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Wind Turbines, Shadow Flicker, and Real Estate Values

Carsten Andersen[1,2] · **Timo Hener**[1,2,3]

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Abstract

We analyze the impact of wind turbines on house prices, distinguishing between effects of proximity and shadow flicker from rotor blades covering the sun. By utilizing data from 2.4 million house transactions and 6,878 wind turbines in Denmark, we can control for house fixed effects in our estimation. Our results suggest strong negative impacts on house prices, with reductions of up to 12 percent for modern giant turbines. Homes affected by shadow flicker experience an additional decrease in value of 8.1 percent. Our findings suggest a nuanced perspective on the local externalities of wind turbines regarding size and relative location.

Keywords Wind turbines · House prices · Shadow flicker

JEL Classification R30 · Q42 · Q51

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✉ Timo Hener
thener@econ.au.dk

Carsten Andersen
candersen@econ.au.dk

1 Department of Economics and Business Economics, Aarhus University, Fuglesangs Alle 4, 8210 Aarhus, Denmark

2 Center for Research in Energy: Economics and Markets (CoRE), Aarhus, Denmark

3 CESifo Research Network Affiliate, Munich, Germany

1 Introduction

Wind power is the second-fastest-growing renewable energy source for electricity production globally (IEA 2020)[1], playing a significant role in the transition towards a more sustainable global energy mix to combat climate change (IBRD 2020). However, while wind turbines offer substantial benefits by reducing the *global* externalities associated with conventional fossil fuels, they also pose negative *local* externalities, as evidenced by their impact on house prices (Lang et al. 2014; Dröes and Koster 2016, 2021; Sunak and Madlener 2016; Dong et al. 2023).

One notable concern among property owners is the visual disturbance from turbines. Indeed, the adverse aesthetic appeal and the disruption of the perceived scenic quality of the surrounding landscape have been shown to suppress house prices (Gibbons 2015). Additionally, turbines produce a less subtle visual nuisance known as shadow flicker. When the sun shines through rotating blades, they cast shadows on nearby houses, creating a sensation of pulsating light intensity. Research shows that homeowners perceive the shadows as flicker (Haac et al. 2022) and report higher levels of annoyance (Voicescu et al. 2016). However, less is known about the willingness-to-pay to avoid shadow flicker or the monetary value of this disamenity.

In this paper, we present new insights into the effect of proximity to turbines and the impact of shadow flicker on house prices. However, estimating the local damages of wind turbines is a complex problem, primarily due to two key factors. First, the impacts of wind turbines vary with the relative position of properties and turbines. While some externalities like noise are predominantly influenced by the distance to turbines, shadow flicker only occurs in specific locations where the rotor blades block sunlight. Second, wind turbines are not randomly distributed across geographic areas, introducing potential biases when comparing house prices near and far from turbines. To disentangle the effects of proximity and shadow flicker, we leverage comprehensive data from Denmark, encompassing the universe of housing transactions and operating wind turbines over a 28-year period. We measure proximity by calculating the distance between turbines and houses based on their geographic coordinates, capturing disamenities associated with proximity. To assess shadow flicker, we determine whether the sun's position is ever blocked by rotor blades as observed from each house.

To establish causal effects, we employ a generalized difference-in-differences framework, leveraging the timing of newly established turbines and decommissioned turbines. Our estimation strategy includes granular geographic, time, and property controls to account for potential confounding factors and unobserved trends. The long time horizon implies that many properties are traded multiple times, which allows us to control for house fixed effects. Our repeat sales model ensures that our estimates are robust to arbitrary correlation between wind turbine exposure and time-constant unobservable characteristics of houses. The large sample of 2.4 million transactions and 6,878 turbines ensures that the inclusion of fixed effects does not compromise the precision of the estimates.

We find that setting up turbines that are taller than 60 m within 2 km of houses reduces property values by 3.8 percent. These negative price effects exhibit substantial heterogeneity across distance and turbine height. Small turbines of less than 60 m in total height exhibit no effect on house prices. Medium-sized turbines between 60 and 120 m show treatment

[1] Solar power had more net capacity addition since 2016.

effects of −4.5 percent at 1 km distance and −2.9 percent at 2 km. Their impact fades out at distances of more than 2 km. Dwarfing these impacts, though, are modern giant turbines of 120 m and higher, which reduce property prices by 12 percent at 1 km distance and 10 percent at 2 km. Their impact declines slowly with distance to the property and fades out after 5 km.

Our results for shadow flicker reveal comparatively sizable impacts on house prices. Exposure to shadow flicker of severe intensity—potentially more than 20 hours per year—results in a 7.7 to 8.1 percent decrease in house prices. Importantly, this effect is net of the impact of turbine proximity. The size of the shadow flicker estimate implies that the placement of turbines outside of the affected areas can severely dampen the house price effects from proximity to turbines.

Understanding the extent and nature of local damages and global benefits caused by wind turbines is crucial for policies aimed at transitioning to a green energy sector, as well as for spatial and urban planning policies. Based on our estimates and the projected avoidance of carbon dioxide from wind energy production, we calculate the societal benefits and costs of wind turbines. Assuming a high (low) social cost of carbon, the medium sized turbines between 60 and 120 m exhibit a societal benefit of €5.9 million (€1.5 million) during their lifetime, while giant turbines of 120 m and larger save carbon emissions worth €22.5 million (€5.6 million). As a thought experiment, we calculate how many houses could be in the vicinity of a turbine without the damages to property prices exceeding the societal benefits of the turbine. Using our damage estimates and assuming a high social cost of carbon, one could have 900 average houses with equally large lots within 2 km of a giant turbine before the damages exceed the benefits. Another interpretation of this number is that the public would be willing to compensate up to 900 homeowners for their damages to operate a giant turbine. Interestingly, for smaller turbines fewer houses should be placed within 2 km. This results comes from the fact that although the absolute damages are smaller from theses turbines, they are relatively larger compared to their smaller social benefits. The second result from this exercise is that the damages are several times larger if the houses are located in the shadow flicker area of the turbine. Avoiding this area vastly improves the social cost-benefit balance of turbines.

Our paper is related to the literature that uses hedonic pricing approaches (Rosen 1974) to estimate the local damages of wind turbines. A small branch of the literature investigates the visual disamenity of nearby turbines. Gibbons (2015) focuses on the impact of the direct view of wind farms using models of elevation and topography of the landscape. The results suggest that house prices in England and Wales fall by 5.8 percent if a wind farm is visible within 2 km. Lang et al. (2014) analyse viewshed of turbines in Rhode Island and find no effect on house prices. Sunak and Madlener (2016) analyze the impact of the visibility of four wind farms in Germany on house prices and find large negative effects. Only few studies attempted to estimate the impact of shadow flicker with inconclusive findings, often due to small samples of affected properties (see, e.g., appendix in Lang et al. (2014) or Sims et al. (2008)).

A larger branch of the literature analyses the proximity effects of wind turbines. Dong et al. (2023) estimate the impact of turbines in two US states, Massachusetts and Rhode Island, and find that house prices decline by 2.5 to 4.5 percent within 1 km of the turbine after construction. The authors do not find anticipatory price changes after the assumed announcement date. Brunner et al. (2024) specifically focus on announcement effects of turbines, using information on the universe of turbine sites in the United States and a large sample of house transactions. They find that house prices within one mile of a turbine decrease by 15% after announcement but recover 5 years after installment. Dröes and Koster (2016, 2021) estimate the effects of distance to turbines on house prices in the Netherlands. They find that the first turbine within 2 km of a property decreases house prices by on average 1.4 to 1.8 percent with sizable anticipation effects, where medium-sized turbines of 50–150 m height reduce house prices by 3 percent and turbines taller than 150 m by 5.4 percent. While this evidence consistently shows negative effects on house prices, earlier literature, based on partly small samples and case studies, did not unequivocally demonstrate declines in prices. Using selected turbines and limited transactions, several studies found no significant effect of proximity on house prices in the United States and the United Kingdom (Sims and Dent 2007; Sims et al. 2008; Hoen et al. 2011). In contrast, a study using one single wind farm with nine turbines and 1,405 transactions found very large negative effects on house prices in Germany (Sunak and Madlener 2017). Studies with larger, medium-sized samples still showed considerable variation in the results, ranging from very large negative effects in New York State (Heintzelman and Tuttle 2012) to moderate negative effects in Denmark (Jensen et al. 2014, 2018), and no effects in Ontario, Massachusetts, Rhode Island, and across the United States (Vyn and McCullough 2014; Lang et al. 2014; Hoen and Atkinson-Palombo 2016; Hoen et al. 2015).

Our paper distinguishes itself from the existing literature in several important ways. First, we provide the first estimates of shadow flicker exposure on house prices on a large scale. To achieve this, we overcome the challenge of small samples and measurement issues in the literature[2] by running a full simulation of shadow flicker for every house in Denmark over a long period of time. Our estimates show that houses affected by shadow flicker are subject to considerable losses in value. This local damage has profound implications for the optimal positioning of wind turbines relative to properties. Second, the scale of our data base makes it particularly suitable for a full repeat sales approach. We can include controls for property-level fixed effects for our entire analysis including heterogeneity tests while maintaining reasonable precision in the estimates. The house fixed effect specification is important for the causal interpretation of the results as it ensures that the estimates are based on the same houses before and after the turbine is installed and holds all stable unobserved house characteristics constant. Other examples of repeat sales approaches in the literature, typically as robustness checks for models with coarser aggregation at a regional or neighborhood level, include Lang et al. (2014), Dröes and Koster (2016, 2021), and Dong et al. (2023). Third, our estimates are substantially larger than what the newest literature finds, even when considering the heterogeneity across turbine height and distance. The comparatively large estimates highlight the importance of studying the impacts in different environments, including a country like Denmark with many spatially dispersed wind turbines.

Lastly, our findings also relate to the literature on the physical and mental health effects of wind turbines. Previous research has shown that low-frequency noise emissions from turbines are associated with cardiovascular diseases (Poulsen and Raaschou-Nielsen 2018). Zou (2017) shows that noise from nearby turbines leads to increased suicide rates.

[2] Attempts with engineering-based tools as in Lang et al. (2014) did not yield any significant results but were subject to very little variation. Others have used rules-of-thumb approximations of shadow flicker that did not result in conclusive findings (Atkinson-Palombo and Hoen 2014; Dröes and Koster 2016).

The remainder of the paper is organized as follows. Section 2 introduces the data. Section 3 describes the estimation strategy. Section 4 presents the estimation results and discusses policy implications. Section 5 concludes.

2 Data

2.1 Data Sources

For our analysis, we combine two data sources: (i) a dataset covering the universe of property transactions in Denmark and (ii) a register of wind turbines.

Property trades. We select all 2,811,188 property transactions in Denmark 1992–2019 using publicly available transaction registers.[3] After first excluding 349,159 transactions within the same family and subsequently excluding 97,627 price outliers as the two lower and upper percentiles, our main analysis sample consists of 2,364,402 transactions. These transactions involve 1,230,698 unique residential units, providing rich variation for specifications with house fixed effects. The data includes exact address information, selling price, date of sale, living area size, and unit type (apartment, row house, detached house, farmhouse, or holiday home). We obtain coordinates from the addresses and match the ground elevation to each house in order to correct elevation differences between houses and turbines.

Wind Turbines. The Danish Energy Agency provides publicly available information on all wind turbines that have been in operation since 1977 (Danish Energy Agency (2021)). This dataset includes geographical coordinates, commissioning and decommissioning dates, and various physical attributes such as ground elevation, turbine height, rotor blade diameter, and power capacity.

We include all onshore wind turbines operating at some point between 1977 and 2019, a total of 6,878 turbines, to be used in the analysis.[4] We use separate proximity indicators for short turbines (< 60 m) and tall turbines ($\geq$ 60 m). We define the total height of a turbine as the axis height plus half the diameter of the rotor blades. For the heterogeneity analysis, we split the tall turbines into medium-sized (60−120 m) and giant turbines (>120 m). Figure 1 displays a map of the turbines included in our analysis sample. From this we can see that turbines are particularly concentrated along the western coast where wind conditions are favorable. Other than that, turbines are fairly evenly distributed across the entire landmass of Denmark.

2.2 Treatment Variables

Our analysis centers around two key variables: the effect of a nearby turbine and the impact of shadow flicker. To determine the distances between traded properties and operational turbines, we calculate haversine distances using the latitude and longitude coordinates from the housing data. These distances are calculated for all properties and turbines in operation during the year of the transaction.

[3] The data were retrieved from boligsiden.dk in June 2020.

[4] We are not including wind turbines that are operated next to a property and primarily provide electricity to the same property, so-called domestic wind turbines (“husstandsvindmølle”).

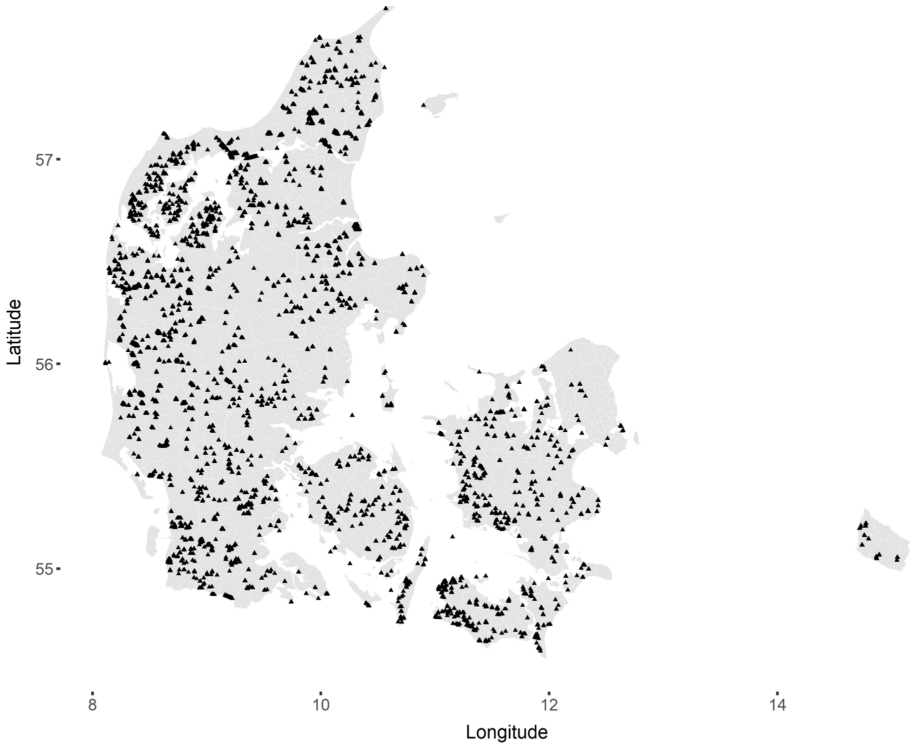


Fig. 1 Onshore turbines in Denmark.
Notes: The figure shows all onshore turbines in Denmark that were in operation between 1977 and 2019

Our main distance treatment variables indicate whether a short or tall turbine is operating close to an address. To construct these indicators, we first define the distance d_{iwt} of each house *i* to every turbine $w = \{1, ..., W\}$ in year *t*. Next, we define the distance to the nearest short (<60 m) turbine $d_{it}^{<60}$ as $\min_{w:h_w<60m} d_{iwt}$, where h_w is the height of turbine *w* in meters, and equivalently the distance to the nearest tall (≥60 m) turbine $d_{it}^{\geq 60}$ as $\min_{w:h_w \geq 60m} d_{iwt}$. Based on the distance to the nearest turbine in each height category, we define two treatment indicators

$$D_{it}^{<60} = 1\left\{d_{it}^{<60} \leq 2km\right\}, \tag{1}$$

and

$$D_{it}^{\geq 60} = 1\left\{d_{it}^{\geq 60} \leq 2km\right\}, \tag{2}$$

where $D_{it}^{<60}$ takes the value of one if house *i* in year *t* is less than 2 km away from its closest turbine that is less than 60 m tall, and zero otherwise. Similarly, $D_{it}^{\geq 60}$ is defined for turbines being at least 60 m tall. For heterogeneity analyses, we use flexible specifications with distances of up to 6 km.

Our second treatment variable, shadow flicker, refers to the rhythmic change in light caused by the rotating turbine blades partially blocking sunlight for a split second. To predict shadow flicker at a specific address, we project all turbines and sun positions throughout the year onto a 360-degree panorama as seen from the property. The projection creates a two-dimensional $(\text{azimuth}, \text{elevation})$ coordinate system, where the turbine blades span a circle representing the area they sweep. Shadow flicker occurs when the sun is within this circle of the swept area, with the radius of the circle corresponding to the rotor blade radius. The shadow flicker variable at a given minute *m* is the product of two indicator functions:

$$\text{sf}_m = 1\Big\{(s_e - r_e)^2 + (s_a - t_a)^2 \leq (r - 0.25)^2\Big\} \cdot 1\Big\{s_e \geq 3\Big\}, \tag{3}$$

where s_e denotes the sun's elevation, r_e denotes the rotor midpoint elevation (adjusted for ground elevation of the property and the turbine), s_a is the sun's azimuth, t_a is the turbine azimuth, and *r* is the rotor radius. All units are in degrees, and all sun positions are computed at a one-minute resolution using standard spherical geometry relations.[5] We consider turbines at distances of up to 15 times their rotor diameter as shadow flicker candidates because the diffusion of light beyond that limit reduces the visibility of shadow flicker (Haac et al. 2022).

The first factor of equation (3) measures whether the sun is within the swept area circle, taking into account the solar disk diameter by subtracting 0.25 from the radius. The second factor of equation (3) reflects that flickering is unlikely to occur at sun elevations below three degrees, considering factors like vegetation and building screening (UK Government, Department of Energy and Climate Change 2011).

For our analysis, we use two indicators for the prevalence of shadow flicker defined as follows:

$$\text{SF}_{it}^{(0,20]} = 1\Big\{0 < \sum_{m=1}^{M} \text{sf}_m \leq 20 * 60\Big\} \tag{4}$$

and

$$\text{SF}_{it}^{>20} = 1\Big\{\sum_{m=1}^{M} \text{sf}_m > 20 * 60\Big\}, \tag{5}$$

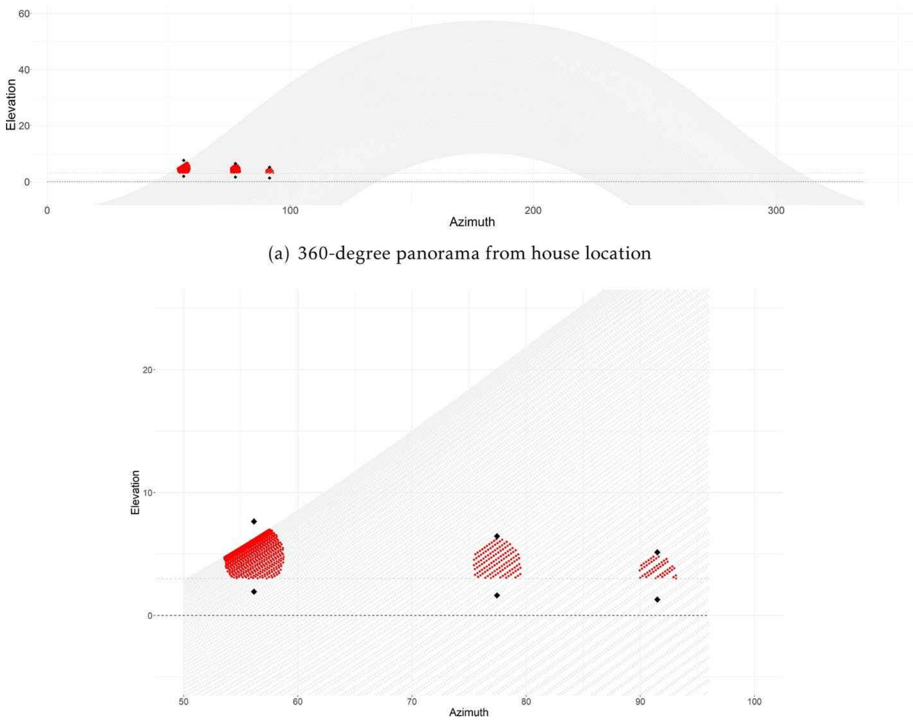
where $m = 1$ is the first minute of January 1 and *M* the last minute of December 31. If the total sum of the one-minute indicators sf_m is between 1 minute and 20 hours, $\text{SF}_{it}^{(0,20]}$

[5] The elevation angle of the sun is given by $\alpha = \sin^{-1}[\sin\delta \sin lat + \cos\delta \cos lat \cos h]$, where *lat* is the latitude of the address, and δ is the declination due to the seasonal tilt of the earth's axis given by $\delta = -23.44^\circ \cos[(360/365)(d + 10)]$, where *d* denotes the number of days since January 1. The solar hour angle *h* describes how far the sun moves away from the zenith at noon. Due to the earth's rotation, the sun moves 15 degrees per hour and thus the hour angle is given by $h = 15^\circ(LST - 12)$, where *LST* is the local solar time (i.e., the time that passes in hours relative to the local solar noon). The azimuth angle of the sun is then given by $azimuth = \cos^{-1}[(\sin\delta \cos lat + \cos\delta \sin lat \cos h)/\cos\alpha]$. The sun position simulation is implemented in the R-package *suncalc*.

equals one and is zero otherwise. Accordingly, $SF_{it}^{>20}$ is an indicator for shadow flicker that exceeds 20 hours.

It is important to note that our simulation of shadow flicker represents a worst-case scenario, assuming constant sunshine, continuous turbine rotation, and no screening from buildings or trees. During turbine site planning in Denmark, public entities are recommended to limit actual shadow flicker at houses to 10 hours per year. The shadow flicker threshold remains a recommendation rather than a strict regulatory mandate and was for the first time distributed in a guidance document related to a government directive on turbine site planning in March 2001. In practice, it may mean that owners are compensated or that turbines limit actual shadow flicker by pausing operations temporarily. As a result, our estimates reflect a lower bound of the potential impact of shadow flicker on house prices. Observed shadow flicker typically deviates from predicted shadow flicker by a factor of three to four (Haac et al. 2022). Therefore, our 20-hour worst-case threshold indicator corresponds to approximately 5–7 hours of visible shadow flicker.

Panel (a) of Fig. 2 provides a visual representation of a full 360-degree projection for a specific address in our dataset. The x-axis represents the azimuth, spanning from due north (0 degrees) to due east (90 degrees), due south (180 degrees), and due west (270 degrees).



(a) 360-degree panorama from house location

(b) Zoom on turbines

Fig. 2 Example of shadow flicker.
Notes: Figure shows shadow flicker from three distinct turbines for one of the houses in the dataset. Each gray dot represents a minute of the sun's azimuth and elevation from the perspective of the house for different days throughout the year. The black diamonds mark the upper and lower points of the turbine blades. The red dots represent minutes where the turbine exposes the house to shadow flicker. Panel (**a**) is a 360-degree panorama, while panel (**b**) zooms in on the area where the turbines are located

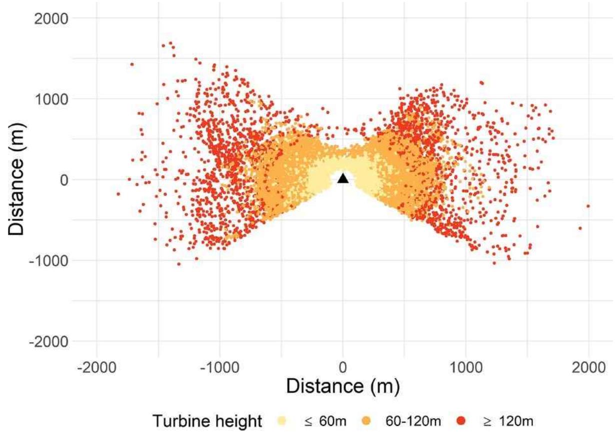


Fig. 3 All shadow flicker transactions.
Notes: Figure shows the positions of houses in relation to turbines that cause shadow flicker. All turbines are centered at the triangular midpoint. Yellow dots are properties that experience shadow flicker from short turbines of less than 60 m, orange dots denote properties that experience shadow flicker from turbines between 60 and 120 m, and red dots represent the largest turbines of more than 120 m in height. The distance on the axes indicate the proximity of the turbine to the property in a coordinate system

The y-axis represents the elevation angle, where values above zero degrees indicate visibility. The gray area represents the sun's positions throughout the year, with the lower boundary indicating the winter solstice (sunrise and sunset south of 90 and 270 degrees) and the upper boundary representing the summer solstice (sunrise northeast and sunset northwest). The projection highlights three turbines in the eastern direction that cause shadow flicker at the given address.

Panel (b) of Fig. 2 zooms in on these turbines, with black diamonds denoting the highest and lowest points of the rotor blades. Each dot represents a one-minute sun position, showcasing the simulation for every second day of the year.[6] The dots are colored in red if the rotor blades fully blocks the sun, while sun positions below three degrees are disregarded. This figure emphasizes an important aspect of shadow flicker prevalence. Turbines situated closer to the summer solstice boundary in the northeast (and northwest) result in more shadow flicker due to smaller azimuth angle changes than those seen in spring and fall. The same applies to turbines near the winter solstice. Additionally, the sun passes the turbines twice a year during its transition between the summer and winter solstice. The total count of minutes with sun blockage contributes to the definitions of $\mathrm{SF}_{it}^{>20}$ and $\mathrm{SF}_{it}^{(0,20]}$.

Figure 3 provides an overview of the positions of houses in relation to turbines that cause shadow flicker in the dataset. The triangular midpoint represents the normalized position of all turbines. Each dot represents a property that experiences shadow flicker, and the distance on the axes indicates the proximity of the turbine to the house in the north-south and west-east directions.

Due to the changing elevation angle of the sun throughout the day, houses located east and west of the turbines have the highest likelihood of experiencing shadow flicker. In the northern direction from the turbines, shadows are only present if the house is very close,

[6] This restriction is only imposed to make the graph easier to read. For the variable definition, the simulation runs for every day.

as the sun tends to be elevated and passes above the turbine for the most part. By contrast, shadows never appear in the southern direction from the turbines.

This shadow pattern implies that there are houses that are the same distance to turbines that will never experience shadow flicker due to their relative angles to the turbine. Additionally, the houses are color-coded to indicate the height of the turbine that causes the shadow flicker. Small turbines below 60 m in height predominantly cause shadow flicker in close proximity to houses, while giant turbines above 120 m can cause shadow flicker at distances of up to 2 km.

2.3 Descriptive Statistics

Table 1 presents the mean values for the variables used in the analysis, along with the standard deviations in parentheses for continuous variables. We show means for the full sample in column 1, and means for the sample of properties with repeated sales in column 2. The key variables of interest are property prices and the main treatment indicator, which identifies properties located within 2 km of a wind turbine in a given year.

The average price of a property is €200,959. 19 percent of all properties in the dataset are within 2 km of a turbine at the time of sale, 13 percent of properties are within 2 km of a short turbine (<60 m), and 6 percent are near a tall turbine (≥60m). The table also indicates that 0.53 percent of all properties are affected by shadow flicker at the time of sale. Furthermore, 0.4 percent of properties experience shadow flicker for between 0 and 20 hours per year, while 0.1 percent of the properties endure shadow flicker for over 20 hours.

In the lower section of Table 1, we present the distribution of property types and characteristics of properties among the sales. The majority of transactions, 56 percent, involve

Table 1 Mean values for main sample

	Full sample	Multiple trades
	(1)	(2)
Price	200,959 (146,184)	199,880 (142,900)
Below 2 km	0.19	0.19
Below 2 km x < 60 m	0.13	0.13
Below 2 km x > 60 m	0.06	0.06
Shadow flicker		
Any shadow flicker	0.0053	0.0051
Shadow flicker 0–20h	0.0043	0.0042
Shadow flicker > 20h	0.0010	0.0009
House type		
Apartment	0.22	0.26
Farmhouse	0.02	0.02
Holiday home	0.11	0.11
Row house	0.09	0.09
Detached house	0.56	0.52
House characteristics		
Size (m2)	124 (54)	120 (54)
Sales year	2005 (8)	2005 (8)
Observations	2,364,402	1,776,490

Notes: Table shows mean values along with standard deviations in parentheses (only for continuous variables). Prices are in 2021 euros detached houses, while 9 percent are row houses. Another 22 percent of sales come from apartments. Farmhouses, meanwhile, represent a smaller portion, comprising only 2 percent of the transactions. Additionally, our sample includes holiday homes, which account for 11 percent of the sales.

One concern with the repeat sales approach is the potential lack of representativeness of the properties that contribute to the identification relative to the broader housing market. As indicated by the means in column 2 of Table 1, properties that have undergone multiple sales do not significantly differ from the average transaction within the market. The most notable distinction is that repeat sales are 4 percentage points more likely to involve apartments rather than detached houses. Additionally, the similarity between the two samples is underscored by the observation that repeat sales constitute approximately 75 percent of the overall sample.

Figure 4 illustrates the growth in house prices for properties located above and below 2 km from a tall wind turbine, respectively. Throughout all years, properties in close proximity to a turbine tend to have lower prices, which can be attributed to a combination of treatment effects and selection effects. The primary objective of the initial part of the analysis is to determine the extent to which the price difference can be attributed to the proximity of wind turbines.

With the exception of the setback caused by the financial crisis, both types of properties exhibit a secular price growth over time. However, the price gap between the two groups is widening. This widening gap can be influenced by factors such as differential price growth between urban and rural areas, changes in treatment effects, or variations in the composition of properties being sold.

3 Methodology

Identifying the causal effect of turbines on house prices is challenging because turbine proximity is not randomly assigned to properties. Indeed, wind conditions, land value, and government regulation affect the decision of where to install turbines. Accordingly, the sites are often close to the coast, where stable wind promises higher efficacy, and in areas with low

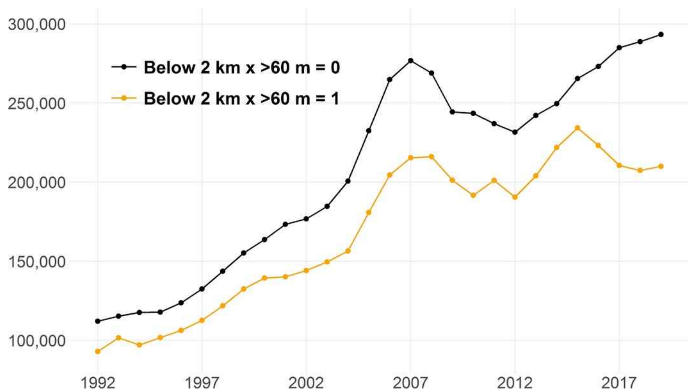


Fig. 4 Average prices by treatment status (2021 euros).
Notes: Figure shows the average property prices from 1992–2019 by treatment status of being within 2 km and turbine above 60 m of any onshore turbine

land values that keep costs down. Governments may impose minimum distances to settlements and compensation for property owners. Any of the factors involved in the decision to place turbine sites in particular locations is a potential determinant of or correlated with property prices, yielding a bias in cross-sectional regressions.

Our identification strategy exploits variation in terms of when and where turbines are installed. We use information on the commissioning and decommissioning date for every turbine to identify whether a property is close to an operating turbine at any point in time. We exploit the fact that turbines are installed and scrapped in the proximity of houses, while other properties either never or at a different point in time have a nearby turbine. Thus, we essentially compare houses before and after a nearby turbine was installed or scrapped to houses in the same period that did not experience any change in nearby turbines.

Our proximity treatments $D_{it}^{<60}$ and $D_{it}^{\geq 60}$ for turbines within 2 km capture both the commissioning and decommissioning of turbines at close distance, so we assume in the baseline that both events have the same impact magnitude with opposite signs. An active turbine may affect close properties through noise exposure (see Zou (2017)) and visibility (see Gibbons (2015)). Given that both impacts increase with proximity and decrease with blockages in direct sight, we regard noise and visibility effects as indistinguishable. Our second treatment, shadow flicker ($\mathrm{SF}_{it}^{(.)}$), however, is in fact distinguishable because the exposure is only partially correlated with proximity.

Our main outcome variable in the hedonic pricing regressions is the log price of a property. The identification strategy builds on a flexible repeat sales estimation approach with fixed effects for the address and year. Our baseline estimation equation at the address-year level is

$$log(Y_{it}) = \alpha_i + \lambda_t + \gamma_1 D_{it}^{<60} + \gamma_2 D_{it}^{\geq 60} + \delta_1 \mathrm{SF}_{it}^{(0,20]} + \delta_2 \mathrm{SF}_{it}^{>20} + \varepsilon_{it}. \quad (6)$$

The dependent variable is the logarithm of the house price *Y* at address *i* in sales year *t*. As turbines are not randomly allocated, it is important to control for factors determining both the location of turbines and house prices. Typically, turbines would be placed in more rural areas with cheaper land. To exclude fixed differences in house prices between addresses, we include address fixed effects in α_i, controlling for all time-constant house-specific unobservable characteristics. To capture temporal rises and falls in house prices that might be correlated with turbine expansions, we include fully flexible year fixed effects in λ_t. These year effects are allowed to differ between the four house types: detached houses, apartments, farmhouses, and vacation homes.

It should also be noted that differential trends in house prices that correlate with turbine installments could bias the results. As the above controls only capture common price changes over time within the same house type, the estimates are biased if turbines are placed in areas that are on the decline (or rise) relative to the control areas. Therefore, we also include municipality-specific year fixed effects that flexibly exclude deviations from common changes over time. The results are therefore robust to turbine positioning that reacts to temporal price shifts in municipalities, rendering the common trend assumption less demanding.

The parameters γ_1 and γ_2 identify the effects of short and tall turbines within a 2 km radius, while the parameters δ_1 and δ_2 identify the effects of low and high intensity of shadow flicker. The parameters identify the effect of a turbine on house prices under the assumptions of being homogeneous across time and addresses, and of having the same magnitude with opposite signs for the commissioning and decommissioning of turbines. Standard errors are clustered at the postal code level to allow for arbitrary correlation across houses in the same area and over time.

4 Results

We begin by discussing the role of address fixed effects in the estimation of turbine proximity impacts, before introducing the shadow flicker treatments. Table 2 presents the main results. Our first set of results is based on the 2 km proximity indicators for short and tall turbines. We document in columns 1 and 2 how the price effect is moderated by address fixed effects. The estimates without address fixed effects are very large. The decreases of 9.7 and 13.0 percent[7] for short and tall turbines are very likely overestimated. Turbines are placed close to houses of significantly lower value than the average, as is evident from the drop in the coefficient when we include address fixed effects in column 2. The negative effect falls to 4.0 percent for tall turbines, still implying a significant drop in market prices for houses when a tall turbine is set up in a 2 km radius. The estimate for short turbines is close to zero and statistically insignificant.[8] Note that the impact of the first turbine is amplified by the presence of additional turbines. In Appendix Table 6, we separate the effects based on the number of tall turbines installed within 2 km of an address, assigning each of the first five turbines its own treatment effect. The first turbine consistently shows a significant negative

Table 2 Effect of wind turbine proximity on log house prices for different specifications

Dependent variable	ln (Price)			
Model	(1)	(2)	(3)	(4)
Below 2 km× >60 m	−0.122***	−0.039***	−0.037***	−0.040***
	(0.019)	(0.008)	(0.008)	(0.009)
Below 2 km× <60 m	−0.093***	−0.003	−0.003	−0.005
	(0.013)	(0.009)	(0.009)	(0.010)
Shadow flicker 0-20h			−0.021	−0.024
			(0.019)	(0.020)
Shadow flicker >20h			−0.096***	−0.090***
			(0.030)	(0.030)
Controls				
Year×Home type	Yes	Yes	Yes	Yes
Address	No	Yes	Yes	Yes
Municipality×Year	Yes	Yes	Yes	Yes
Sample	Full	Full	Full	< 6 km
Observations	2,364,402	2,364,402	2,364,402	1,840,087

Notes: Table shows estimation results of equation (6). Standard-errors clustered at postal code in parentheses. Significance levels:$^{***}p < 0.01$,$^{**}p < 0.05$,$^{*}p < 0.1$.

[7] The coefficients from the log-level regression are transformed into percentage effects by $(e^{\beta} - 1) * 100$.

[8] Although based on a different sample of houses and turbines and estimated without address fixed effects, Jensen et al. (2018) find comparable results. The effect of an additional turbine averaged across all turbine heights is a price drop between 0.2 and 1.1 percent.

impact on house prices. Our main estimate is roughly equivalent to the combined impact of the first and second turbines.

In column 3, we add the shadow flicker treatments and show the results for the full specification in equation 6. Low shadow flicker exposure produces an insignificant −2.1 percent effect on house prices, whereas high exposure to shadow flicker of more than 20 hours yields statistically significant price decreases of 10.1 percent. Including the shadow flicker treatment does not change the proximity estimates. Thus, shadow flicker, only partially correlated with distance, has an additional negative effect on house prices on top of the distance effect. As we assume that the view of the turbine is unobstructed, some houses enter the estimation as affected by shadow flicker although they are not, implying that our estimates are lower bounds of the impacts from shadow flicker.

In column 4, we restrict our sample to houses that are not farther away from turbine locations than 6 km. With this restriction, we rely on a control group of houses that are more localized. None of the estimates significantly change compared to the estimates in column 3, using the full sample. This lack of change in the estimates highlights that our identification, based on house fixed effects estimations, does not rely on local control groups. Instead, the untreated observations only contribute to the identification of the common controls and fixed effects in the estimation.

Several hypotheses could explain the decline in housing market prices. Potential buyers may gather information on property-specific assessments of nuisances and compensations paid to homeowners living near newly installed turbines. While the value of these compensations may directly influence house valuations, buyers might also anticipate greater damages from future wind park expansions or a deterioration in neighborhood quality. One potential counteracting mechanism to falling house prices is preference-based sorting, where buyers less affected by turbine nuisances are willing to purchase these properties at reduced or even no discounts. However, empirically, this sorting mechanism does not appear strong enough to significantly limit the observed price declines.

Taking into account the staggered timing of the turbine treatments and the fact that the underlying treatment effects were heterogeneous across houses, the estimates from the fixed effects regressions may be subject to biases from negatively weighted and poorly identified treatment effects that are described in more detail in Goodman-Bacon (2021) and Borusyak et al. (2022).[9] We use an imputation estimator (Borusyak et al. 2022) to test for the robustness of our main estimates against arbitrary heterogeneity in treatment effects and find very similar results. The robust estimator for our tall turbine proximity indicator is also −0.037 with a standard error of 0.009.[10] It is not surprising that in this setting, where there are large numbers of never-treated houses, the estimates are fairly stable.

The dummy specifications in Table 2 for distance and shadow flicker are motivated by the literature and convenience in interpretation, but they may mask important heterogeneity. We therefore estimate a flexible specification of distance to the closest turbine, where each bin dummy represents a 500-m-wide circle of the radius around the property, and show coef-

[9] The large number of never-treated observations in our data alleviates the potential for bias from negative weights; see Borusyak et al. (2022).

[10] The estimates rely on the simplifying assumption that a property is forever treated after the first time a turbine is located within its 2 km radius. The robust estimate for the long duration of shadow flicker is similar, too. The imputation estimator yields -0.113 with a standard error of 0.022. Note that this estimate is conducted under a further simplifying assumption that the first (tall) turbine within 2 km determines the year of the first shadow flicker.

ficients in panel (a) of Fig. 5 with 95% confidence bands. The negative house price effects are largest at short distances and decay up to a 2km distance. All estimates thereafter are close to zero, and the threshold of 2 km in the baseline estimation is thus supported by the data.[11]

We similarly test the shadow flicker specification by estimating a flexible binned version of flicker duration in 5-hour bins in panel (b) of Fig. 5. There is a negative effect for up to 5 hours of shadow flicker of approximately −5 percent and the confidence interval just includes zero. Estimates for 5 to 20 hours of flicker are statistically insignificant and relatively close to zero. At a flicker of 20 hours or more, the three estimates become strongly negative at around −10 percent. All confidence bands reach close to the zero mark. They are large because there are fewer observations in the 5-hour bins, which is still consistent with significant impacts of the broader category in the baseline estimation. The results suggest that a split at 20 hours of shadow flicker would be sufficient to capture the treatment intensity differences.

Figure 5(b) also suggests that the effective cap could be reduced to about 15 hours of worst case scenario shadow flicker, or 3.75–5 hours of actual flicker, while avoiding detrimental house price effects. It is worth considering the tradeoff between reduced electricity production and nearby real estate values, or alternatively, to invest in systems that shut down the turbines at exactly the times at which shadow flicker occurs (Res-Group (2024)).

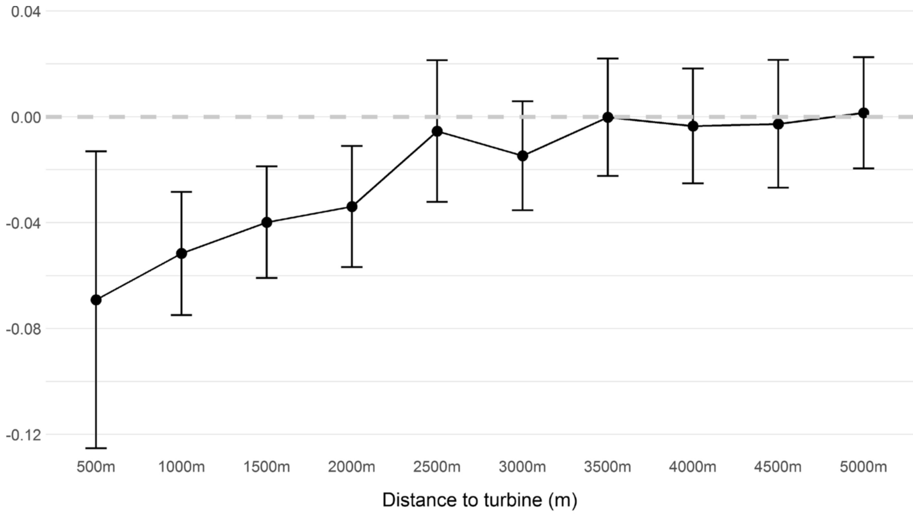
In Fig. 6, we investigate the timing of the turbines' impacts before and after commissioning, for which we focus on the effect of tall turbines. An involved planning phase precedes the installment of new turbines, which can create anticipation effects. The process of setting up a wind turbine requires an application at the municipality and, usually, an environmental impact assessment. The municipality is given up to one year to decide whether the project can be included in a local plan if the turbine should be placed in a pre-approved area for turbine developments. The process may take longer if it concerns a location outside the development areas. After a positive municipal evaluation, the local plan is made public. Typically within eight weeks of the evaluation, stakeholders are then permitted to comment and litigate, after which the physical building phase can begin. Hence, anticipation effects of one year are not unlikely. If all price effects are realized immediately, we would expect the property prices to drop once and remain at a lower level.

In the analysis shown in Fig. 6, we set the baseline period to $t = -2$. From 10 years prior to three years before commissioning, we see no significant price changes and no indication of differing pre-trends between the treated and non-treated properties. Moreover, one year prior to commissioning there is only a slightly negative coefficient but no statistically significant anticipation effect. Thus, we do not find that the housing market anticipates the installment of turbines.[12] In the year of commissioning, the coefficients turn negative to just over 2 percent and are at the border of statistical significance. The estimates remain similar until four years later, and increase in magnitude to approximately −4 percent in year 8 and −6 percent in year 10.

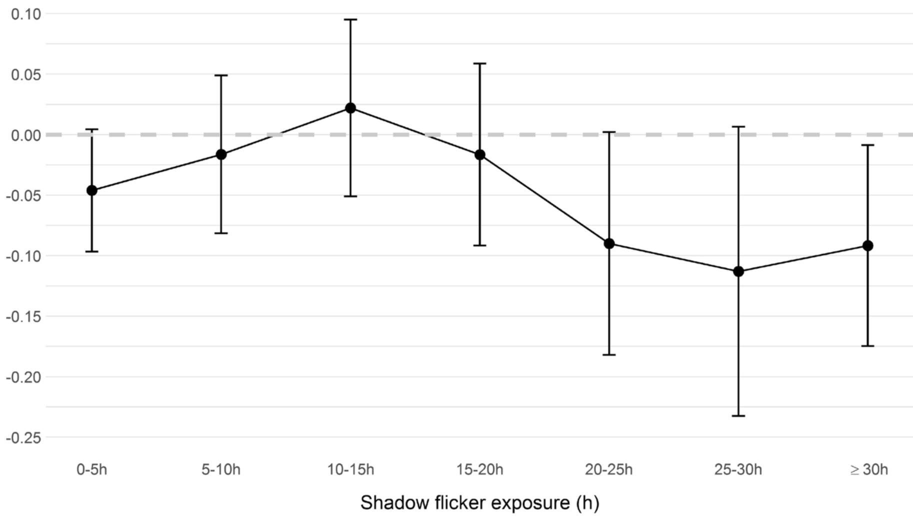
Although the point estimates are increasing in magnitude in later years, they lack some precision and their confidence bands all include the main estimate of −4 percent. Taking the

[11] For comparison, Dong et al. (2023) find effects mostly within 1 km, Dröes and Koster (2016, 2021) use a 2 km impact limit, while other studies suggest farther reach (e.g., Gibbons (2015); Sunak and Madlener (2016); Jensen et al. (2018); Zou (2017)).

[12] This finding of weak or no anticipation effect mirrors the finding in Dong et al. (2023). In contrast, there are strong anticipation effects in Dröes and Koster (2016), see Fig. 5 therein for comparison.



(a) Distance bins



(b) Shadow flicker duration

Fig. 5 Effects of distance and shadow flicker duration.
Notes: Panel (**a**) shows the estimated coefficients for turbine proximity split into 500 m bins of distance to the property, while panel (**b**) shows the estimated coefficients for shadow flicker divided into length intervals of 5 hours and a category of 30 hours or more. The estimation controls for the fixed effects, as in column 2 of Table 2. The whiskers show 95% confidence intervals

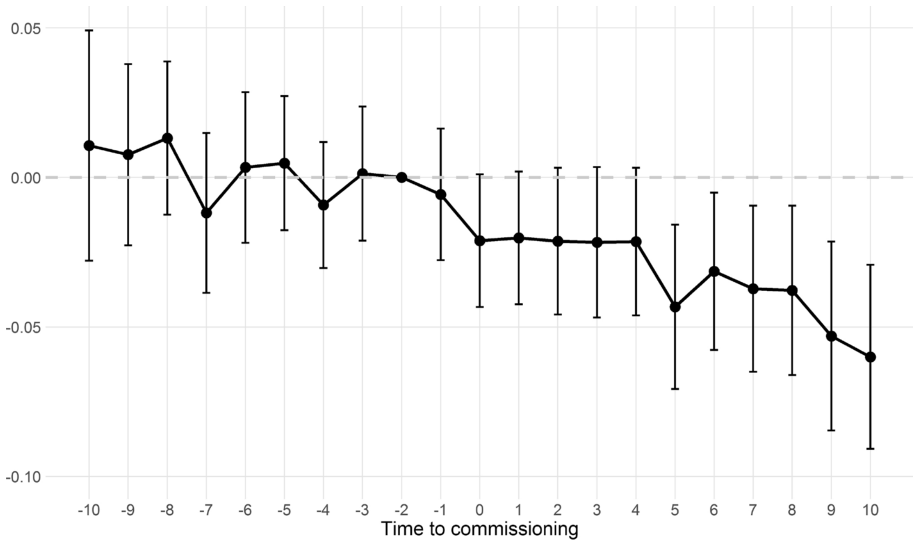


Fig. 6 Event study of turbine proximity effects.
Notes: Figure shows the estimated coefficients for tall turbines within 2 km with yearly lags and leads from 10 years prior until 10 years post the commissioning. The excluded category is $t = -2$. The estimation controls for the fixed effects, as in column 3 of Table 2. The whiskers show 95% confidence intervals

point estimates at face value, compositional and technical reasons are candidate explanations for the increase over time. First, salience of damages to house prices may take time to take full effect after the establishment of a turbine. Local newspapers may report about lower sales values and local opposition may grow over time, exacerbating the impacts. Second, when houses are sold for lower prices, the socio-economic composition of the neighborhood may change and lead to prices falling further. Third, we are estimating the impact of the first turbine in proximity. The impacts could be exacerbated by additional turbines being added to the site in later years. Fourth, our estimation sample is an unbalanced panel and may include a varying composition of turbines across years, and indeed we find a more stable pattern of impacts in later years when we restrict the sample of turbines.[13] One of the main differences of our results compared to estimates from the United States is that the reductions in house prices do not rebound in Denmark, while they largely do in the United States (Dong et al. 2023; Brunner et al. 2024). We can only speculate about the reasons for these differences. One compelling argument put forward in Dong et al. (2023) hypotheses that individuals with lower intrinsic disutility from turbines may sort into affected areas over time and counteract the initial price drops.

[13] We show an event study graph with an alternative setup in the Appendix, where we exclude turbines established after 2009 and before 2002. This restriction allows all pre- and all post-periods to be affected by the same turbines, whereas the estimates in Fig. 6 are potentially from different sets of turbines. Appendix Fig. 11 shows a comparable pattern of dynamic treatment effects, however, the estimates are more stable at just under -5 percent even after 10 years. The late increase in Fig. 6 may therefore also be caused by a change in the composition of turbines.

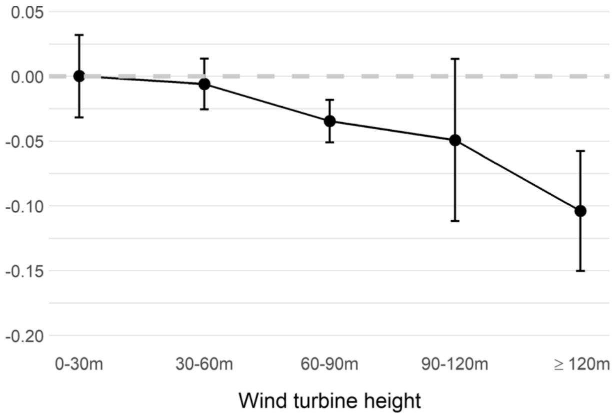


Fig. 7 Effects on log house prices of nearest turbine below 2 km away—interacted with height. *Notes:* Figure shows estimated coefficients for turbine proximity split into turbine height categories of 0–30m, 30–60m, 60–90m, 90–120m, and 120m and higher. The estimation controls for the fixed effects, as in column 2 of Table 2. The whiskers show 95% confidence intervals

4.1 The Role of Turbine Height

Not all turbines are alike and therefore they do not represent a uniform treatment. The height of a turbine in particular shapes the effect of distance as taller turbines are more easily visible, have longer blades (implying a larger nuisance), and host stronger and louder generators. In Fig. 7, we split the effect of the closest turbine by the total height, measured at the highest point of the blades, in 30 m bins. There is no effect whatsoever for the smallest turbines of up to 60 m in height, but we begin to see a negative and statistically significant effect for 60–90 m high turbines of around −3 percent. The effect then increases to −5 percent for the next larger turbine category. The bin is sparse, which is why the confidence band becomes too wide to distinguish the effect statistically from zero. Finally, for the largest turbines of 120 m and taller, we find a strong and statistically significant effect of roughly −11 percent. Turbine height thus has a huge influence on the impact on house prices. The tallest turbines, which are also the newest and most powerful generators, inflict six times as much damage as the medium turbine at 2 km distance.

Our estimates for the tallest turbines are about twice as large in magnitude as those found in Dröes and Koster (2021). They show three height categories—0–50 m, 50–150, and more than 150 m—where the largest effect size for the tallest turbines is −5.4 percent. Overall, the pattern of increasing impacts with turbine height in our results is consistent with their findings.

Going one step further, we allow distance to have a differential impact according to the height of the turbine in Fig. 8. Consistent with the above, turbines shorter than 60 m inflict no damage at any distance to a house. Meanwhile, turbines in the 60–120 m category have a moderate impact at distances up to 2000 m. The effect size then very gradually diminishes before falling to zero at distances above 2,000 m. Giant turbines, by contrast, have a large and statistically significant effect of around 12 percent (10 percent) on house prices for distances up to 1000 m (2000 m).[14] The effect then decreases with distance and drops to 5 percent and is statistically insignificant above 2,000 m. The point estimates suggest a meaningful negative impact of up to 5000 m and fall to zero above 5000 m.

[14] Giant turbines are sparse, which means they require a cruder distance bin width.

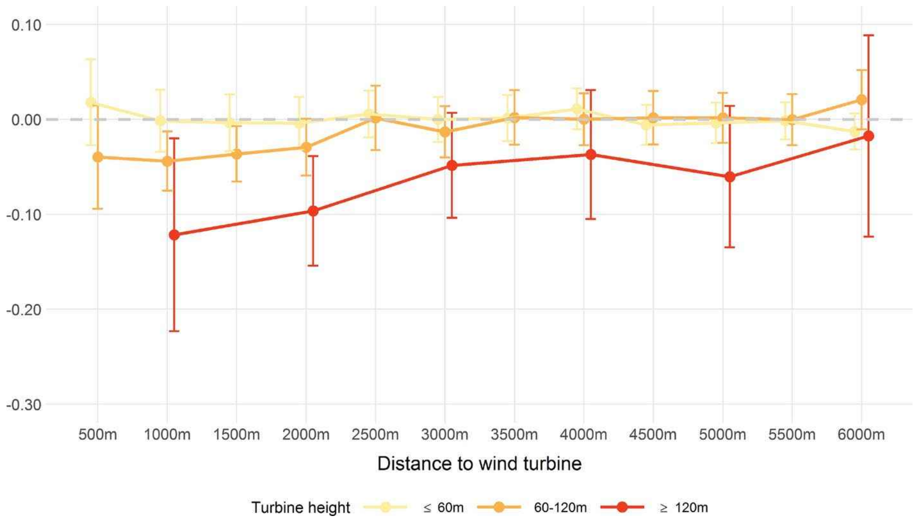


Fig. 8 Effects on log house prices of nearest turbine—by height and distance.
Notes: Figure shows the estimated coefficients for turbine proximity with a combination of distance intervals and turbine height. The yellow line denotes the effects of short turbines below 60 m, while the orange line represents medium-sized turbines between 60 and 120 m of height. Both lines depict coefficients for 500 m distance intervals. The red line, meanwhile, indicates tall turbines above 120 m in height with coefficients for 1000 m distance intervals. The estimation controls for the fixed effects and shadow flicker, as in column 3 of Table 2. The whiskers show 95% confidence intervals

4.2 Robustness of Shadow Flicker Results

The previous results highlight the heterogeneous effects of shadow flicker, depending on the intensity of the treatment. To test a more agnostic model, we summarize shadow flicker into one dummy variable irrespective of intensity, as shown in column 1 of Table 3. The effect of any intensity of shadow flicker on house prices is a modest 3.7 percent reduction, which is just about statistically significant.

Turbines can cause differential damages to house prices depending on their height and distance from the property. Closer and taller turbines potentially cause more shadow flicker because they cover larger areas of the visible horizon. However, given that shadow flicker intensity is correlated with distance and height, its impact on prices may be partly confounded. To address this, we test the robustness of shadow flicker in estimations where we exclude the variation originating from distance and height combinations.

The result in column 2 of Table 3 repeats the main estimates from Table 2 for comparison. In columns 3 to 7, we test the robustness of the shadow flicker intensity results. Column 3 introduces the same distance by height controls as in Fig. 8. Compared to the main estimate, the high-intensity shadow flicker effect is somewhat reduced from 10.1 to 8.0 percent, but the estimates are not statistically different from each other. As in the baseline, there is no detectable impact of the low-intensity shadow flicker. In columns 4 and 5, we introduce more granular distance bins and we find comparable impacts from high-intensity shadow flicker of 7.7 resp. 8.1 percent. Column 4 includes bins that are half the size of those in column 3, and column 5 uses turbine height intervals of 0–40, 40–60, 60–80, 80–100, and >120

Table 3 Effect of shadow flicker on house prices for different specifications

Dependent variable	ln (Price)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Any shadow flicker	−0.036**						
	(0.017)						
Below 2 km × > 60 m	−0.037***	−0.037***				−0.037***	−0.031***
	(0.008)	(0.008)				(0.008)	(0.009)
Below 2 km × > 60 m	−0.003	−0.003				−0.002	0.002
	(0.009)	(0.009)				(0.009)	(0.010)
Shadow flicker 0–20 h		−0.021	−0.010	−0.013	−0.016	−0.020	−0.020
		(0.019)	(0.020)	(0.021)	(0.021)	(0.019)	(0.019)
Shadow flicker > 20 h		−0.096***	−0.077**	−0.074**	−0.078**	−0.096***	−0.096***
		(0.030)	(0.030)	(0.033)	(0.036)	(0.030)	(0.030)
Controls							
Distance by height in bins			Yes				
Distance by height in bins (as Fig. 8)				Yes			
Distance by height in bins (fine granularity)					Yes		
Direction of turbine						Yes	
Number of turbines							Yes
Year × Home type	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Municipality	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Address	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,364,402	2,364,402	2,364,402	2,364,402	2,364,402	2,364,402	2,364,402

Notes: Table shows the effects of shadow flicker for various sets of controls. Column (2) replicates column (3) of Table 2. Column (3) controls for the distance by height indicators from Fig. 8. In column (4) we replicate column (3) but with distance indicators that are twice as granular (i.e., the tall turbine category is now in 500m-bins, and the other turbines in 250m-bins). Column (5) includes the finest granularity of distance by height controls, with turbine height intervals 0, 40, 60, 80, 100, and >120, and distance in 100 meter intervals. Column (6) controls for the direction of the nearest turbine (west or east). Column (7) controls for the number of turbines within 2 km flexibly with the following dummies for the number of turbines: 1, 2, 3, 4, 5, 6–10 and 10 or above. Standard-errors clustered at postal code in parentheses. Significance levels:$^{***}p < 0.01$,** $p < 0.05$,* $p < 0.1$.

meters, and distance in 100 meter intervals. In summary, the estimates are largely unaffected by the finer distance controls and height interactions.

To the best of our knowledge, these estimates are not directly comparable to any findings in the literature. However, it confirms findings that visual pollution in itself has an impact on surrounding property prices. In particular, Gibbons (2015) and Sunak and Madlener (2016) find that the visibility of turbines has negative price effects. It is, therefore, important for the interpretation of the shadow flicker estimates to recognize that turbine visibility is a necessary condition for shadow flicker. If we assume that the probability of turbine visibility is determined by the interaction of height and distance, the estimates in columns 3–5 of Table 3 isolate the effect of shadow flicker irrespective of visibility. These estimates essentially compare houses at the same distance from turbines of equal height, with shadow flicker being present or absent depending solely on direction (see Fig. 3). However, the estimate in column 2 only roughly controls for distance and may, therefore, capture a combined effect of visibility and shadow flicker, which is approximately 2 percentage points larger than the preferred estimates.

In column 6, we test whether the direction of the turbine relative to the property affects the estimates by including an indicator for whether the nearest turbine is east or west. The direction matters both for whether shadow flicker appears in the morning or evening and for how the sound travels with the dominant winds. Notably, the estimates do not change in comparison to our main estimates—neither the shadow flicker estimates nor the distance estimates. In column 7, we take account of the number of turbines within 2 km by including indicators for 2, 3, 4, 5, 6 to 10, and 10 or more turbines. Again, none of the estimates is affected by the additional control variable and the main estimates are robust to the number of turbines in proximity to the property.

Finally, comparing shadow flicker estimates with other externalities helps put them into perspective. For instance, the presence of a power plant within 2 miles reduces house prices by 4–7 percent in the United States (Davis 2011). In Taiwan, house prices within 15 miles of a large coal-fired thermal plant decline by as much as 25 percent (Tsai 2022).

4.3 Effect Heterogeneity Across Population Density and House Type

The issue of wind turbines affecting house prices is increasingly becoming an urban phenomenon when land-use areas are sparse. In panel A of Table 4, we document how turbines affect house prices across population densities. Density is split into three equal-sized groups based on 1x1 km grids of houses. House prices decline by 3.8 percent in rural areas when a tall turbine is active within 2 km, while the point estimate is even larger (−5.3 percent) in medium-density areas, which are mostly composed of suburbs and local towns. Thus, the effect of turbines carries over to more densely populated areas. We do not find any effect, though, in high-density areas, where other local amenities and disamenities are more important for price differences and there is a greater probability of negative externalities from turbines being physically blocked or dampened.

The disamenity from turbines affects houses because residents can see or hear the turbines from inside their houses or from their balconies, terraces, and gardens. Larger effects should thus manifest in properties with windows on many sides, outside areas around the house, and unobstructed views. In panel B, we show estimates for separate types of houses as approximations of susceptibility. We control for short turbines in the first row. The house-type-specific effects are from tall turbines within 2 km of the respective house types. The entire negative effect on prices is driven by detached houses, which is consistent with the susceptibility hypothesis. Detached houses are also the most common properties in the medium population density areas, where we find the largest impacts. By contrast, we find no significant effect on row houses or apartments,

Table 4 Effect of wind turbine proximity on house prices for different specifications

Dependent variable	ln (Price)		
Panel A: By population density	Low density	Medium density	High density
Below 2 km$\times$ $>$60 m	−0.037***	−0.052***	−0.005
	(0.009)	(0.014)	(0.018)
Below 2 km$\times$ $<$60 m	−0.001	−0.017	0.0004
	(0.009)	(0.015)	(0.023)
Observations	781,890	778,752	803,760
Panel B: Interaction by home type			
Below 2 km$\times$ $<$60 m	−0.003		
	(0.009)		
Below 2 km$\times$ $>$60 m$\times$...			
Apartment	−0.005		
	(0.016)		
Farm house	−0.052		
	(0.032)		
Holiday home	−0.034		
	(0.028)		
Row house	−0.009		
	(0.022)		
Detached house	−0.048***		
	(0.008)		
Observations	2,364,402		
Controls			
Year$\times$Home type	Yes	Yes	Yes
Year$\times$Municipality	Yes	Yes	Yes
Address	Yes	Yes	Yes

Notes: Table shows estimated coefficients for turbine proximity. In Panel A, the sample is split by population density, coefficients for short and tall turbines are reported. In Panel B, the effect of tall turbines is split by housing types. The share of treated observations by house type is 3.0% for apartments and holiday homes, 16.1% for farm houses, 4.0% for row houses and 8.1% for detached houses. Standard-errors clustered at postal code in parentheses. Significance levels:$^{***}p < 0.01$,** $p < 0.05$,* $p < 0.1$.

which are often situated in more densely populated areas. Nor do we find a significant effect on farmhouses or holiday homes, which are most common in rural areas.[15]

4.4 Societal Costs and Benefits of Turbines

To provide a policy-relevant comparison of the social costs and benefits of turbine installments, we provide additional estimates. First, we discuss an estimate of the environmental benefits of wind turbines as the monetary value of avoided greenhouse gas emissions. Second, we estimate the total damages of a turbine in a hypothetical residential area as a comparison. Third, we discuss the policy implications of different scenarios for the social cost of carbon and the placement of the turbine.

[15] A limitation of this analysis is, of course, whether we are sufficiently powered to detect differences. For example, the estimate on holiday homes (-0.034) is just within the 95% confidence interval of the estimate on detached houses (-0.048+0.008 1.96), although the holiday home estimate is not statistically different from zero with its standard error of 0.028. Further, different types of houses are treated to a different extent (see notes of Table 4).

Societal benefits. The social benefits of turbines accrue from avoiding pollution of traditional forms of electricity production and the associated damages of pollution. We focus on avoided carbon dioxide emissions as the major contributor to the environmental damages of production. To do so, we require estimates of the electricity production of a turbine and the amount of replaced carbon dioxide emissions. The potential power output of medium-sized turbines 60–120 in height in our dataset is 0.811 MW, while that of giant turbines taller than 120 m is 3.095 MW. To calculate the total production of a turbine, we assume conservative estimates of a lifetime of 20 years and capacity usage of 30 percent. The two types of turbines run for 175,200 hours[16] and, thus, produce 42,606 resp. 162,699 MWh over their lifetime. The emission replacement factor for Danish turbines is 0.69 (Christensen et al. 2021), implying that for every MWh of electricity produced, one avoids 0.69 tonnes of carbon dioxide emissions from other forms of production. We assume a range of values for the social cost of carbon (SCC). The lowest value of €50 corresponds roughly to the SCC assumed by the Biden Administration of 190 that the United States Environmental Protection Agency considers the most likely actual cost (EPA 2021).

Table 5 summarizes the benefits of the two types of turbines. Medium-sized turbines (60–120m) produce 42,606 MWh during their lifetime, avoiding 29,398 tonnes of carbon dioxide emissions. Giant turbines produce as much as 162,699 MWh, reducing the emissions of carbon dioxide by 112,262 tonnes. Assuming the high SCC of €200, medium-sized turbines have a social benefit of 5.9 million Euros, while giant turbines save society 22.5 million Euros. These figures are likely lower bounds because a full account of the social benefits would also include the reduction in air and toxic pollutants other than greenhouse gases.

Societal costs. The societal costs of a turbine from reduced house prices depend on the number of affected houses, the values of those houses, the distance to the turbine, and the location with respect to the shadow flicker. There are numerous ways to illustrate the total costs in order to compare them to the societal benefits. We show in the following how densely populated an area around a turbine can be before the costs exceed the benefits.[17]

To do this, let us assume an illustrative settlement in the shape of a square. All houses in the settlement have the same quality and the same lot size. We assume a house value of €250,000, corresponding to roughly the average price of transactions in 2019. To determine the lot size, we assume that 20 percent of the land is used for infrastructure and 80 percent for residential housing. Turbines are in reality seldom placed in the middle of a settlement. Thus, for this illustration, we place the turbine on one of the corners of the residential area, as depicted in Fig. 9. The circles around the turbine show the affected areas with distances of

Table 5 The social benefits of a turbine

	60–120 m	$\geq$ 120 m
Lifetime production	42,606 MWh	162,699 MWh
Avoided CO_2	29,398 t	112,262 t
Social benefits (in €)		
High SCC (€200)	5.880mill.	22.452mill.
Low SCC (€50)	1.470mill.	5.613mill.

[16] Assuming the turbines run at 30 percent capacity for 24 hours on 365 days over 20 years.

[17] We deliberately do not exploit the realized spatial distribution of houses, turbines, and damages as it would not be informative about the optimal distribution or the damages of the marginal turbine.

up to 2km. The dashed lines indicate where the settlement is located towards the southeast of the turbine. This enables us to compute the total area that can be occupied by housing as 80 percent of a quarter circle, for a total area of 2,356,194 m^2. The first affected inner circle from 500 to 1,000 m hosts a residential area of 471,239 m^2, the second from 1,000 to 1,500 m an area of 785,398 m^2, and the third from 1,500 to 2,000 m an area of 1,099,557 m^2. No houses are placed within 500 m of the turbine.

We now ask how many houses we can fit into the residential areas such that the benefits of the turbine are equal to the damages on house prices. The benefits as described above are the social cost of carbon *SCC* multiplied by the turbine-height-specific carbon dioxide savings $CO2S_h$, where height categories *h* are medium-sized and giant. The total costs are a function of the lot size *l* and the damage estimates $\beta_{h,d}$ specific to the turbine height *h* and the distance ring $d \in (1, 2, 3)$ for 500–1,000 m, 1,000–1,500 m, and 1,500–2,000 m. We can write the equality of benefits and costs as

$$\begin{aligned} SCC \times CO2S_h &= C(l, \beta_{h,d}) \\ &= \sum_{d=1}^{3} \beta_{h,d} \times 250,000 \times \frac{A_d}{l}, \end{aligned} \tag{7}$$

where A_d is the available area in each of the distance rings *d* and €250,000 the uniform house price. We can solve for the lot size and insert the area values as in

$$l = \frac{250,000 \times (\beta_{h,1} \times 471,239 + \beta_{h,2} \times 785,398 + \beta_{h,3} \times 1,099,557)}{SCC \times CO2S_h} \tag{8}$$

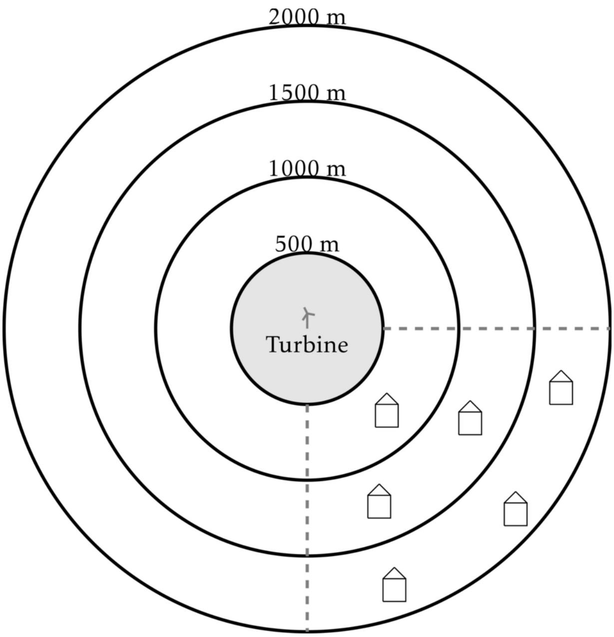


Fig. 9 Illustration of turbine with affected housing areas

We solve equation 8 by using the damage estimates $\beta_{h,d}$ that are specific to each of the three distance rings from Fig. 8 and the carbon dioxide savings from Table 5 for medium-sized and giant turbines.

We plot the resulting lot size from equation 8 as a function of the *SCC* separately for medium-sized and giant turbines in Fig. 10. As the benefits increase with the SCC, the lot size decreases such that more houses can be close to a turbine without the damages exceeding the benefits. For giant turbines and an SCC of €200, lot sizes can be as small as 2,600 m^2. In the hypothetical settlement area, this lot size corresponds to approximately 900 affected houses. This means that it is still beneficial from a societal perspective to place a giant turbine in the proximity of up to 900 affected houses if the SCC is €200.[18] Notably, the solid line for giant turbines is always below the solid line for medium-sized turbines, implying that the housing density can be larger closer to giant turbines. This result stems from the fact that even though giant turbines inflict larger damage to house prices, they also produce much more energy and, thus, avoid more emissions.

The estimates above ignore the damages caused by shadow flicker. To illustrate how shadow flicker affects the social costs, we extend Eq. 8 using the estimates from column 4 of Table 3 and assume that all houses are affected by high-intensity shadow flicker. The dashed lines in Fig. 10 that take into account the damages from shadow flicker are far above the solid lines. This implies that if houses are subject to shadow flicker, turbines are much less worthwhile close to a settlement. This is especially true for the smaller turbines that avoid fewer emissions and have smaller societal benefits. These additional costs illustrate how

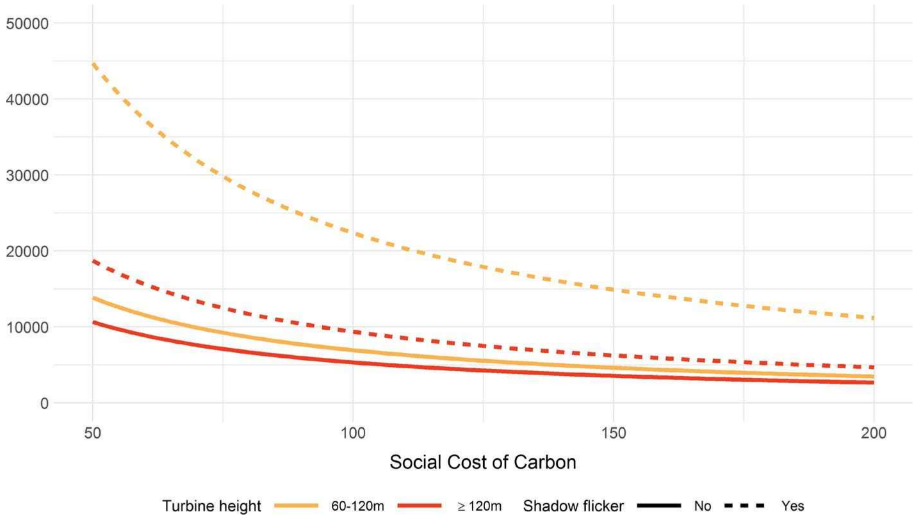


Fig. 10 Cost-benefit analysis: break-even lot sizes of houses.
Notes: Figure shows the break-even lot size for equidistant houses that equate the benefits and damages of a single turbine. Calculations are based on the specification in Fig. 8 and column 4 of Table 3. There were 4054 active onshore turbines in 2019

[18] Our analysis does not account for distributional inequities. While turbines provide societal benefits, the associated costs are primarily borne by a few affected property owners. Additionally, as shown in Fig. 4, homes close to a turbine are significantly less valuable, likely also for reasons unrelated to any treatment effect of nearby turbines. A more comprehensive analysis would need to incorporate the mitigating role of compensation payments, which, at least partially, address these distributional concerns.

important it is not only to determine how close a turbine is to a certain location but also to determine the direction in which the turbine is facing. Indeed, the additional shadow flicker damages can be avoided, for example, by placing turbines north of settlements.

5 Conclusion

We have shown that wind turbines inflict significant damage on the value of nearby properties. Moreover, this impact increases in line with the turbine's height, such that more modern giant turbines reduce housing values more heavily. Houses within the area where turbines produce shadow flicker suffer an additional drop in value. While the house price effects are significant both in a statistical and an economic sense, wind turbines, especially newer tall versions, mostly overcompensate for their more considerable damages with savings in carbon dioxide emissions when the social costs of carbon are assumed at conventional levels.

For policy purposes, our results have several implications. First, to fully compensate property owners for their losses, at least three indicators—distance, turbine height, and shadow flicker—must be taken into account. Second, turbines produce a considerable social net benefit. Thus, expanding wind farms is socially beneficial even if it means adversely affecting multiple houses. Strict minimum distance requirements, such as maintaining a distance of four or ten times the turbine height from residential buildings, overlook the fact that turbines can still provide net benefits in moderately populated areas. Third, giant turbines with greater efficiency are preferable even if their damage is more substantial.

Appendix

See Table 6 and Fig. 11.

Table 6 Effect of shadow flicker on house prices for different specifications

Dependent variable	ln (Price)				
	(1)	(2)	(3)	(4)	(5)
Below 2 km x >60 m	− 0.0229**	− 0.0228**	− 0.0229**	− 0.0229**	− 0.0228**
	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)
≥2 tall turbines	− 0.0242**				
	(0.0119)				
2 tall turbines		− 0.0138	− 0.0138	− 0.0137	− 0.0136
		(0.0158)	(0.0158)	(0.0158)	(0.0158)
≥3 tall turbines		− 0.0289**			
		(0.0126)			
3 tall turbines			− 0.0227	− 0.0227	− 0.0226
			(0.0148)	(0.0148)	(0.0148)
≥4 tall turbines			− 0.0355**		
			(0.0160)		
4 tall turbines				− 0.0408**	− 0.0412**
				(0.0167)	(0.0167)
≥5 tall turbines				− 0.0314	
				(0.0209)	
5 tall turbines					0.0009
					(0.0325)
≥6 tall turbines					−0.0561***
					(0.0204)
Controls					
Year×Home type	Yes	Yes	Yes	Yes	Yes
Year×Municipality	Yes	Yes	Yes	Yes	Yes
Address	Yes	Yes	Yes	Yes	Yes
Observations	2,364,402	2,364,402	2,364,402	2,364,402	2,364,402

Notes: Table shows estimation results of equation 6 with an alternative treatment specification. In columns 1 to 5, the treatment is split into dummies for the first and subsequent turbines, with a top-coded category. In column 1, a dummy for the first turbine and a dummy for subsequent turbines is included. In column 2, a dummy for the first and one for the second turbine as well as a dummy for subsequent turbines is included. In column 5, dummies for each of the first five turbines is included. Standard-errors clustered at postal code in parentheses. Significance levels:$^{***}p < 0.01$,$^{**}p < 0.05$,$^{*}p < 0.1$.

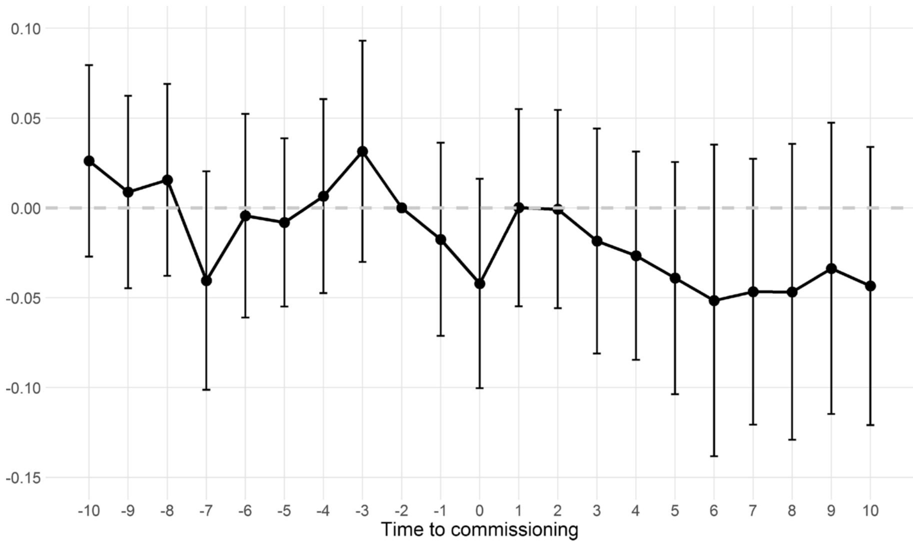


Fig. 11 Event study of turbine proximity effects for turbines 2002–2009.
Notes: Figure shows the estimated coefficients for tall turbines within 2 km with yearly lags and leads from 10 years prior until 10 years post the commissioning. The excluded category is $t = -2$. We include only turbines that were established between 2002 and 2009. Houses affected by other turbines are excluded. The estimation controls for the fixed effects, as in column 3 of Table 2. The whiskers show 95% confidence intervals

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