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Carsten Andersen, Timo Hener

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Abstract

We analyze the effect of wind turbines on the prices of houses in their proximity. Utilizing the universe of Danish house transactions since 1992 and data on all turbines ever established in Denmark, we are able to control for individual house fixed effects. We distinguish between effects of proximity and shadow flicker from rotor blades partly covering the sun. Our results suggest that nearby turbines have a significant adverse impact on house prices, and this impact is notably more pronounced for taller turbines. Furthermore, homes affected by shadow flicker experience an additional decrease in value comparable to the effect of the tallest turbines. Our findings suggest a nuanced view regarding the local externalities of wind turbines that heavily depend on size and relative location.

JEL-Codes: JR310, P180, Q420.

Keywords: wind turbines, house prices, shadow flicker.

Carsten Andersen
Department of Economics and Business Economics, Aarhus University / Denmark
candersen@econ.au.dk

*Timo Hener**
Department of Economics and Business Economics, Aarhus University / Denmark
thener@econ.au.dk

*corresponding author

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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 give rise to negative *local* externalities. These include issues such as noise emissions, visual disamenities, and the phenomenon of shadow flicker, caused by the rotor blades obstructing sunlight. The principal method to assess the size of these externalities is hedonic pricing (Rosen, 1974), which estimates the impact of turbines on house prices (Gibbons, 2015; Dröes and Koster, 2016, 2021). Understanding the extent of damages caused by wind turbines is crucial for policy makers seeking to strike a balance between the external costs and the environmental benefits associated with the installation of new turbines.

In this paper, we present new insights into the effects of proximity to turbines and the occurrence 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, thus ensuring that our

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

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 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 3.7 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 effects of -4.4 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 7.4 to 9.6 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.

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 most closely related to a small literature that estimates the effects of turbine proximity on house prices in large and representative samples. Two studies from the Netherlands (Dröes and Koster, 2016, 2021) comprehensively estimate the effects of distance to turbines on house prices. Dröes and Koster (2016) find that the first turbine within 2 km of a property decreases house prices on average by 1.4 percent. They also show that taller turbines of 100 m and higher have a larger effect of 3.7 percent. They estimate the total costs to owner-occupied houses to be €900 million in the Netherlands. Updated estimates in Dröes and Koster (2021) show that medium-sized turbines of 50-150 m height reduce house prices by 3 percent, turbines taller than 150 m reduce house prices by 5.4 percent. One study for England and Wales, Gibbons (2015), focuses on the impact of the direct view of wind farms from postcode areas, using models of elevation and topography of the landscape. The results suggest that house prices fall by 5.8 percent if a wind farm is visible within 2 km.

A number of papers on the impact of turbines on house prices that used case studies or smaller samples of houses and turbines find ambiguous results ranging from no effects to very large effects. Early studies used small samples of house transactions connected to selected turbines in cross-sectional regressions and did not find significant effects 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), while results from Germany point to very large impacts from direct views of turbines (Sunak and Madlener, 2016, 2017). More recent studies with larger samples of property transactions allowed for the inclusion of neighborhood fixed effects. However, these studies still yielded ambiguous conclusions, 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 simulated exposure to shadow flicker[2] and show that houses affected by it are subject to considerable losses in value. This shadow flicker damage has profound implications for the optimal positioning of wind turbines relative to properties. Second, due to

[2] Dröes and Koster (2016) investigate shadow flicker in their heterogeneity analysis. They use a rule of thumb to define shadow flicker, such that houses within one km and north of the turbine are indicated as treated, while houses south of the turbine are untreated. Estimates based on this definition likely do not represent the full price effect of shadow flicker, as the properties mostly affected by shadow flicker are located at the treatment split line in the east and west. See for comparison the butterfly shape of shadow dispersion in Figure 3. Indeed, the estimate in Dröes and Koster (2016) is small and insignificant.

the sample length and size of our data, we can implement a full repeat sales approach that uses house fixed effects, whereas most of the literature relies on a coarser aggregation at a regional or neighborhood level. Only Dröes and Koster (2016, 2021) implement a full fixed effects specification as a robustness check and show that their main results are consistent with it. 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. 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.

Lastly, our findings also relate to the literature on the 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). Similarly, (Zou, 2017) shows that noise from nearby turbines leads to increased suicide rates. Regarding shadow flicker, evidence indicates that exposure to changes in light leads to annoyance (Voicescu et al., 2016; Haac et al., 2022).

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) and a register of wind turbines.

Property trades. We select all 2,810,039 property transactions in Denmark 1992–2019 using publicly available transaction registers.[3] After excluding transactions within the same family and price outliers, 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

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

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 (<60m) and tall turbines (≥60m). 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 (60-120m) and giant turbines (>120m). 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.

We define several measures of distance to the *nearest* short (<60m) and tall (≥60m) turbines. The main treatment indicator variables are defined as follows:

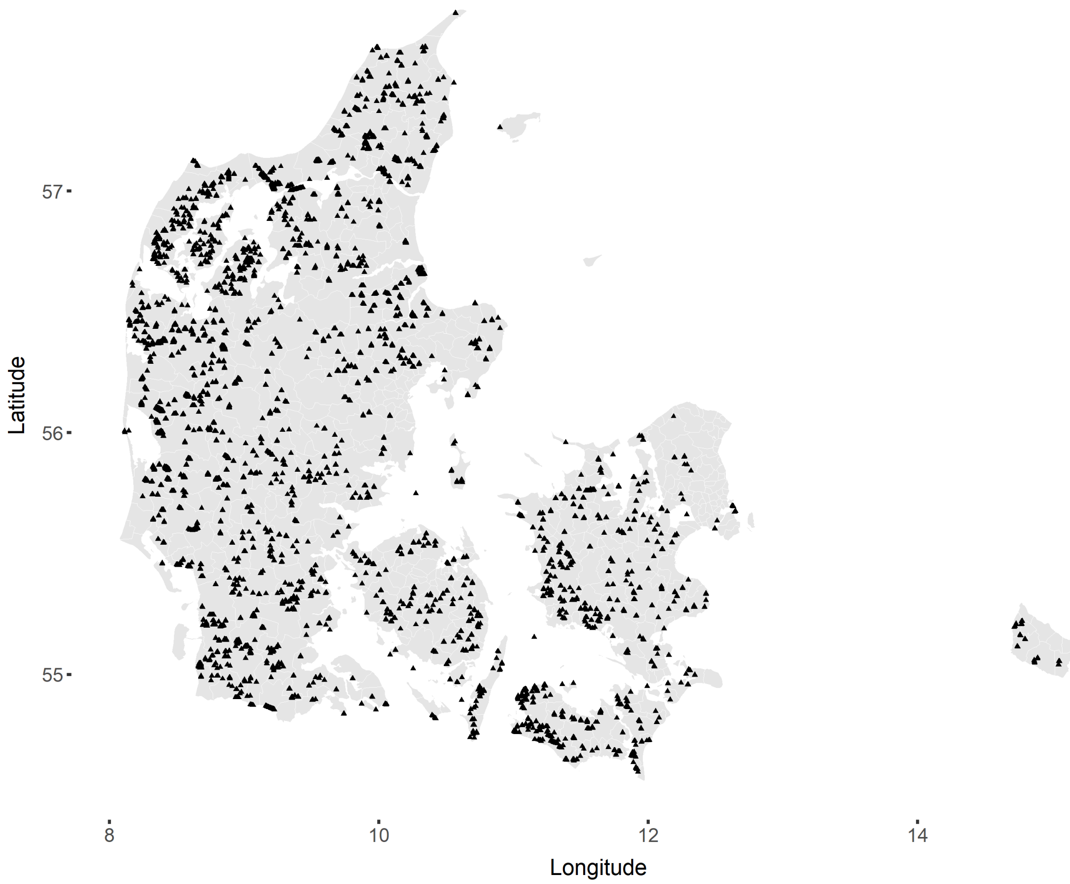
$$D_{i,t}^{<60} = \mathbb{1}\Big\{d_{w,t} \leq 2km\Big\}, \quad \forall \quad w = 1, ..., W, \tag{1}$$

and

$$D_{i,t}^{\geq 60} = \mathbb{1}\Big\{d_{w,t} \leq 2km\Big\}, \quad \forall \quad w = 1, ..., W, \tag{2}$$

[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”).

Figure 1: Onshore turbines in Denmark



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

where $D^{<60}$ takes the value of one if house i in year t has a distance d to its closest turbine w of at most 2 km and turbine w is below 60 m tall, and zero otherwise. Similarly, $D^{\geq 60}$ is defined for turbine w being taller than 60 m. 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 (azimuth, 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:

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

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:

$$\mathrm{SF}_{i,t}^{(0,20]} = \mathbb{1}\left\{0 < \sum_{m=1}^{M} \mathrm{sf}_m \leq 20 * 60\right\} \tag{4}$$

and

$$\mathrm{SF}_{i,t}^{>20} = \mathbb{1}\left\{\sum_{m=1}^{M} \mathrm{sf}_m > 20 * 60\right\}, \tag{5}$$

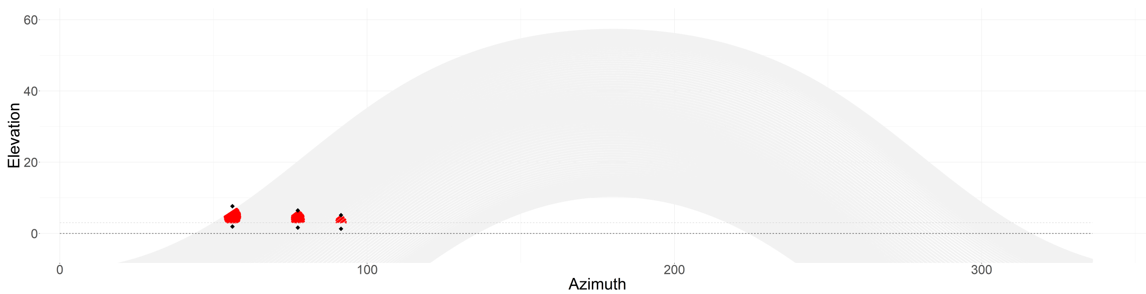
where $m = 1$ is the first minute of January 1 and M the last minute of December 31. If the total sum of the one-minute indicators sf_m is between 1 minute and 20 hours, $\mathrm{SF}_{i,t}^{(0,20]}$ equals one and is zero otherwise. Accordingly, $\mathrm{SF}_{i,t}^{>20}$ is an indicator for shadow flicker 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. Additionally, Denmark imposes a maximum of 10 hours on actual shadow flicker at an address, implying that turbines exceeding 10 hours would need to stop operations when

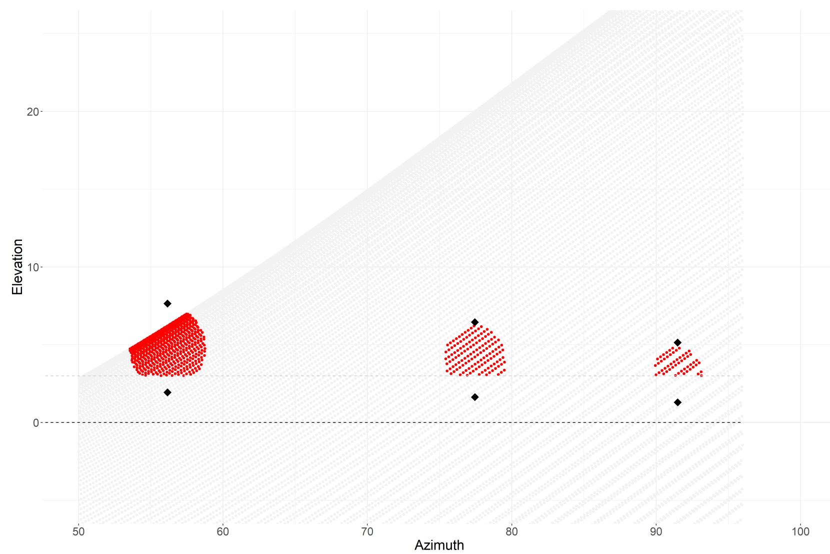
[5] The elevation angle of the sun is given by $\alpha = \sin^{-1}[\sin\delta \sin lat + \cos\delta \cos lat \cos h]$, where lat is the latitude of the address, and δ is the declination due to the seasonal tilt of the earth's axis given by $\delta = -23.44° \cos[(360/365)(d+10)]$, where d denotes the 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 $h = 15°(LST - 12)$, 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*.

the turbine produces shadow flicker. The observed shadow flicker typically differs from the predicted shadow flicker by a factor of approximately three to four (Haac et al., 2022). Hence, our 20 hour worst-case threshold indicator corresponds to 5 hours or more of visible shadow flicker and half of what is allowed by the 10 hour restriction.

Figure 2: Example of shadow flicker



(a) 360-degree panorama from house location



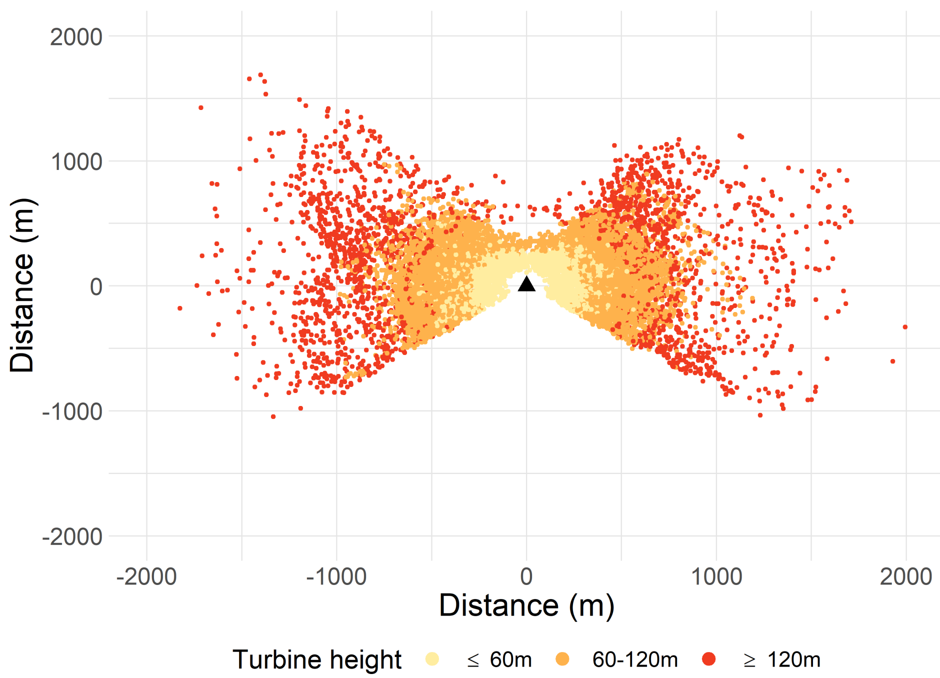
(b) Zoom on turbines

Notes: Figure 2 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.

Panel (a) of Figure 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). 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 Figure 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 $SF_{i,t}^{>20}$ and $SF_{i,t}^{(0,20]}$.

Figure 3: All shadow flicker transactions



Notes: Figure 3 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.

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

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, 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. 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. Additionally, 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 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.

Table 1: Mean values for main sample

	Mean
Price	200,959 (146,184)
Below 2 km	0.19
Below 2 km x <60 m	0.13
Below 2 km x >60 m	0.06
Shadow flicker	
Any shadow flicker	0.0053
Shadow flicker 0-20h	0.0043
Shadow flicker >20h	0.0010
House type	
Apartment	0.22
Farmhouse	0.02
Holiday home	0.11
Row house	0.09
Detached house	0.56
House characteristics	
Size (m2)	124 (54)
Sales year	2005 (8)
Observations	2,364,402

Notes: Table 1 shows mean values along with standard deviations in parentheses (only for continuous variables). Prices are in 2021 euros.

Additionally, our sample includes holiday homes, which account for 11 percent of the sales.

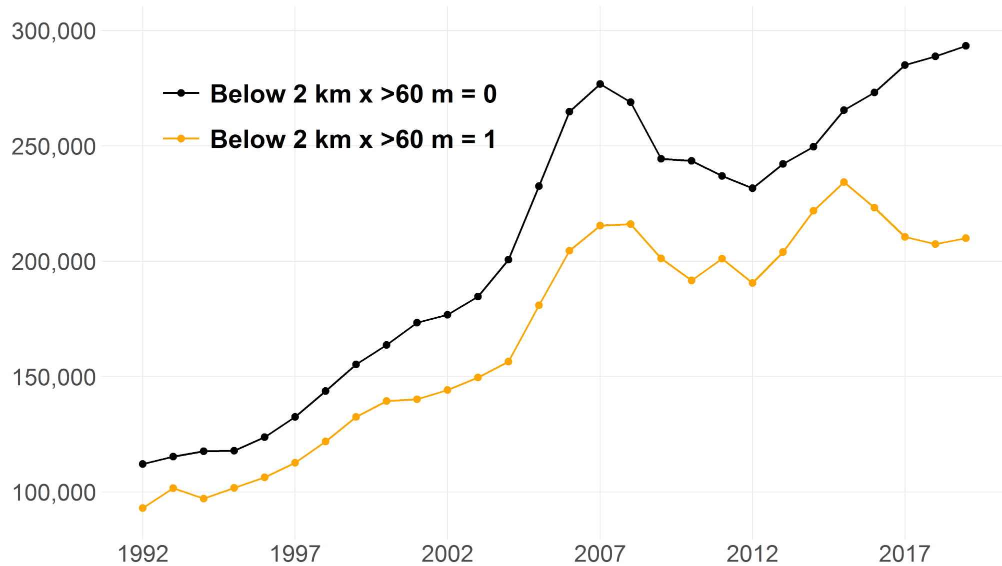
Figure 4 illustrates the growth in house prices for properties located above and below 2 km from a tall wind turbine, respectively. Throughout all years, properties in close proximity to a turbine tend to have lower prices, which can be attributed to a combination of treatment effects and selection effects. 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 Methods

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 land values that keep

Figure 4: Average prices by treatment status (2021 euros)



Notes: Figure 4 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.

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 $D^{<60}$ and $D^{\geq 60}$ 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

($SF^{(.)}_{i,t}$), 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 difference-in-differences type estimation with fixed effects for the address and year. Our baseline estimation equation at the address-year level is

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

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 and 12 percent 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 3.9 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.

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	<6km
Observations	2,364,402	2,364,402	2,364,402	1,840,087

Notes: Table 2 shows estimation of equation (6). Standard-errors clustered at postal code in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

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 9.6 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.

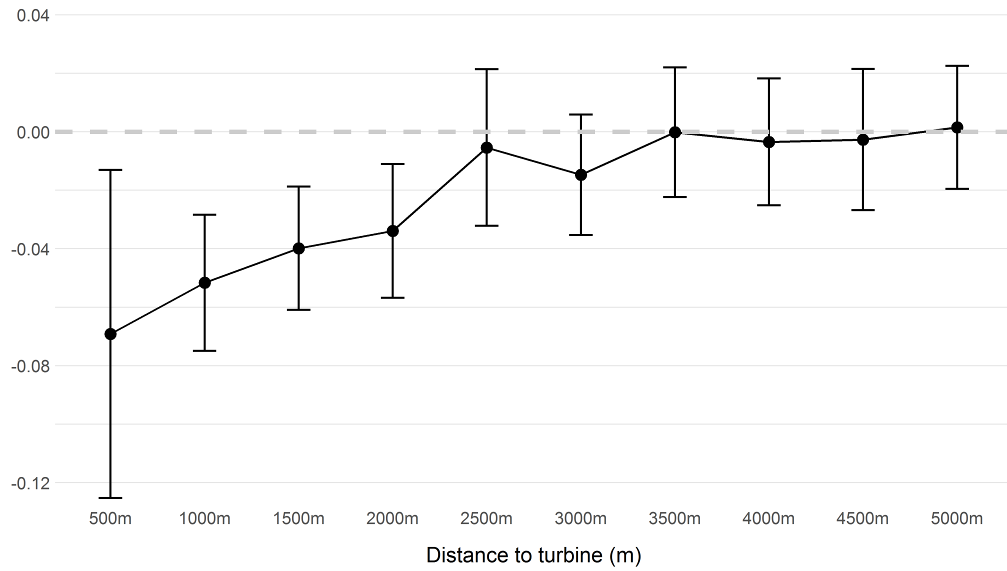
Taking into account the staggered timing of the turbine treatments and the fact that the underlying treatment effects were heterogeneous across houses, the estimates from the fixed effects regressions may be subject to biases from negatively weighted and poorly identified treatment effects that are described in more detail in Goodman-Bacon (2021) and Borusyak et al. (2022).[7] 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.[8] 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 coefficients in panel (a) of Figure 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. The threshold of 2 km in the baseline estimation is thus supported by the data and is consistent with Dröes and Koster (2016, 2021), while other studies suggest much farther reach (e.g., Gibbons (2015); Zou (2017)).

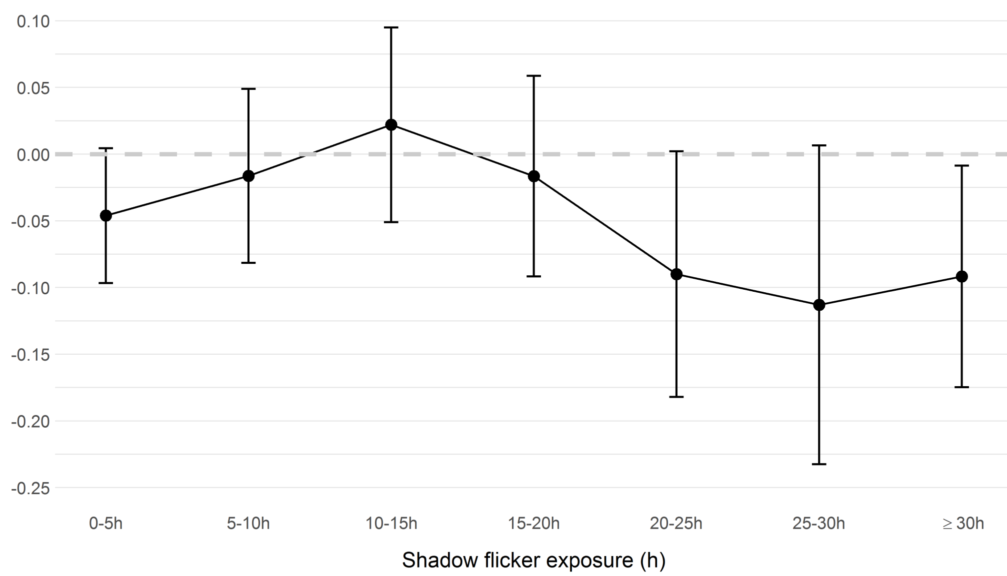
[7] The large number of never-treated observations in our data alleviates the potential for bias from negative weights; see Borusyak et al. (2022).

[8] 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.

Figure 5: Effects of distance and shadow flicker duration



(a) Distance bins

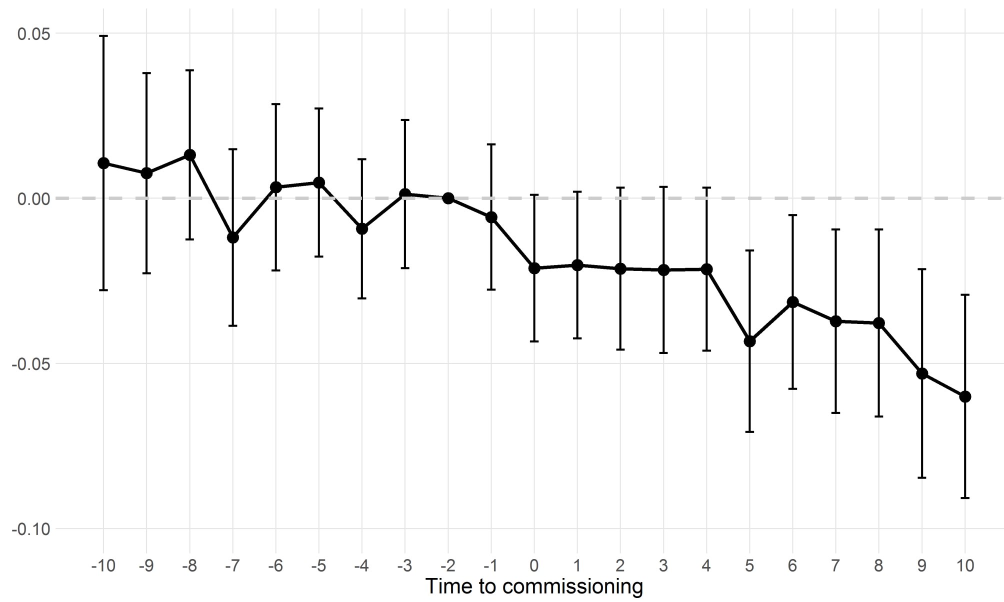


(b) Shadow flicker duration

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.

We similarly test the shadow flicker specification by estimating a flexible binned version of flicker duration in 5-hour bins in panel (b) of Figure 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 very 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 6: Event study of turbine proximity effects



Notes: Figure 6 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.

In Figure 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.

In the analysis shown in Figure 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.[9] 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. As to why prices start to fall even further after several years, we can only speculate. It seems conceivable that a combination of a change in ownership in the neighborhood, further developments of wind turbines, and salience of the negative externalities is at play.[10]

4.1 The role of turbine height

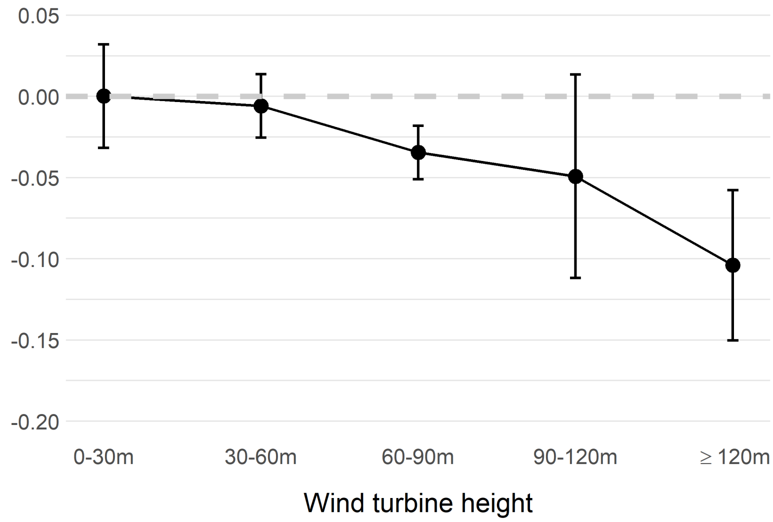
Not all turbines are alike and therefore they do not represent a uniform treatment. The height of a turbine in particular shapes the effect of distance as taller turbines are more easily visible, have longer blades (implying a larger nuisance), and host stronger and louder generators. In Figure 7, we 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 -10 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

[9] In contrast, there are strong anticipation effects in Dröes and Koster (2016), see Fig. 5 therein for comparison.

[10] 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 Figure 6 are potentially from different sets of turbines. Appendix Figure 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 Figure 6 may therefore also be caused by a change in the composition of turbines.

at 2 km distance.

Figure 7: Effects on log house prices of nearest turbine below 2 km away—interacted with height



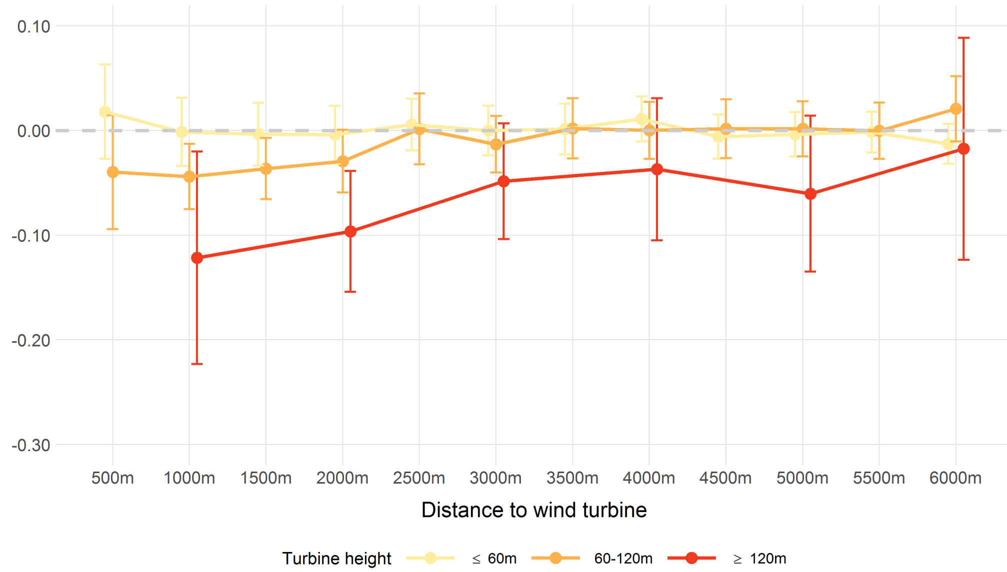
Notes: Figure 7 shows estimated coefficients for turbine proximity split into turbine height categories of 0–30m, 30–60m, 60–90m, 90–120m, and 120m and higher. The estimation controls for the fixed effects, as in column 2 of Table 2. The whiskers show 95% confidence intervals.

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—0–50m, 50–150, and more than 150m—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 Figure 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 2,000 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 10 percent on house prices for distances up to 2,000 m.[11] 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 5,000 m and fall to zero above 5,000 m.

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

Figure 8: Effects on log house prices of nearest turbine—by height and distance



Notes: Figure 8 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 3.6 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 6, we test the robustness of the shadow flicker intensity results. Column 3 introduces the same distance by height controls as in Figure 8. Compared to the main estimate,

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

Dependent Variable:	ln(Price)					
	(1)	(2)	(3)	(4)	(5)	(6)
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 0-20h		-0.021	-0.010	-0.013	-0.020	-0.020
		(0.019)	(0.020)	(0.021)	(0.019)	(0.019)
Shadow flicker >20h		-0.096***	-0.077**	-0.074**	-0.096***	-0.096***
		(0.030)	(0.030)	(0.033)	(0.030)	(0.030)
Controls						
Distance and height in bins			Yes			
Distance and height in bins (more granular)				Yes		
Direction of turbine					Yes	
Number of turbines						Yes
Year × Home type	Yes	Yes	Yes	Yes	Yes	Yes
Year × Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Address	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

Notes: Table 3 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 figure 8. In column (4) we replicate column (3) but with distance indicators that are twice as granular (e.g., the tall turbine category is now in 500m-bins, and the other turbines in 250m-bins). Column (5) controls for the direction of the nearest turbine (west or east). Column (6) 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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

the high-intensity shadow flicker effect is somewhat reduced from 9.6 to 7.7 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 column 4, we introduce more granular distance bins that are half the size of those in column 3. The estimates are largely unaffected by the finer distance controls. In column 5, 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 6, 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.

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 3.7 percent in rural areas when a tall turbine is active within 2 km, while the point estimate is even larger (-5.2 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 more than it does to rural farmhouses and is even larger there. 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

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 × > 60 m	-0.037***	-0.052***	-0.005
	(0.009)	(0.014)	(0.018)
Below 2 km × < 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 × < 60 m	-0.003		
	(0.009)		
Below 2 km × > 60 m ×...			
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 × Home type	Yes	Yes	Yes
Year × Municipality	Yes	Yes	Yes
Address	Yes	Yes	Yes

Notes: Table 4 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. Standard-errors clustered at postal code in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

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, 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.

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.

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[12] 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 $51. The highest value of €200 is close to the $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

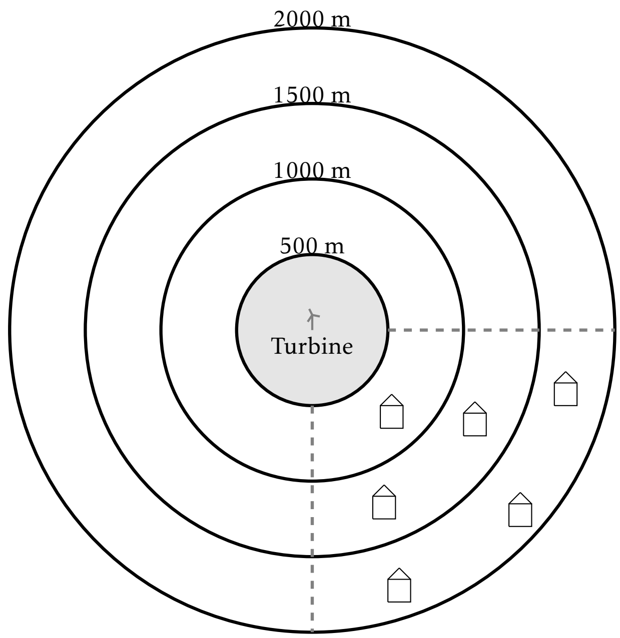
[12] Assuming the turbines run at 30 percent capacity for 24 hours on 365 days over 20 years.

Table 5: The social benefits of a turbine

	60-120m	≥ 120m
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.

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.

Figure 9: Illustration of turbine with affected housing areas



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.[13]

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,

[13] 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.

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 Figure 9. The circles around the turbine show the affected areas with distances of 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 m². The first affected inner circle from 500 to 1,000 m hosts a residential area of 471,239 m², the second from 1,000 to 1,500 m an area of 785,398 m², and the third from 1,500 to 2,000 m an area of 1,099,557 m². 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

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

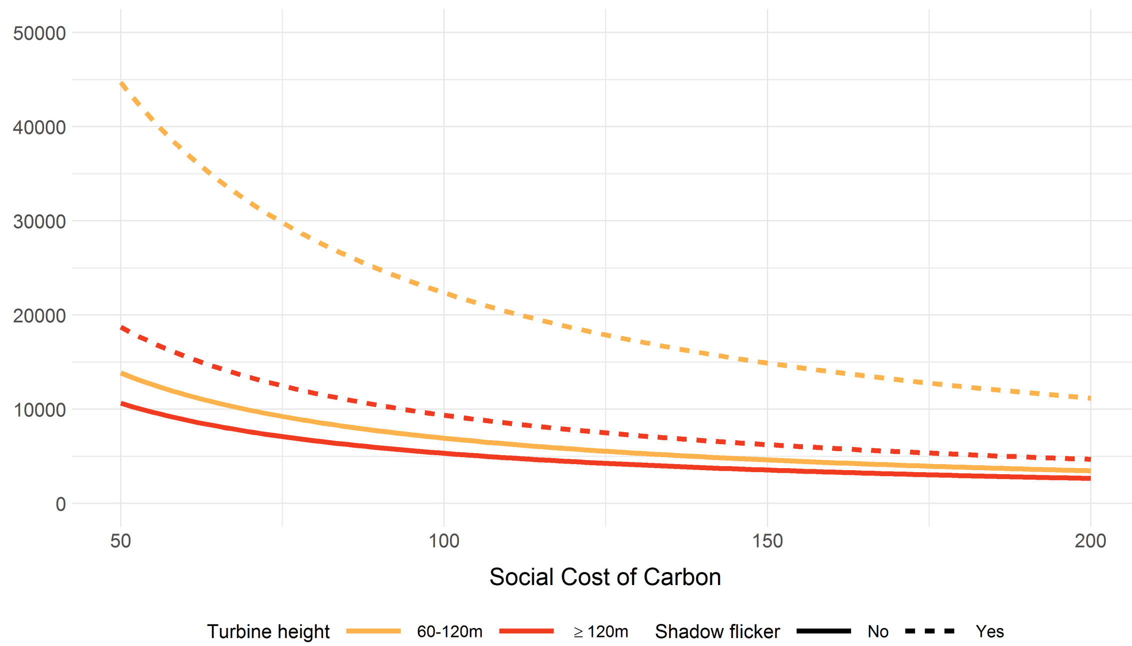
where A_d is the available area in each of the distance rings d and €250,000 the uniform house price. We can solve for the lot size and insert the area values as in

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

We solve equation 8 by using the damage estimates $\beta_{h,d}$ that are specific to each of the three distance rings from Figure 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 Figure 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 m². 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. 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.

Figure 10: Cost-benefit analysis: break-even lot sizes of houses



Notes: Figure 10 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 Figure 8 and column 4 of Table 3. There were 4,054 active onshore turbines in 2019.

The estimates above ignore the damages caused by shadow flicker. To illustrate how shadow flicker affects the social costs, we extend equation 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 Figure 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 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 distance requirements to any residential building of a multiple of turbine height (such as 4H or 10H rules) do not adhere to the fact that turbines are still net beneficial in somewhat densely populated areas. Third, giant turbines with greater efficiency are preferable even if their marginal damage to house prices is more extensive.

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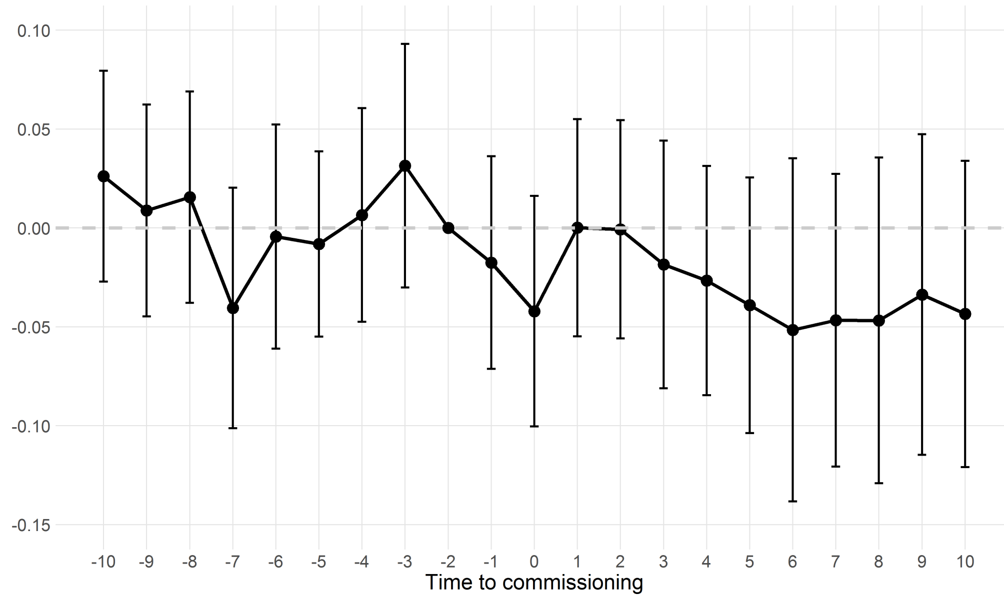
Appendix

Figure 11: Event study of turbine proximity effects for turbines 2002–2009



Notes: Figure 11 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.