and lags of the treatment, which also provides information on the credibility of assuming parallel trends.

In our baseline model, we use a standard DiD identification strategy, in which the treatment and control groups are defined by distance to the wind farm. Information on whether the property was sold before or after the start of operation of the wind farm determines treatment status. The properties located close to the wind farm constitute the treatment group, while those located

[3] A Norwegian website that has a near-monopoly on the sale of marketing real estate and properties online. This platform is the most employed website in Norway for advertising and searching for properties.

[4] All operational wind farms in Norway that were license-required in 2022.

[5] See Rosen (1974).

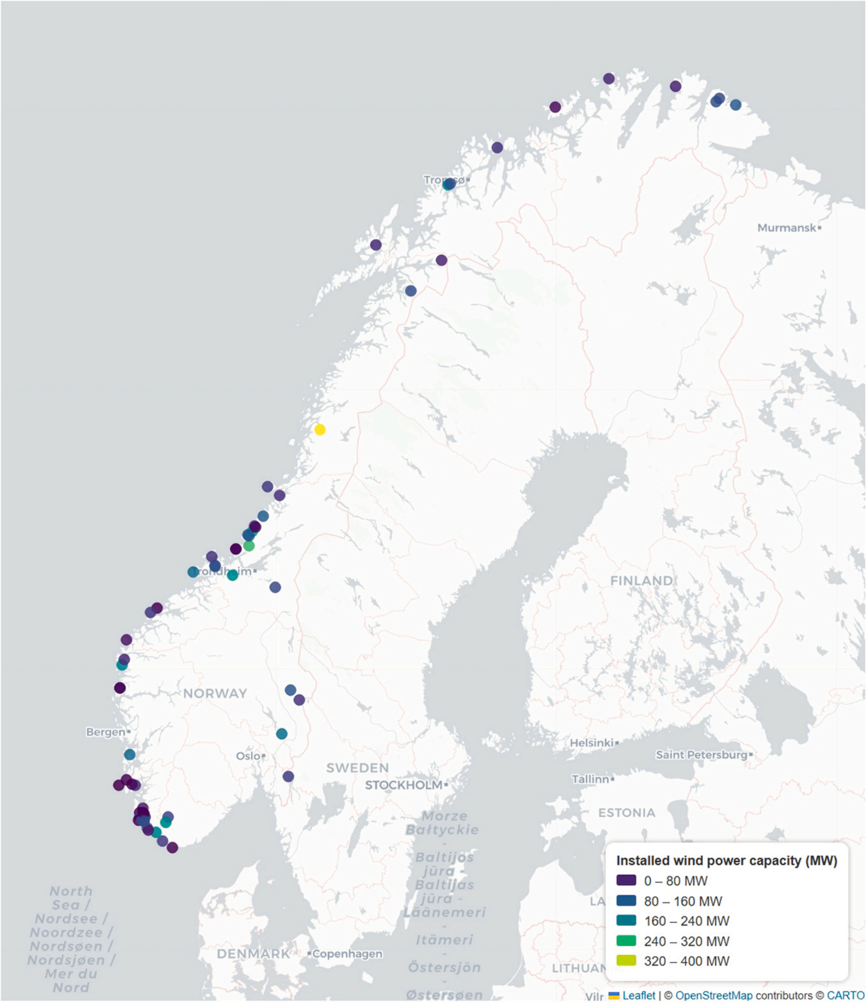

Fig. 1. Overview of all wind farms in Norway in 2022. The colour of the circle represents the size of the wind farm (MW production capacity). Source: NVE.

sufficiently far from the wind farm serve as the control group. We apply dummy variables for every km interval up to 10 km to indicate the degree of impact from proximity to wind turbines. Properties closer than 10 km to the wind turbines are therefore in the treatment groups (10 treatment groups for every km interval), while properties 10–20 km from the wind turbines are in the control group.

Larger treatment intervals provide more statistical power, while smaller intervals offer greater precision. The literature varies in its definition of distance bounds. Gibbons (2015), for example, uses 2 km intervals extending up to 14 km to indicate treatment, Sunak and Madlener (2012) use 0.5 km intervals extending up to 5 km, and Mei et al. (2024) and Guo et al. (2024) use 1 km intervals extending up to 10 km. We follow the distance bounds used by Mei et al. (2024) and Guo et al. (2024), as they represent some of the latest research in the field. Additionally, none of the studies identified by Parsons and Heintzelman (2022) and Schütt (2024) found statistically significant negative estimates beyond 10 km. Finally, we have not identified any literature indicating a price effect beyond this distance.

We apply a semi-log functional relationship between the property price and associated attributes and amenities. The use of a semi-log functional form[6] in the application of HPM is dominant in the literature, based on the analysis by Cropper et al. (1988) of which form is best suited to estimate marginal values in the possible presence of omitted variable bias.

The specification of the estimated baseline regression model is:

$$\log(P_{i\mu t}) = \quad \alpha + \quad \beta O_{\mu t} + \quad \sum_{k \in K} \gamma_k I_{ik\mu} + \sum_{k \in K} \delta_k I_{ik\mu} O_{\mu t}$$

[6] With natural logarithm.

$$+ \quad \boldsymbol{\theta} \boldsymbol{z_{it}} + \quad \lambda_{\mu t} + \quad \rho W_t + \quad \varepsilon_{i\mu t}, \tag{1}$$

where $\log(P_{i\mu t})$ is the natural logarithm of the price[7] of residential property i at time t, α is the constant term[8] and $\varepsilon_{i\mu t}$ is the residual term for the property. $O_{\mu t}$ is a dummy variable equal to 1 if the property was sold after the start of operation of the wind farm and $I_{ik\mu}$ are dummy variables for each kilometre interval k from 0 to 1 km up to 9–10 km ($k \in K = \{0-1,\ 1-2,\ \ldots,\ 9-10\}$), which equals 1 if the property is in the kilometre interval k from the nearest wind turbine. $\boldsymbol{\theta}$ is a vector of unknown coefficients to be estimated corresponding to various attributes, amenities and controls in $\boldsymbol{z_{i\mu t}}$, where most variables are time-invariant, while some may vary over time (e.g. renovations). $\lambda_{\mu t}$ are the interaction between year- and spatial fixed effects (wind farm indicators, μ), controlling for heterogeneity in price levels and price trends across areas. W_t is a dummy variable indicating whether the property transaction took place in the winter or not, controlling for seasonal variation. β, γ_k, $\boldsymbol{\theta}$ and ρ are unknown coefficients, while δ_k is the DiD coefficients of interest that reflects the average price effect of distance k to a wind farm becoming operational.

The DiD approach controls for heterogeneity in residential property prices between the treatment and control groups caused by unobservable characteristics of the properties, given that these characteristics remain constant at the mean over time for each group. This includes spatial factors that influence residential property prices, such as neighbourhood-level socioeconomic characteristics or degree of centrality.[9] The latter is particularly important, as wind farms in Norway are often built in remote mountainous or coastal areas. By including spatial and time fixed effects (with interactions), we further control for unobserved spatial characteristics that vary across properties and for differential price trends across areas over time.

The models are estimated using the ordinary least squares (OLS) method with cluster-robust standard errors on wind farm indicators (spatial fixed effects), with the intention to control for heteroskedasticity.[10]

4. Results

4.1. Effect of distance to wind farms on residential property prices

In Fig. 2, we present the estimated DiD coefficients from the baseline model. The DiD estimates reflect the average treatment effect from being near a wind farm, within each specific distance radius to the turbines of an operational wind farm. See Table B1 in Appendix B for the complete regression table.

The results show that the installation of wind farms leads to a significant reduction in residential prices for properties in proximity of the wind turbines, and that this price effect diminishes with distance. We find a substantial negative effect on prices for properties located within 2 km of a wind turbine at around −9.1 % to −13.9 %. For properties situated 2–7 km away, the estimated effects are smaller (around 5 %) and only statistically significant out to 6 km. The estimated effects are not statistically significant above 6 km, and close to zero above 7 km.

The estimate for the 0–1 km interval is less negative than the estimate for the 1–2 km interval, and is not statistically significant, with a relatively wide confidence interval. This is likely driven by the small number of properties located within 1 km distance, and therefore, larger uncertainty. An additional factor that may contribute to this pattern is that residential properties most strongly affected within 1 km are often acquired by developers prior to construction to facilitate the permitting process, or are a part of the landholdings associated with the wind power project.[11] These transactions do not take place in the open market and therefore do not appear in our data, reducing the number of observable pre-operation sales for the most exposed residential properties. As a result, the remaining sample under 1 km may omit properties that would have experienced the largest price effects, potentially biasing the estimated impact toward zero. However, this mechanism cannot be established with certainty.

Furthermore, we estimate that prior to the wind farm installation, the treatment groups (below 10 km from a wind farm) have prices that are around 1–10 % lower than the control group (above 10 km from a wind farm). This price difference cannot be explained by observable property characteristics. We can therefore assume that the observed difference is related to wind farms typically being located in areas with lower property prices. An observation that was also made by Guo et al. (2024). However, it is difficult to determine the exact cause of this pattern — it may reflect unobserved differences in centrality or other location-specific factors that influence residential property prices.

[7] Total purchase price, including fees and shared debt.

[8] The empirical model includes a global intercept term α. In estimation, the intercept is absorbed by the high-dimensional fixed effects (wind farm × year fixed effects).

[9] Centrality refers to the importance or influence of a location within a system or network, often characterized by accessibility to resources and socio-economic activities. In geography, central places are typically hubs for transportation and services.

[10] All models are estimated in R using the feols estimator from the fixest package (Bergé et al., 2026). This estimator is designed for high-dimensional fixed-effects settings and implements the Frisch–Waugh–Lovell transformation, allowing us to absorb large sets of fixed effects efficiently.

[11] According to the Norwegian Water Resources and Energy Directorate (NVE), recommended noise limits are typically reached 600–800 m from a turbine, and NVE therefore advises a minimum separation distance of approximately 800 m between wind turbines and noise-sensitive buildings. However, NVE may grant a permit even if these noise limits are exceeded for a small number of residential properties (NVE, 2025c).

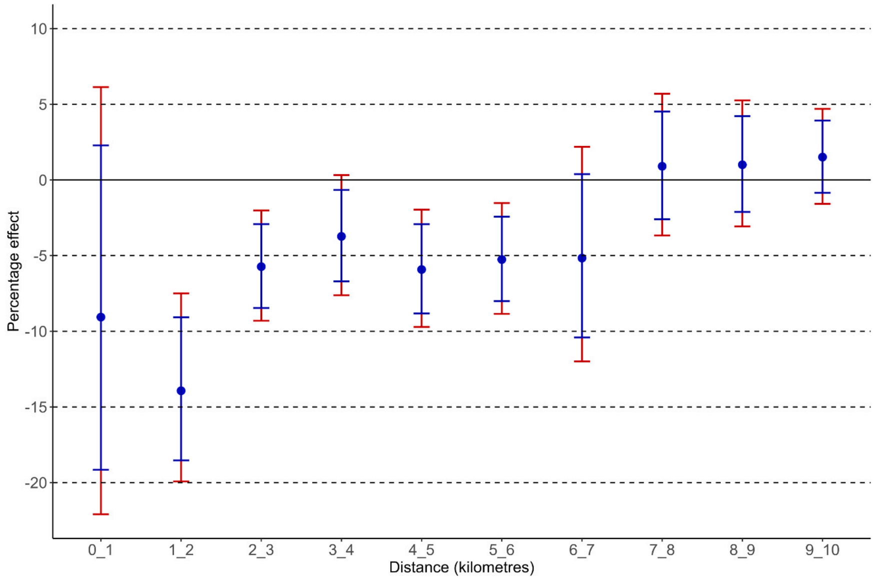

Fig. 2. The effect of wind farms on residential property prices at different distances, DiD and fixed wind farm effects. *Regression results from DiD model (1) with fixed wind farm effects. The points represent the estimated price effect as percentage of the property price for having an operational wind turbine within the given distance interval from the property. The red area represents the 99 % confidence interval, and the blue area represents the 95 % confidence interval for the corresponding estimate.*

4.2. Robustness tests

In addition to the baseline model, we estimate alternative specifications that incorporate different layers of spatial fixed effects to test robustness and to further control for unobserved spatially correlated characteristics. Following Parsons and Heintzelman (2022), we vary the definitions of spatial fixed effects as part of the robustness checks and include both municipal and sub-municipal fixed effects. We estimate the following models:

- **Baseline + municipality FE:** We add municipality indicators alongside the wind farm fixed effects to control for broader spatial price differentials. Housing markets and settlement centrality often align with municipal boundaries, making them suitable as spatial fixed effects units. In Norway, it is common in statistical analyses to define centrality at the municipal level. For instance, Statistics Norway has developed a centralization index[12] at the municipal level. Including municipalities as spatial fixed effects will thus be collinear with this centrality index.
- **Baseline + basic statistical unit FE:** We estimate a model with sub-municipal fixed effects to control for fine-grained spatial variation in prices, while retaining wind farm–by–year fixed effects. The sub-municipal units are "basic statistical unit" defined by Statistics Norway.[13] These units are geographically contiguous and relatively homogeneous with respect to settlement patterns and land use. They constitute the standard small-area unit in Norwegian empirical research based on administrative data and are smaller than ZIP codes.
- **Baseline + sparse settlement × time FE:** We add an interaction between sparse settlement status and time to control for price differentials within the existing spatial fixed effect's structure (wind farm-by-year indicators) that may vary systematically over time between dense and sparsely populated areas. The variable "sparse settlement" indicates whether the property is in an area with dense or sparse settlement. The variable is not valuable in determining centrality on a larger scale (rural vs. urban) but indicates whether the property is centrally located on a smaller scale, whether it is located alone or in some form of housing cluster. This variable is developed by Statistics Norway, which defines a property's position as in dense settlement if the property is in a collection of properties in a locality where at least 200 people live, and the distance between properties normally does not exceed 50 m (Thomassen, Melby, 2009). The variable is included as a dummy in all other models to incorporate spatial time invariant factors into the hedonic price function, relating to the residential property density of the built-up area in which the property is located. In this model it is also interacted with time.
- **Baseline with restricted control and treatment areas:** Finally, we estimate a specification that assigns treatment indicators for each 1 km interval up to 7 km, consistent with the baseline results showing effects within this distance. Properties located 7–10 km from the wind farms serve as the control group, and the sample is restricted to properties within 10 km. Although this reduces the

[12] See: https://www.ssb.no/befolkning/folketall/artikler/sentralitetsindeksen.

[13] See: https://www.ssb.no/a/metadata/conceptvariable/vardok/135/en.

available data relative to using a 10–20 km control group, it increases the similarity between treated and control areas by narrowing the spatial scope, thereby reducing potential spatial heterogeneity and concerns about differential price trends.

The results from the robustness tests, along with how they differ from the baseline model, are presented in Fig. 3.

The specification interacting sparse settlement status with time (orange dots in Fig. 3) deviates only marginally from the baseline model, suggesting that it captures little additional time-varying price heterogeneity correlated with sparse settlement. Adding municipality fixed effects (green dots) yields somewhat smaller estimated price declines, suggesting that broader municipal-level indicators absorb some additional spatial heterogeneity. When we introduce sub-municipal fixed effects at the basic statistical unit level (grey dots), the estimated effects reduce noticeably. This indicates that the larger baseline estimates could reflect unobserved fine-scale variation in local amenities and housing-market conditions that are correlated with turbine placement. However, the qualitative pattern remains unchanged: properties located within 1–3 km of an operating wind farm still experience negative and statistically significant price effects, on the order of -2 to -4 %.[14] We therefore view the basic statistical unit specification as a stricter design, providing a conservative lower-bound estimate of the localized disamenity effect.

The model that restricts the control group to properties located 7–10 km from the wind turbines (red dots) also generates smaller estimated effects than the baseline model, which is expected given that the control properties are geographically closer to the treated areas. In this specification, the estimated pre-treatment price differences between treatment and control groups are also closer to zero across distance intervals than in the baseline model. This indicates that unobserved differences between the groups are likely reduced when the control area is more spatially comparable to the treated area. See the Tables B1 and B2 in Appendix B for complete regression results.

The robustness tests show that the estimated negative effect for properties located close to operating wind turbines are relatively robust to changes in model specification and spatial fixed effects boundaries. Nonetheless, the magnitude and spatial extent of treatment vary, reflecting uncertainty associated with model specification, and that the estimated effect is reduced when increasingly fine-grained spatial fixed effects are introduced. In the remainder of the paper, we examine the effects in the baseline specification through heterogeneity analyses by wind farm size, an event-study design, and models that separately identify the roles of turbine visibility and distance.

4.3. *Effect of wind farm size*

Larger wind farms involve more extensive infrastructure impacts in the landscape. Hence, it is likely that the local population has stronger negative preferences towards larger wind farms, measured by the number of wind turbines, compared to smaller ones. Consequently, we also investigate whether a larger decline in residential property prices can be observed in the vicinity of installations of larger wind farms relative to smaller ones, all else being equal.

When observations are divided between small and large wind farms, we reduce the statistical power to estimate the price effect in different distance intervals for different wind farm sizes. To increase the statistical power, we use 2 km intervals as boundaries for the treatment groups in this analysis for wind farms with both more and fewer than 10 turbines.

Regardless of the number of turbines at the nearest wind farm, the models estimate statistically negative price effects for proximity under 2 km from a wind farm becoming operational, see Table C1 in Appendix C. However, the magnitude of this effect varies with the number of turbines, and we find a 13 % price decrease for a distance under 2 km from small wind farms and 17 % for large wind farms. For properties impacted by small wind farms, the effect is slightly negative (around -3 %) and not significant up from 2 to 6 kilometres, and converges to zero after 6 km. In contrast, for properties affected by larger wind farms, the effect is significant and highly negative, even at greater distances from the wind farms.

The analysis of the significance of turbine count is limited because the majority of properties impacted by wind power development, specifically those properties within a 2 km radius of an operational wind farm, are located near smaller wind farms (mostly wind farms with less than or equal to five turbines). This presents challenges in estimating more precise models of the effect of wind farm size. The limited number of observations near large wind farms can result in a Type M error,[15] as we observe a substantial negative effect for the large wind farms even at greater distances, these estimates are somewhat uncertain (Gelman et al., 2020). However, the models suggest that larger wind farms may lead to a greater negative impact on property prices, as one would expect.

The heterogeneity analysis by wind farm size shows that large wind farms are the primary drivers of the significant price declines observed beyond 2 km in the baseline model. As shown in Fig. 2, the baseline specification identifies a substantial price reduction within 2 km of the wind farm. For properties located 2–7 km away, the estimated effects are smaller and only intermittently statistically significant, indicating greater uncertainty. The heterogeneity analysis demonstrates that this uncertainty, both in effect size and statistical significance, is largely driven by wind farm size. At these distances, small wind farms are associated with a small, statistically insignificant price effect, whereas large wind farms generate estimates that point toward a negative and statistically significant impact.

It is noteworthy that our data primarily consists of residential properties affected by small wind farms with a mean of 8.3 turbines.

[14] We have also estimated an alternative specification with ZIP-code fixed effects, which yields results very similar to those obtained with basic statistical unit fixed effects.

[15] A Type M (magnitude) error occurs when the estimated effect size is substantially exaggerated or understated, typically due to low statistical power or small sample sizes. It arises when an effect is detected, but the magnitude of that effect is inaccurately estimated, often because of high uncertainty or variability in the data.

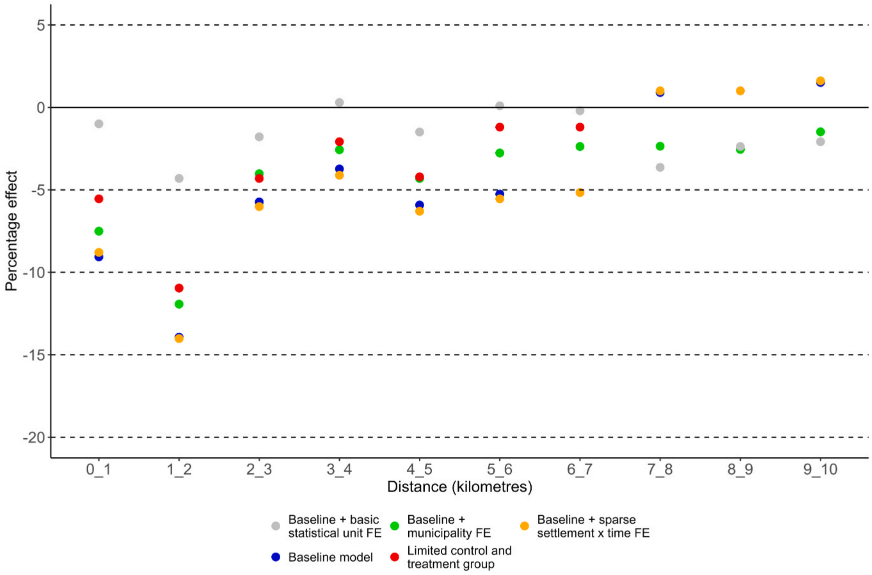

Fig. 3. The effect of wind farms on residential property prices at different distances with different model specifications. *Regression results from DiD model (1) with wind farm fixed effects (blue), wind farm and municipal fixed effects (green), wind farm fixed effects but with 7–10 km as control group (red), wind farm and basic statistical unit fixed effects (grey) and wind farm and sparse settlement fixed effects (orange). The points represent the estimated price effect as percentage of the property price for getting an operational wind turbine within the given distance interval from the property.*

This means that the results of this analysis predominantly apply to houses near smaller wind farms. See Table C1 in Appendix C for regression results for the analyses on the size of the wind farm, and more detailed discussion of the results.

4.4. *Event study results*

Our baseline model is static, assuming that the change in property prices occurs immediately when the wind farm becomes operational, and that the price effect remains constant thereafter. However, this price change may manifest itself partially or entirely during the construction or planning phases and evolve after the operational start.

To deepen our analysis, we conduct an event study to examine price developments both before and after the wind farm becomes operational. This allows us to explore expectation and anticipation effects in the pre-operation period, as well as potential adaptation dynamics and diminishing sensitivity after operational start. The event study also provides a direct assessment of the common trends assumption by comparing pre-treatment price paths between treatment and control properties. We implement this by estimating the DiD model with a set of lead and lag indicators relative to the year of operational start.

Market adaptation and potential price shifts can occur before wind farms become operational. Agents in the property market may pre-emptively adjust property prices due to anticipated externalities signalled by the licensing and construction process. Additionally, agents may anticipate future developments and facilities even before construction begins, influenced by news during the planning phase and government licensing procedures. Price effects may also vary after the operational start of the wind farm. Adaptation effects and diminishing sensitivity over time may influence how property prices adjust in the longer run. The actual impacts of the wind farm on nearby residents may differ from what was initially anticipated and capitalised into market prices at the time of operation, leading to further price adjustments as these realised effects become known.

We unfortunately have no information about the start of construction in the data, but we know that the construction time for wind farms is consistently ca. 2 years in Norway.[16] The information about the assumed construction time is used to define the start of construction as 2 years prior to the start of operations. Hence, we include a lead variable that estimates price effects occurring up to 2 years before the start of operation (ACPO). We also include additional lead variables to estimate price effects occurring from 2 years before the assumed construction time up to the start of construction (PC) and 2–4 years (PCL) before the assumed construction time up to the start of construction. The series of lead variables is constructed to investigate whether price adjustments occur pre-construction, and to investigate common trend. To estimate the development of the price effect after the wind farm starts operating, we include a variable that estimates the price effect occurring up to 2 years after the start of operation (O), a lag variable that estimates the price effect occurring 2–4 years after construction (OL) and a lag variable that estimates the price effect occurring at any time beyond this period (OLL).

When dividing the time period before and after the start of operation into several subperiods, the statistical power to estimate the

[16] According to Enova (2014), Riise et al. (2016) and THEMA (2019).

development in each subperiod is reduced. As highlighted by Miller (2023), this often leads to uncertain estimates and wide confidence intervals in event studies. Based on Miller's recommendations, we define time periods that span several years, instead of estimating an effect for each year before and after the start of operation. To further increase the statistical power, we use 2 km intervals as boundaries for the treatment groups for this analysis.

The event study model is inspired by Hoen et al. (2011) and is specified as:

$$\begin{aligned}\log(P_{i\mu t}) = {} & \alpha + \beta^{PCL}PCL_{\mu t} + \beta^{PC}PC_{\mu t} + \beta^{ACOP}ACOP_{\mu t} + \beta^{O}O_{\mu t} + \beta^{OL}OL_{\mu t} + \beta^{OLL}OLL_{\mu t} \\ & + \sum_{k\in K}\gamma_k I_{ik\mu} + \sum_{k\in K}\delta_k^{PCL}I_{ik\mu}PCL_{\mu t} + \sum_{k\in K}\delta_k^{PC}I_{ik\mu}PC_{\mu t} + \sum_{k\in K}\delta_k^{ACPO}I_{ik\mu}ACPO_{\mu t} \\ & + \sum_{k\in K}\delta_k^{O}I_{ik\mu}O_{\mu t} + \sum_{k\in K}\delta_k^{OL}I_{ik\mu}OL_{\mu t} + \sum_{k\in K}\delta_k^{OLL}I_{ik\mu}OLL_{\mu t} \\ & + \theta \mathbf{z_{it}} + \lambda_{\mu t} + \rho W_t + \varepsilon_{i\mu t}. \end{aligned} \tag{2}$$

In Eq. (2), $PCL_{\mu t}$ is a dummy variable that takes the value 1 if the property was sold 4–6 years prior to the operational start of the wind farm, otherwise 0. $PC_{\mu t}$ is a dummy variable that takes the value 1 if the property was sold 2–4 years prior to the operational start of the wind farm. $ACPO_{\mu t}$ is a dummy variable that takes the value 1 if the property was sold up to 2 years prior to the operational start of the wind farm (assumed during construction). $O_{\mu t}$ is a dummy variable that takes the value 1 if a property was sold between 0 and 2 years after the nearest wind power plant became operational, otherwise 0. $OL_{\mu t}$ is a dummy variable that takes the value 1 if the property was sold 2–4 years after the wind farm becomes operational. $OLL_{\mu t}$ is equal to 1 if the property was sold over 4 years after the wind farm became operational. The time period before PCLL serves as the reference for the time indicators (over 6 years prior to operational start). δ are the unknown DiD coefficients of interest and show the price effect on the properties of being within k km from a wind farm in one of the defined time periods ($k \in K = \{0-2,\ 2-4,\ \ldots,\ 8-10\}$). The estimated coefficients of interest are presented in Fig. 4.

As shown in Fig. 4, it is primarily properties within 0–2 km from an operational wind farm that experience a larger price decline. The coefficients for this distance indicate a price decline for the time periods after operational start, where estimates for 0–2 and over 4 years are statistically significant. We also observe a minor price decrease during the construction period (-2–0 years relative to operational start), although this estimate is not significant. The estimates before the construction period for the price effect of proximity within 2 km from a wind farm are also not statistically significant and close to zero. See Table B3 in Appendix B for complete regression table.

The results suggest that some market agents tend to adapt to the wind farm prior to its operational start. Some price adjustments for residential properties within 2 km of a wind farm seem to occur during the construction phase, although the estimates are not significant. We therefore observe trends indicating premature treatment effects.

We observe little evidence of price recovery over time, although there is a slight increase in all distance intervals 2–4 years after operational start. However, this increase is offset by a larger decline after 4 years, and the variation in price development during this period is likely due to the constraints arising from small sample sizes for each period. Price recovery in similar analyses has typically occurred at a later stage. In Guo et al. (2024), the rebound does not occur until 7 years after the wind farm starts operations. At the same time, some studies find no evidence of long-run price recovery. For example, Andersen and Hener (2025) observe property prices up to 10 years after operational start without detecting any signs of recovery. Westlund and Wilhelmsson (2025) find no effect of recovery after observing properties up to 7 years after operational start. However, we do not have enough observations long enough after operational start to extend the event study by more years, consequently it is possible that a price recovery might be observed in the longer run.

We also observe a small price decrease for residential properties located 2–6 km from the wind turbines after four years (around −5 %), although these estimates are not statistically significant. These later-period observations are therefore likely to be the main drivers of the significant negative price estimates in the baseline model for the 2–6 km range.

Despite the statistical power issues, we observe that the assumption of a common trend holds. The price development between distance intervals diverges little from the control group in the years before the construction period of the wind farms. In addition, the price developments for properties located 6–10 km from the wind turbines deviate little from the control group during the entire period.

4.5. The effect of wind turbine visibility

Existing research varies in its approach to estimating the impact of wind farm development on property prices, employing both proximity and visibility as treatment indicators for visual disamenity. However, we examine these effects jointly and isolate the two distinct impacts to determine which exerts a greater influence on property prices.

Proximity to wind turbines serves as a suitable treatment indicator as it captures the extent to which the neighbourhood is affected by visual effects and noise pollution, as well as shadow flickering. While proximity effectively represents the broader neighbourhood

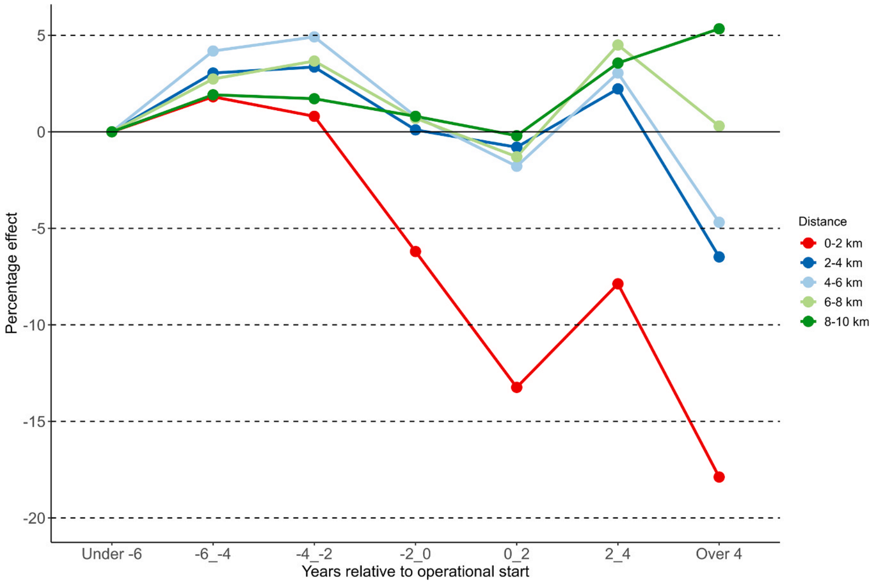

Fig. 4. Event study; the effect of wind farms on residential property prices at different time periods and distance bounds. *The effect on property prices of being within a given km interval of a wind farm at different time periods, before and after start of operation, relative to the control group. Model (2) has fixed wind farm effects. The points represent the estimated price effect as percentage of the property price for position within given distance interval of a wind farm.*

impact and can be used to estimate its effect on property values, having a direct view of a wind turbine may further increase the visual impact of wind farms. Therefore, we develop a model that distinguishes between the effects of visibility and proximity, estimating the additional impact of having a direct view of wind turbines beyond the effect of proximity.[17]

To identify whether each property has a view of a wind turbine, we used ArcGIS and a digital elevation model (DEM)—a bare-earth surface model that contains detailed information about the topography and elevation of the landscape.[18] We then incorporated the geographic location and height of both the properties and all wind turbines. To estimate the turbine viewshed, we used the turbine height up to the blade tip at the twelve o′clock position, following the approach of Gibbons (2015) and Dong et al. (2024). Furthermore, we refined the DEM by overlaying maps of forest cover and vegetation height from the Norwegian Institute of Bioeconomy Research (NIBIO) to account for potential visual obstructions caused by trees and vegetation between the property and the turbine.[19] This means that the visibility calculation explicitly accounts for whether vegetation or forest between the property and the wind turbine is sufficiently tall to obstruct the line of sight from the property to the turbines. It is important to note that most wind farms in Norway are situated in mountainous and coastal areas, which are sparsely populated and have limited infrastructure that can obstruct the view.

Recent research has examined which viewshed models are most suitable. Dong et al. (2024) conducted a study in New England, USA, analysing the impact of views of wind turbines using both digital surface model (DSM) and DEM within a DiD identification strategy, and compared the two methods.[20] They recommend DSM over the more commonly used DEM as the preferred viewshed model, as it accounts for trees and buildings that obstruct views.

However, we combine DEM with vegetation data, thereby addressing the vegetation challenges highlighted by Dong et al. (2024).[21] In doing so, we advance the literature, which has primarily relied on DEM without accounting for vegetation.[22] Our data also support the findings of Dong et al. (2024), highlighting the importance of incorporating surface obstructions in viewshed calculations. Our data

[17] We thank an anonymous referee for suggesting this approach.

[18] Digital elevation model data from the National Mapping Authority. See: https://kartkatalog.geonorge.no/metadata/hoeydedata-laser/f297e948-8a34-4e6c-9740–54b3a657f8d5 and https://hoydedata.no/LaserInnsyn2/.

[19] Visibility is measured as a binary variable equal to one when there are no obstacles in the line of sight from the property to the top of at least one wind turbine, defined as the blade tip at the twelve o'clock position. The line-of-sight assessment is conducted from the building's centroid at a height of two meters above ground level. Direct visibility may be obstructed by topography, such as hills, mountains, and ridgelines, as well as by vegetation or forest cover between the property and the turbine which is tall enough to obstruct the view.

[20] A DEM is a bare-earth surface model that provides detailed information about the topography and elevation of the landscape, whereas a DSM includes three-dimensional features on the surface, such as vegetation.

[21] Since we use DEM combined with information about surface vegetation, our model can be considered a hybrid between DEM and DSM. However, it does not fully correspond to a DSM, as there may still be surface elements that obstruct views but are not incorporated into our viewshed model beyond vegetation.

[22] Some previous studies that have utilized DEM in analyzing viewshed impacts from onshore wind turbines include Guo et al. (2024), Mei et al. (2024) and Gibbons (2015).

indicate that accounting for forests and vegetation reduces the share of residential properties within 20 kilometres of a wind farm with a view of at least one turbine from 32 to 25 %.[23]

We extend our baseline DiD model by incorporating a visibility variable into a Difference-in-Difference-in-Differences (DiDiD) identification strategy. The objective is to estimate the average effect of proximity to a wind farm after it becomes operational for properties without visibility of the wind turbines (isolating the distance effect), as well as the additional effect of visibility among properties that are both proximate and affected after the wind farm becomes operational (isolating the visibility effect).

We estimate the following regression model:

$$\log(P_{i\mu t}) = \alpha + \beta O_{i\mu t} + \delta^{V} V_{i\mu} + \delta^{VO} V_{i\mu} O_{i\mu t} + \sum_{k\in K} \gamma_k I_{ik\mu} + \sum_{k\in K} \delta_k^{IO} I_{ik\mu} O_{i\mu t} + \sum_{k\in K} \delta_k^{IV} I_{ik\mu} V_{i\mu} + \sum_{k\in K} \delta_k^{IOV} I_{ik\mu} O_{i\mu t} V_{i\mu} + \boldsymbol{\theta} \boldsymbol{z_{it}} + \lambda_{\mu t} + \rho W_t + \varepsilon_{i\mu t}, \tag{3}$$

where $V_{i\mu}$ is a time-invariant indicator equal to one if property i has line-of-sight visibility to at least one wind turbine. To increase statistical power, we expand the distance intervals of the treatment variables for proximity to 2 km increments ($k \in K = \{0-2,\ 2-4,\ \ldots,\ 8-10\}$). δ_k^{IO} is the DiD estimate that captures the average price effect of proximity to a wind farm after it becomes operational for properties where the wind turbines are not visible. δ_k^{IOV} is the coefficient that represents the DiDiD estimate for the additional effect of visibility among properties that are in proximity to a wind farm becoming operational. $\delta_k^{IO} + \delta_k^{IOV}$ represents the combined effect of proximity k and visibility of a wind farm becoming operational.

The results indicate that the DiDiD estimate reveals a significant additional negative effect of visibility of 14.2 % for properties within 2 km of a wind farm after it becomes operational. Corresponding estimates for distance intervals between 2 and 10 km are close to zero and not statistically significant. See Table D1 in the Appendix D for complete results.

Including both visibility and proximity as treatment indicators shifts part of the price effect previously attributed to proximity to the DiDiD coefficient for visibility. This is because proximity originally captured all disamenities — noise, visual pollution, and shadow flicker — whereas visibility now isolates the impact of direct visual pollution. Although the effects of noise and shadow flicker are likely correlated with both distance and visibility.

Including visibility in the model reduces the DiD estimate of the price effect of proximity to an operational wind farm to −1.2 % for properties located within 2 km without a view of the turbines. This estimate is not statistically significant. The proximity effect remains negative and statistically significant out to 6 km. The price effect of proximity to an operational wind turbine is −3.7 % at 2–4 km and −4.9 % at 4–6 km. Beyond 6 km, the effect is not statistically significant and converges towards zero.

The results align with the baseline model, indicating a negative effect of approximately 15.4 % for properties within 2 km with a view to a wind farm becoming operational, with the effect diminishing with distance and approaching zero at around 7 km. However, the DiDiD model reveals that most of the price effect for properties within 2 km is attributable to turbine visibility. For distances between 2 and 6 km, the price decline is relatively similar for properties with and without turbine visibility. In these cases, the findings suggest that the general disamenity associated with the mere presence of the wind farm is the primary driver of the price decline.

5. Discussion and conclusion

This study aimed to estimate the local people's preferences to avoid living near a wind farm and determine costs and externalities experienced by local homeowners. This is the first such study in Norway. By applying a hedonic pricing model in combination with spatial fixed effects and difference-in-differences design, it has been possible to utilize a large number of property transactions to reveal quantitative evidence that residential property prices are significantly lower near operational wind farms in Norway. Although the various models with different associated assumptions occasionally yield different estimates, there is a consistent and robust result that onshore wind farm development decreases the residential property prices.

The baseline model estimates an average price effect of about −9.1 to −13.9 % for properties located within 2 km of a wind farm becoming operational. This effect diminishes with distance from the wind turbines and becomes insignificant at 6 km and converges towards zero at 7 km. While the price effect within 2 km is substantial and robust, the price decrease observed between 2 and 7 km is smaller, typically around 5 %, and only intermittently statistically significant. This indicates that the price effect at these distances is more uncertain.

The robustness tests indicate that the magnitude and spatial extent of the estimated price effects are somewhat sensitive to model specification. Introducing increasingly fine-grained spatial fixed effects leads to smaller negative estimates. Under the specification with sub-municipal fixed effects (basic statistical unit level fixed effects), the estimated price declines are limited to around −4.4 % in the 1–2 km distance bins. This highlights uncertainty regarding the precise magnitude and geographic reach of the disamenity effect. Nevertheless, the overall pattern—negative impacts in the immediate vicinity of turbines that fade with distance—remains robust across specifications.

The heterogeneity analyses show that only residential properties located near large wind farms, measured by the number of turbines, experience a price reduction beyond 2 km, whereas properties near small wind farms do not. Moreover, the event study analysis

[23] Share of residential properties with a view of at least one wind turbine in an operational wind farm, or that will obtain such a view from a wind farm becoming operational in the future.

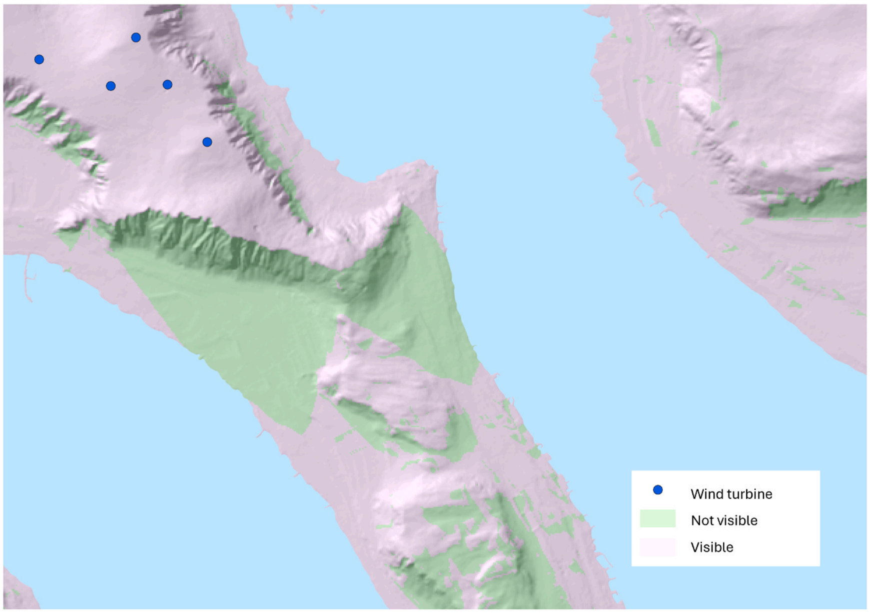

Fig. 5. Map of the DEM viewshed from the turbines. *The map is based on our DEM model in ArcGIS. It illustrates the viewshed from the wind turbines at Haram Wind Farm in Ålesund municipality on the west coast, determining whether a property is classified as having visibility of at least one turbine. The illustration does not account for the effects of forest cover or surrounding vegetation on visibility.*

indicates that the estimated price decline at these distances is driven by transactions occurring some time after the wind farm becomes operational. At the same time, there is likely substantial variation across wind farms in whether the price effect persists beyond 2 km and, if so, how far it extends, as several characteristics of the wind farm and the surrounding area may influence the magnitude and spatial reach of any specific local price effect.

To put the results in perspective, a back-of-the-envelope calculation suggests that onshore wind power development in Norway led to a reduction in residential property values by approximately USD 27 million to USD 341 million for properties sold between 2010 and 2022, depending on the model applied.[24] If one includes homes sold after 2022 or those not yet sold, the total depreciation in property values would be even greater.

Several similar studies have been conducted in other countries, and our results are at the upper end of the range of negative estimates. Parsons and Heintzelman (2022) review of 18 comparable studies over the past 10 years shows that 13 of the studies had negative estimates that were statistically significant. The average price effect across all studies for properties within 1 km of the nearest operational wind farm was −5 %. Most of the studies had a price effect that converged towards zero at around 5 km distance, which is a bit closer but similar to what we find. Schütt's (2024) meta-regression analysis of hedonic studies of wind farms finds an average negative price effect of 0.68 % for properties at about 3 km, which converges to zero for a distance of about 4.5 km.

Interestingly, these distances are comparable to those reported in studies that investigate how wind farms affect people's quality of life or willingness to pay to avoid impacts, as measured by stated-preference methods. Krekel and Zerrahn (2017), for example, show using quality-of-life data over many years in Germany that the negative impacts of wind farms are primarily felt within 4 km distance (and moreover, diminish over a five-year period).

The most relevant studies in relation to our results are the hedonic price studies conducted in comparable areas with similar topography and income levels as Norway, such as other Scandinavian countries. Jensen et al. (2014), for example, study the effect of wind farms on property prices in Denmark and find up to a 3 % reduction in property prices associated with visual pollution and a 3–7 % reduction associated with noise pollution. A more recent study from Denmark finds a reduction in residential property values of up to 12 %, with an additional decrease of 8.1 % for properties exposed to shadow flicker (Andersen and Hener, 2025). Denmark has a flatter topography than Norway, but the two countries are otherwise comparable in terms of culture and income levels. In Sweden, Westlund and Wilhelmsson (2025) find that property values within 2 km of wind turbines decline by approximately 10–15 %, with the effect diminishing to zero at distances beyond 6–10 km. That Norway, Sweden and Denmark have estimates that are somewhat larger than in an international context may be due to differences in preferences, for example, that Norwegians are somewhat more sensitive to

[24] The upper-bound estimate is derived from the baseline specification and includes properties within 6 kilometres of an operational wind farm, the furthest distance at which the estimated effect remains statistically significant. The lower-bound estimate is derived from the specification with basic statistical unit-level fixed effects and is limited to properties within 3 kilometres, consistent with the corresponding significance threshold. Aggregate effects are calculated using the estimated coefficients for each one-kilometre distance band. Note that we are unable to identify unique properties in the dataset, and some units may therefore be counted multiple times.

local infrastructure interventions.[25] If this is the case, it may have to do with there being less infrastructure in Norwegian nature, that people are more concerned with both nature conservation and nature-based recreation, and it may have to do with where Norway chooses to build wind farms relative to other countries. von Detten et al. (2023), for example, find that less densely populated areas in Germany had larger land value depreciation from proximity to wind farms than more populated areas, which is interesting as wind farms in Norway are often built in less populated areas. Lindhjem et al. (2022) find, by comparing results with an international study on acceptable distance to energy facilities (Harold et al., 2021), indications that Norwegians have more negative preferences for living close to wind power facilities than people in other countries. Guo et al. (2024) conduct a heterogeneity analysis that shows rural and mountainous areas experience larger percentage price reductions on average compared to urban and non-mountainous areas. This is particularly interesting as wind farms in Norway are typically constructed in remote mountain-adjacent regions. Norway also has distinctive topography, with rugged terrain, high-lying hills, and mountainous areas that are often used for wind farms. It is therefore possible that the wind farms are more visible from a long distance than in other countries.

Parts of the costs of developing onshore wind power are borne by local homeowners and the local population more generally. The wind farm owner does not currently pay the full costs of development (Handberg et al., 2020). It can therefore be argued that the local population is effectively paying a subsidy to the wind farm operator by covering part of the total social costs.

In the future, the number of property transactions in the vicinity of wind farms is expected to increase, with a greater number of nearby properties being sold multiple times. This trend will yield more robust data for analyses employing the repeated sales method in subsequent research. Such an approach would serve as a logical extension of our analysis and offer a valuable complement to spatial fixed effects, presenting an alternative to the difference-in-differences method for controlling unobserved factors and pre-existing price differentials.[26]

Other studies have attempted to disentangle the impacts of various externalities, such as noise and visual pollution, from one another (Jensen et al., 2014; Gibbons, 2015). The results of our viewshed analysis indicate that a significant portion of the price effect for properties within 2 km can be attributed to turbine visibility. For distances between 2 and 6 km, the price decline is relatively similar for properties regardless of turbine visibility. These findings suggest that the general disamenity associated with the mere presence of the wind farm is the main factor driving the price decline for properties 2–6 km from the wind farm.

In this analysis, we have investigated how the number of wind turbines affects the price. A natural extension of the study would be to examine this using more precise models, in addition to turbine height or other factors at the wind farm level that may affect the price. In our analysis, we find that larger wind farms, measured by the number of wind turbines, lead to a greater reduction in prices. Furthermore, we find that the price effect primarily occurs after the wind farm has started operation, although there are indications that some price adjustment happens already during the construction process. We further observe no evidence of price adjustments over time due to adaptation effects or diminishing sensitivity among the locals. However, our data covers only a limited number of years, and prices may rebound after a longer period.

Our analysis does not include recreational properties, such as cabins and larger vacation homes, which are both numerous and popular in Norway. These properties are also likely to be affected by wind power development but have been excluded from the analysis due to current data limitations. Looking ahead, there is potential for more extensive development of offshore wind power. The visibility of these offshore wind farms from land and their impact on property prices remain underexplored areas with potential for further investigation. [27]

CRediT authorship contribution statement

Henrik Lindhjem: Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Methodology, Investigation, Conceptualization. **Kristine Grimsrud:** Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation. **Markus Lund Andersen:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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[25] Parsons and Heintzelman (2022) also finds more negative net-effects of wind power on property values in European countries than in North America.

[26] We explored the possibility of estimating a repeat-sales specification in this study, however, it was infeasible because our data does not include complete property identifiers, like address. We attempted to create identifiers from a combination of property characteristics and incomplete cadastral numbers, but this yielded few observations, less than 5% of the full sample, and matches may still be incorrect.

[27] Some recent examples include Nytte et al. (2024), Dong and Lang (2022) and Jensen et al. (2018).

Declaration of Competing Interest

We have nothing to declare.

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Appendix A. Structural explanatory variables and descriptive statistics

Table A1
Overview of structural explanatory variables included in the HP function

Variable	Description	Expected effect
Log(Area)	Natural logarithm of the living area in square meters	+
Number of bedrooms	Number of bedrooms in the property	+
Floor	Which floor the apartment is located on	+
Basement	Dummy = 1 if the apartment is below the 1st floor	-
Boat space	Dummy = 1 if the property includes a boat space	+
Sparse Settlement	Dummy = 1 if the property is located in a sparsely populated area	-
Fireplace	Dummy = 1 if the property has a fireplace	+
Parking space	Dummy = 1 if the property includes a parking space	+
Shared laundry	Dummy = 1 if the property has a shared laundry facility	+
Elevator	Dummy = 1 if the building has an elevator	+
Detached house	Dummy = 1 if the property is a detached house	?
Apartment block	Dummy = 1 if the property is an apartment in a block	?
Terraced house	Dummy = 1 if the property is a terraced house	?
Townhouse	Dummy = 1 if the property is a townhouse	?
Duplex	Dummy = 1 if the property is a duplex	?
Modernized 2013–2022	Dummy = 1 if the property was modernized sometime from 2013 to 2022	+
Modernized 2003–2012	Dummy = 1 if the property was modernized sometime from 2003 to 2012	+
Construction year	A series of dummy variables for time intervals of construction years[28]	-

[28] Regression Table B1 in the appendix show an overview of the time intervals for the construction year.

Table A2
Descriptive statistics over relevant variables in the analysis

Statistic	Mean	Std. Dev	Min	Pctl(25)	Pctl(75)	Max
Distance in meter (to turbine)	12,527.5	4689.4	383.1	9139.5	16,167.4	20,000
Quantity turbines	8.276	12.9	1	1	7	80
Visible (surface and vegetation)	0.245	0.430	0	0	0	1
Visible (only surface)	0.315	0.465	0	0	1	1
Production start	2017	3.672	1998	2015	2020	2022
Price	3067,922	1371,585	505,000	2170,000	3650,000	9995,000
Area	104.9	55.87	16	64	136	397
Number of bedrooms	2.491	1.340	0	2	3	15
Floor	1.129	1.608	-2	0	2	15
Basement	0.0002	0.013	0	0	0	1
Sparse Settlement	0.076	0.265	0	0	0	1
Boat space	0.003	0.053	0	0	0	1
Fireplace	0.201	0.401	0	0	0	1
Parking space	0.467	0.499	0	0	1	1
Shared laundry	0.017	0.128	0	0	0	1
Elevator	0.099	0.298	0	0	0	1
Detached house	0.300	0.458	0	0	1	1
Townhouse	0.062	0.242	0	0	0	1
Apartment block	0.542	0.498	0	0	1	1

(continued on next page)

Table A2 (*continued*)

Statistic	Mean	Std. Dev	Min	Pctl(25)	Pctl(75)	Max
Duplex	0.040	0.195	0	0	0	1
Terraced house	0.056	0.229	0	0	0	1
Construction year	1976	31.668	1838	1960	2004	2021
Modernized 2013–2022	0.066	0.247	0	0	0	1
Modernized 2002–2012	0.278	0.448	0	0	1	1
Sales year	2016	3.752	2010	2013	2020	2022
Winter	0.445	0.497	0	0	1	1

Descriptive statistics for a total of 166,934 observations, including average value (Mean), standard deviation (Std. Dev.), minimum value (Min), lower quartile (25th Percentile), upper quartile (75th Percentile), and maximum value (Max). All variables with a 0 in Min and 1 in Max are binary.

Table A3
Number of observed transactions of residential properties in proximity to wind turbines

	Number of observations			Number of observations	
Pre/post operational start	Pre	Post	Pre/post operational start	Pre	Post
0–1 km	35	180	5–6 km	2771	3690
1–2 km	515	598	6–7 km	2886	3037
2–3 km	1891	1599	7–8 km	2990	2395
3–4 km	2749	2112	8–9 km	3839	2448
4–5 km	3256	3512	9–10 km	4716	3498

Appendix B. Regression tables

Table B1
Model (1) DiD and spatial fixed effects

	Independent variable: ln(price)					
	Baseline		Baseline + municipality FE		Baseline with limited study area	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
0–1 km	-0.102	0.062	-0.104*	0.048	-0.072	0.044
1–2 km	-0.026	0.052	-0.041	0.055	0.030	0.045
2–3 km	-0.062	0.039	-0.087*	0.039	0.013	0.035
3–4 km	-0.050	0.036	-0.067*	0.032	-0.004	0.027
4–5 km	-0.017	0.039	-0.031	0.034	0.027	0.026
5–6 km	-0.014	0.040	-0.023	0.032	0.014	0.023
6–7 km	-0.037	0.059	-0.015	0.032	-0.009	0.017
7–8 km	-0.144**	0.049	-0.051*	0.022		
8–9 km	-0.111*	0.044	-0.011	0.021		
9–10 km	-0.104**	0.036	-0.005	0.019		
0–1 km*operation	-0.095	0.060	-0.078	0.048	-0.057	0.044
1–2 km*operation	-0.150***	0.028	-0.127***	0.029	-0.116***	0.029
2–3 km*operation	-0.059***	0.015	-0.041**	0.015	-0.044**	0.013
3–4 km*operation	-0.038*	0.016	-0.026	0.019	-0.021	0.012
4–5 km*operation	-0.061***	0.016	-0.044*	0.018	-0.043**	0.013
5–6 km*operation	-0.054***	0.015	-0.028	0.018	-0.012	0.015
6–7 km*operation	-0.053	0.029	-0.041*	0.015	-0.012	0.013
7–8 km*operation	0.009	0.018	-0.024	0.014		
8–9 km*operation	0.010	0.016	-0.026*	0.011		
9–10 km*operation	0.015	0.012	-0.015	0.009		
Log area	0.616***	0.026	0.611***	0.025	0.670***	0.016
Number of bedrooms	0.006	0.003	0.006*	0.003	0.001	0.002
Floor	0.012***	0.001	0.010***	0.001	0.005**	0.002
Basement	-0.007	0.023	-0.017	0.021	-0.003	0.058
Sparse Settlement	-0.149***	0.024	-0.102***	0.017	-0.078***	0.019
Boat space	0.228***	0.028	0.219***	0.022	0.235***	0.050
Parking space	0.019***	0.004	0.018***	0.002	0.022**	0.007
Fireplace	0.028***	0.006	0.024**	0.007	0.004	0.005
Shared laundry	0.004	0.011	0.001	0.008	-0.006	0.009
Elevator	0.030**	0.009	0.021*	0.009	0.041	0.026

(continued on next page)

Table B1 (*continued*)

	Independent variable: ln(price)					
	Baseline		Baseline + municipality FE		Baseline with limited study area	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Townhouse	-0.040**	0.015	-0.069***	0.013	-0.053***	0.007
Duplex	-0.037	0.023	-0.063**	0.019	-0.068***	0.008
Terraced house	-0.054***	0.014	-0.086***	0.014	-0.056***	0.010
Apartment block	-0.014	0.022	-0.053*	0.023	-0.016	0.010
Modernized 2013-2022	0.058***	0.010	0.054***	0.013	0.071***	0.011
Modernized 2003-2012	0.048***	0.010	0.046**	0.013	0.063***	0.006
Construction 1993-2007	-0.061***	0.009	-0.071***	0.009	-0.063***	0.012
Construction 1978-1992	-0.184***	0.009	-0.203***	0.014	-0.188***	0.015
Construction 1958-1977	-0.202***	0.020	-0.230***	0.021	-0.230***	0.022
Construction 1938-1957	-0.183***	0.049	-0.210***	0.043	-0.279***	0.030
Construction 1913-1937	-0.130*	0.055	-0.166**	0.050	-0.253***	0.035
Construction 1888-1912	-0.101	0.051	-0.139**	0.049	-0.231***	0.032
Construction 1863-1887	-0.099*	0.046	-0.142**	0.046	-0.225***	0.055
Construction 1838-1862	-0.077	0.044	-0.126**	0.046	-0.254***	0.066
Winter	-0.018***	0.002	-0.017***	0.002	-0.015***	0.003
Wind farm FE interacted with Time FE	Yes		Yes		Yes	
Municipality FE	No		Yes		No	
Control group distance to wind farm	10–20 km		10–20 km		7–10 km	
Property characteristics	Yes (see above)		Yes (see above)		Yes (see above)	
Observations	166,272		166,272		48,603	
Adjusted R^2	0.764		0.792		0.786	

Overview of the estimated effect on property prices in the DiD model as per Model (1). Note that: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table B2
Model (1) DiD and spatial fixed effects

	Independent variable: ln(price)			
	Baseline + sparse settlement interacted with time FE		Baseline + basic statistical unit FE	
	Coefficient	Standard error	Coefficient	Standard error
0–1 km*operation	-0.092	0.056	-0.010	0.024
1–2 km*operation	-0.151***	0.028	-0.044*	0.017
2–3 km*operation	-0.062***	0.016	-0.018*	0.008
3–4 km*operation	-0.042*	0.016	0.003	0.013
4–5 km*operation	-0.065***	0.017	-0.015	0.009
5–6 km*operation	-0.057***	0.016	0.001	0.012
6–7 km*operation	-0.053	0.030	-0.002	0.010
7–8 km*operation	0.010	0.017	-0.037***	0.009
8–9 km*operation	0.010	0.016	-0.024***	0.006
9–10 km*operation	0.016	0.012	-0.021***	0.004
Wind farm FE interacted with time FE	Yes		Yes	
Sparse settlement interacted with time FE	Yes		No	
Basic statistical unit FE	No		Yes	
Control group distance to wind farm	10–20 km		10–20 km	
Property characteristics	Yes		Yes	
Observations	166,272		166,001	
Adjusted R^2	0.763		0.858	

Overview of the estimated effect on property prices in the DiD model with km intervals up to 10 km as per Model (1). Only the DiD estimates are displayed in this table. Note that: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table B3
Model (2), DiD and fixed wind farm effects with leads and lags

	Independent variable: In(price)	
	Event study	
	Coefficient	Standard error
0–2 km*PCL	0.018	0.039
2–4 km*PCL	0.030	0.015
4–6 km*PCL	0.041*	0.016
6–8 km*PCL	0.027*	0.010

(*continued on next page*)

Table B3 (*continued*)

	Independent variable: ln(price)	
	Event study	
	Coefficient	Standard error
8–10 km*PCL	0.019	0.015
0–2 km*PC	0.008	0.035
2–4 km*PC	0.033	0.019
4–6 km*PC	0.048	0.030
6–8 km*PC	0.036	0.020
8–10 km*PC	0.017	0.021
0–2 km*ACPO	-0.064	0.058
2–4 km*ACPO	0.001	0.027
4–6 km*ACPO	0.008	0.036
6–8 km*ACPO	0.007	0.012
8–10 km*ACPO	0.008	0.027
0–2 km*O	-0.142*	0.057
2–4 km*O	-0.008	0.028
4–6 km*O	-0.018	0.039
6–8 km*O	-0.013	0.013
8–10 km*O	-0.002	0.018
0–2 km*OL	-0.082	0.048
2–4 km*OL	0.022	0.021
4–6 km*OL	0.030	0.024
6–8 km*OL	0.044	0.037
8–10 km*OL	0.035	0.025
0–2 km*OLL	-0.197***	0.050
2–4 km*OLL	-0.067	0.042
4–6 km*OLL	-0.048	0.052
6–8 km*OLL	0.003	0.065
8–10 km*OLL	0.052	0.036
Wind farm FE interacted with time FE	Yes	
Control group distance to wind farm	10–20 km	
Property characteristics	Yes	
Observations	166,272	
Adjusted R^2	0.763	

Overview of the estimated effect on property prices in the DiD model with leads and lags and 2-km intervals up to 10 km as per Model (2). Only the DiD estimates are displayed in this table. Note that: $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Appendix C. The effect of quantity of turbines on the price effect

Table C1
DiD-model (1) with fixed wind farm effects, with only few or many wind turbines

	Independent variable: ln(price)			
	< 10 wind turbines		**≥ 10 wind turbines**	
	Coefficient	**Standard error**	**Coefficient**	**Standard error**
0–2 km*operation	-0.139**	0.029	-0.188*	0.080
2–4 km*operation	-0.034	0.022	-0.085	0.042
4–6 km*operation	-0.034	0.026	-0.121**	0.026
6–8 km*operation	0.018	0.018	-0.109***	0.026
8–10 km*operation	0.007	0.019	-0.058*	0.027
Wind farm FE interacted with time FE	Yes		Yes	
Control group distance to wind farm	10–20 km		10–20 km	
Property characteristics	Yes		Yes	
Observations	138,439		27,833	
Adjusted R^2	0.773		0.642	

Overview of the estimated effect on property prices in the DiD model with 2-km intervals up to 10 km for both properties effected by small (< 10 wind turbines) and large (≥ 10 wind turbines) wind farms. Only the DiD estimates are displayed in this table. Note that: $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Table C1 presents the regression results from the heterogeneity analyses examining differences in price effects between properties located near wind farms with many or few wind turbines. Here, model (1) with fixed wind farm effects is used, but we have included treatment variables for every 2 km interval up to 10 km both for turbine count over and under 10.

We have used a threshold of 10 wind turbines to differentiate between small and large wind farms, based on the observation that the average property in the dataset is situated near a wind farm with 8.3 turbines. The results from Table C1 indicate that property prices are more affected by proximity to large operational wind farms. It is noteworthy that among the residences impacted by development, specifically those within a 3 km radius of an operational wind farm, the majority are located near smaller wind farms. Out of a total of 2337 properties in this category, 1923 (or 82 %) are situated near an operational wind farm with 5 or fewer turbines, while 5 properties are located near a wind farm with between 5 and 10 turbines. Only 400 properties are within 3 km of an operational wind farm with 10 or more turbines, and 303 are within the same distance from a wind farm with 20 or more turbines. This suggests that wind farms established near residential areas typically feature a smaller number of turbines. The lack of data on property affected by larger wind farms also limits the potential for more detailed heterogeneity analyses of the effect of wind farm size, for instance, by employing narrower intervals for the number of turbines.

Appendix D. The effect of visibility on property prices

Table D1
DiDiD Model with fixed wind farm effects and treatment variable differentiated on visibility and distance

	Independent variable: ln(price)	
	Visibility and distance	
	Coefficient	Standard error
0–2 km	-0.204***	0.034
2–4 km	-0.084*	0.033
4–6 km	-0.032	0.039
6–8 km	-0.108	0.073
8–10 km	-0.124**	0.038
Visible	-0.024**	0.007
0–2 km*operation	-0.012	0.053
2–4 km*operation	-0.038*	0.015
4–6 km*operation	-0.050**	0.017
6–8 km*operation	-0.030	0.030
8–10 km*operation	0.007	0.015
Operation*visible	-0.018	0.022
0–2 km*visible	0.227***	0.034
2–4 km*visible	0.044*	0.020
4–6 km*visible	0.022*	0.009
6–8 km*visible	0.038	0.031
8–10 km*visible	0.060***	0.010
0–2 km*operation*visible	-0.153*	0.057
2–4 km*operation*visible	0.011	0.027
4–6 km*operation*visible	0.018	0.028
6–8 km*operation*visible	0.037	0.028
8–10 km*operation*visible	0.010	0.026
Wind farm FE interacted with time FE	Yes	
Control group distance to wind farm	10–20 km	
Property characteristics	Yes	
Observations	166,272	
Adjusted R^2	0.763	

Overview of the estimated effect on property prices in the DiDiD model that investigates the effect of visibility, as per Model (3). Note that: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Data availability

The authors do not have permission to share data.

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