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Abstract

Huge low-carbon investments are required to reach the goals of the Paris Agreement. However, one obstacle for these investments may be public opposition to the installment of low-carbon technology due to high perceived net costs. In this paper, we analyze the local net costs of both wind turbines and PV farms, employing a hedonic price analysis on the universe of housing ads from German's largest online real estate platform for the period spanning from 2009 to 2021. Beyond estimating average treatment effects, we focus on distance and intensity specific effects of wind turbines and PV farms on property prices. Moreover, we add to the existing literature by estimating the effect not only of the nearest energy facility. We find that wind turbines exhibit a negative effect of 1.8–1.9 % on property prices that fades out after 3 km of distance. This effect seems to become larger the more wind turbines are installed in the proximity of a property. PV farms reduce property prices more locally only up to a 2 km distance by 1.9 %.

JEL-Codes: Q21, D12, R31

Keywords: Renewable energy; hedonic prices; heterogeneity

February 2025

** Felix Heuer, RWI and RUB; Stephan Sommer, Bochum University of Applied Sciences and RWI.* *– We are highly grateful for valuable comments and suggestions by Thomas Bauer, Phillip Breidenbach, Paul Lehmann, and Hans Köster. We gratefully acknowledge financial support by the Federal Ministry of Economics Affairs and Climate Action (BMWK) under grant 03EI522233.* *– All correspondence to: Felix Heuer, RWI, Hohenzollernstraße 1–3, 45128 Essen, Germany, e-mail: felix.heuer@rwi-essen.de*

1 Introduction

In 2015, nearly every country in the world committed to reducing carbon emissions and limiting global warming to a maximum of 2°C, with efforts to aim for 1.5°C. Achieving these targets will require a comprehensive decarbonization of the global energy system in the 21^{st} century (Kriegler et al., 2014). To rebuild its energy system, Germany has set a target of generating 80% of its electricity from renewable sources by 2030 (BMJ, 2023). Currently, around 56% of total electricity generation comes from renewable sources (Destatis, 2024), and especially wind and solar energy play a key role, since they accounted for 31% and 12% of total electricity production in 2023 (Destatis, 2024), respectively.

However, substantial efforts are needed to significantly accelerate the energy transition and meet the 2030 target, and legislation has been passed to set aside 2% of the national land area for such projects (BMJ, 2023). Despite their environmental benefits, however, wind and PV installations often face local opposition, primarily due to concerns about visual aesthetics in the landscape, impacts on the local environment and animal populations, noise, and even negative health effects (Jensen et al., 2014; Krekel and Zerrahn, 2017; Zerrahn, 2017). Therefore, understanding the negative externalities of such installations is crucial for policy makers to (i) optimally site energy facilities to minimize overall negative externalities, and (ii) potentially design compensation schemes to mitigate negative local externalities and increase public acceptance.

In this paper, we analyze the local costs and benefits of both onshore wind turbines and large PV farms by conducting a hedonic price analysis. Our data are the universe of wind turbines and large PV farms and housing ads from Germany's largest online real estate platform for the period spanning from 2009 to 2021. Employing small-scale regional fixed effects at the 1 km^2 level allows us to identify the effects of installing a wind turbine or a PV farm in the proximity of a property in a spatial difference-in-differences framework. Beyond estimating average treatment effects, we analyze whether the effect varies with the distance to the next energy facility and whether the effect depends on the number of energy facilities. Moreover, we add to the existing literature by estimating property price effects not only of the nearest energy facility, that is, the effect of an installment at distance d conditional on other installments closer or further away from the property.

Our findings show that the effects of installing wind turbines and PV farms are locally very concentrated. Wind turbines within a radius of 1-3 km lower property prices, by roughly 2%. These effects appear to be the same irrespective of whether other turbines are installed within a 6 km radius. The property price effects seem to be larger for wind turbines with a higher capacity and among properties that are located in areas with a low population density and income. Moreover, we find that a larger number of wind turbines leads to a greater decline in property prices. However, each additional wind turbine only has a small effect on property prices. For instance, the installation of one or two wind turbines in the radius of up to 3 km reduces property prices by roughly 2%, while more than ten wind turbines in the same radius lead to a cumulated effect of -4.8%. Yet, also for higher numbers of wind turbines we cannot find significant property price effects beyond a 3 km distance. Regarding PV farms, we find that the installation lowers property prices by 1.9% in the distance of 1-2 km. We do not find a cumulative effects of PV farms.

The literature generally finds a negative externality of wind turbines and PV systems (Heintzelman and Tuttle, 2012; Lang et al., 2014; Krekel and Zerrahn, 2017; Frondel et al., 2019; Joly and De Jaeger, 2021). A recent meta-analysis finds an average reduction in property values of 0.68% within a radius of about 2 miles or 3.2 km from the nearest wind turbine (Schütt, 2024). Using transaction data from the Dutch real estate market, Dröes and Koster (2016) find that the presence of a wind turbine within 2 km of a property reduces prices by an average of 1.4%. Other studies use additional data to gain more insights by estimating the effect of visibility rather than proximity. For example, Gibbons (2015) show that property prices in England and Wales are on average 5-6% lower for homes with a visible wind turbine within 2 km. Similarly, Jensen et al. (2014) disentangle different externalities and show that visual pollution reduces the sales price of a house in Denmark by up to about 3%, while noise pollution reduces the price by between 3% and 7%. The literature therefore suggests that wind turbines may generate notable negative local externalities. The local externalities, however, remain relatively small in comparison to industrial plants (Davis, 2011; Currie et al., 2015), and are of similar size compared to noise pollution from airports (Boes and Nüesch, 2011; Breidenbach and Thiel, 2024) and train traffic (Thiel, 2022).

With respect to the cumulative effect of wind turbines, Guo et al. (2024) use extensive viewshed data from the US to detect that having at least one wind turbine in a home's viewshed of a 10 km radius reduces the sales price of such a property on average by 1.12%. In addition, the authors show that the capitalization of the disamenity effects increases only marginally with the number of wind turbines in the viewshed and does not change the overall local externality notably. To be precise, each additional 10 wind turbines in the viewshed lower sales prices by 0.2%. In contrast to this, Gibbons (2015) finds larger differences in property price effects by the number of wind turbine for England. His results suggest a 1.6% decrease in property prices due to 1-10 wind turbines at a 2-4 km distance, while 11-20 (21$\leq$) wind turbines reduce prices by 2.1% (5.3%).

The literature on property price effects of other renewable energy sources, such as solar farms, is scarcer. Dröes and Koster (2021) show that a solar farm in the Netherlands reduces property prices in a 2 km radius by 2.6%. In contrast, Maddison et al. (2023) finds a large property price effect of -5.4% for real estate in England and Wales, but only within less than 750 m south of a PV farm. Jarvis (2021) finds no statistically significant effect of PV farm construction on property values in the UK.

We contribute to this literature with new evidence on distance- and intensity-specific property price effects of wind turbines and PV farms. Most of the existing literature focuses on the property price effect of wind turbines and PV farms within a certain radius, using distance to the nearest facility as the treatment definition. In contrast to this, we estimate property price effects for energy facilities at distance d conditional of other proximate facilities and therefore account for a property's exposure to multiple facilities. By allowing properties to be treated at different distances we are able to estimate treatment effects for facilities other than the nearest one. In particular, we answer the questions (i) up to what distance do energy facilities other than the nearest one exert a negative externality, (ii) do externalities vary with the number of facilities, (iii) and how do distance and intensity effects interact.

The remainder of this paper is structured as follows. Section 2 describes the underlying data together with some descriptive statistics as well as the used methodology. Section 3 and 4 report the estimation results for wind turbines and PV farms, respectively. Section 5 concludes.

2 Data and Methods

2.1 Data

Our analysis is based on two main data sources: real estate data from Germany's largest online real estate platform and the universe of all wind turbines and ground-mounted PV farms. The real estate data comes from the *RWI-GEO-RED* data set, which includes all properties listed for sale on the real estate platform *ImmobilienScout24* between January 1, 2009 and December 31, 2021. According to the latest estimates by the German Federal Cartel Office, ImmobilienScout24 has a market share of over 70% of all (Federal Cartel Office, 2016) and can therefore be considered an adequate representation of the German housing market.[1] The data includes asking prices, date of listing, a wide range of property characteristics and exact geo-coordinates (Schaffner and Thiel, 2023). For our analysis, we only consider properties with a given asking price and floor area, and exclude observations with implausible or missing geocoordinates. The data set is cleaned by removing duplicates and keeping only the most recent listing of a property if the listing has been updated over time, which should best capture the value of the property. We also exclude unique property types, such as those labelled 'castle', and drop outliers, which we define as the top one percent in terms of number of rooms, and the top and bottom one percent in terms of asking price, floor area and plot size.

The data set on renewable energy facilities includes all planned and installed wind turbines and ground-mounted PV farms from the Core Energy Market Data Register (CEMDR). This ensures a full representation of all relevant installations in Germany and eliminates selection bias and measurement error of treatment (intensity) due to unobserved energy facilities. In addition, the large number of energy facilities allows for various heterogeneity analyses based on different facility characteristics. However, we rely on Manske et al. (2022), who have pre-processed and cleaned this data set and thus provide an updated and improved version of the data collected by Eichhorn et al. (2019). Compared to the original data, this data set provides more granular and accurate geocoordinates of energy facilities. However, the data set ends on May 7, 2021, which is the last date in our observation period. The data set provides the exact coordinates of

[1] We do not consider property rentals due to the small number of observations. We also exclude apartments, as they are mostly located in urban areas and not close to wind turbines and PV farms.

the energy facilities and includes various facility-specific characteristics, such as hub height and gross capacity, as well as the exact dates of (planned) start of operation.

We combine the two data sets based on the exact geocoordinates of both the properties and the energy facilities. First, we use the geocoordinates to count the number of energy facilities at different distances from a property, specifically at distances of 0-1 km, 1-2 km, 2-3 km, 3-4 km, 4-5 km, and 5-6 km for both wind turbines and PV farms. In addition, we merge regional characteristics at the one square kilometer grid level based on the *RWI-GEO-GRID* data set (Breidenbach and Eilers, 2018). The RWI-GEO-GRID dataset contains detailed socio-demographic characteristics, such as local population, housing composition, income, and unemployment rates. After merging, we obtain a rich real estate data set linked with information on nearby energy facilities and small-scale neighborhood characteristics.

2.2 Descriptives

Table 1 presents summary statistics on the windmill and PV farm samples. In total, the sample includes 31,762 wind turbines, of which 29,561 are installed and operating as of 7^{th} May 2021. The remaining 2,201 wind turbines are under development and planned for installation after our observation period. All PV farms in our sample are installed and operational by May 2021. The first wind turbine and PV farm were installed in 1983 and 1988, respectively. However, the vast majority was installed after 2000 (Figure A1).

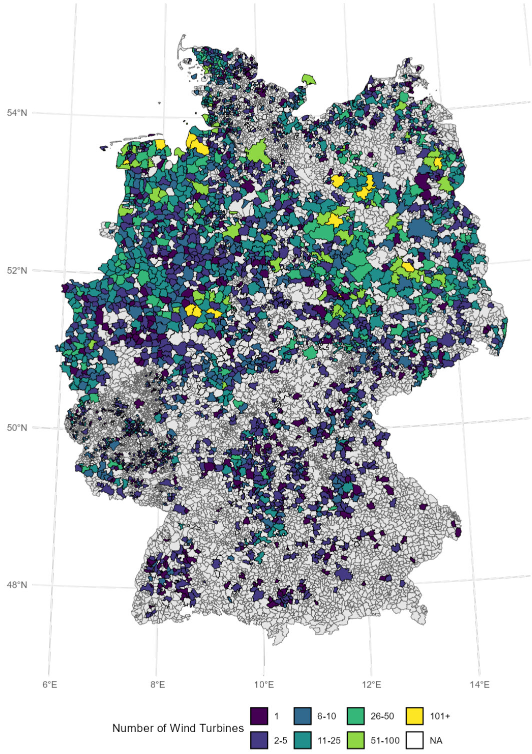
Table 1: Descriptive Statistics: Wind Turbine & PV Farm Sample

	Mean	Std. Dev.	Min	Max	Obs.
Wind Turbines					
(Planned) Installation Year	2008	7.5	1983	2053	31,762
Hub Height (m)	100.6	33.6	18	200	31,176
Rotor Diameter (m)	86.4	32.0	10	200	31,404
Installed Capacity (MW)	2,221	1,289	30	20,000	31,762
PV Farms					
(Planned) Installation Year	2013	4.3	1988	2021	6,621
Installed Capacity (MW)	2,085	3,599	30	98,988	6,621
Size (sqm)	34,437	60,709	156	1,871,304	6,621

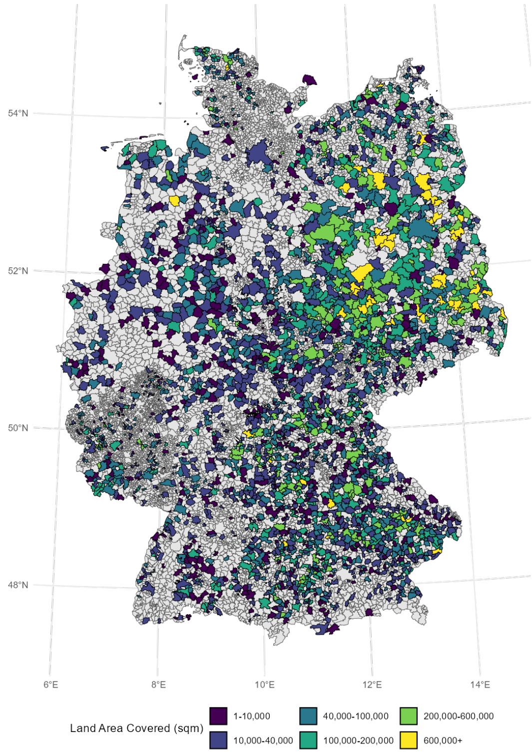
Note: The sample is based on the Core Energy Market Data Register (CEMDR) (Manske et al., 2022) and includes 31,762 wind turbines and 6,621 PV farms.

The wind turbines in our sample vary considerably in terms of height, rotor diameter, and

Figure 1: Spatial Distribution of Wind Turbines and PV Farms in Germany in 2021



(a) Wind Turbines



(b) PV Farms

Notes: The maps show the number of installed wind turbines and the area covered by PV farms (in sqm) in each municipality in 2021. NAs refer to the absence of wind turbines or PV farms in a given municipality.

installed capacity (Table 1).[2] For instance, while the average wind turbine height is around 100 meters, we observe wind turbine heights ranging from 18 to 200 meters. There is a similar variation in rotor diameter, with an average of 86.4 meters. PV farms appear to vary even more, both in terms of size in square meters and installed capacity. With 2,085 MW, PV farms have a similar average capacity as wind farms. However, the largest PV farm has an installed capacity of around 100,000 MW, enough to meet the average annual consumption of more than 20,000 4-person households.

Figures 1(a) and 1(b) illustrate differences in the spatial distribution of wind turbines and PV farms in Germany in 2021. We find the highest concentration of wind turbines in northern

[2] We impute missing values for some wind turbines on the basis of the reported wind turbine type, using the average characteristic for the type.

Germany, with a higher number of municipalities with installed wind turbines and more installed wind turbines in general. These differences in the spatial distribution of wind turbines appear to be persistent over time and throughout our observation period. We find a similar pattern in the distribution of wind turbines in 2009 (Figure A2(a)) and a greater expansion of wind energy between 2009 and 2021 in municipalities that already had installed wind turbines in 2009 (Figure A3(a)). For PV farms, we observe a greater land area covered by PV farms in East Germany (Figure 1(b)). At the beginning of our observation period in 2009, only a few PV farms were installed in individual municipalities (Figure A2(b)). Hence, we observe the major part of installment during our observation period.

Table 2 presents descriptive statistics for the property sample. During our observation period from 2009 to 2021, about 7 million properties are listed for sale. Of these, 3.4 million properties are within 6 km of a wind turbine, which is the maximum distance up to which we estimate distance-specific treatment effects in our main analysis. The remaining 3.7 million properties are beyond a 6 km distance from a wind turbine and are considered to be untreated. It is noticeable that properties within a 6 km radius have a significantly lower asking price per square meter (sqm) and also differ in several other characteristics. Properties located closer to wind turbines are more likely to be single-family homes, are on average two years older, and have a (slightly) larger plot size (living space). In addition, properties within a radius of 6 km are more often located in poorer and rural areas with lower population density, as wind turbines are mostly located in regions with greater land availability and lower land prices.[3]

We partially account for differences between treated and untreated properties by restricting our sample to properties within 8 km of the nearest wind turbine, following Dröes and Koster (2016, 2021), and Gaur and Lang (2023), to reduce the risk of omitted variable bias in our analysis.[4] This restricted sample leaves us with 4.6 million observations, of which 1.2 million properties are located beyond 6 km from the nearest wind turbine. For the restricted sample, the differences in property and neighborhood characteristics are significantly smaller. Except for asking price (per sqm), we do not observe sizeable differences in property characteristics

[3]Descriptive statistics for properties within (beyond) 3 km of the nearest wind turbine are presented in Table A1 in the Appendix. The 3 km distance marks an alternative distance threshold for treatment definition in the estimation of treatment effects by treatment intensity and the maximum distance up to which we find significant property price effects of wind turbines.

[4]We test the robustness of our results to different cut-offs in section 3.

between properties within and outside a 6 km radius of the nearest wind turbine. However, we still observe notable differences in neighborhood characteristics. Therefore, we control for the neighborhood characteristics in our estimations. Moreover, we account for time-constant spatial differences, such as altitude, by including small-scale regional fixed effects.[5]

Table A2 presents descriptive statistics for the property sample differentiated by proximity to the nearest PV farm. Similar to the case of wind turbines, the full sample exhibits differences between properties within and beyond a distance of 6 km from the nearest PV farm. However, these differences tend to be smaller than in the case of wind turbines. Properties within a 6

Table 2: Descriptive Statistics: Property Sample

	Full Sample			Restricted Sample		
		Nearest WT			Nearest WT	
	All	within 6 km	beyond 6 km	All	within 6 km	beyond 6 km
Property Attributes						
Price (€)	299,489	259,884	335,865	268,404	259,884	291,400
Price per sqm	1,825	1,583	2,046	1,627	1,583	1,744
Year of Construction	1974	1973	1975	1973	1973	1972
Last Modernization	2006	2006	2006	2006	2006	2005
Living Space (sqm)	170.8	172.1	169.6	172.8	172.1	174.8
Plot Area (sqm)	660.9	710.5	615.2	699.5	710.5	669.9
Single House	49.5	54.8	44.6	54.7	54.8	54.5
Serial House	4.6	4.2	5.0	4.5	4.2	5.2
First Occupancy	16.3	15.8	16.8	15.9	15.8	16.3
Refurbished	12.6	11.5	13.6	11.8	11.5	12.6
Clean	17.1	16.2	18.0	16.3	16.2	16.7
Work Required	6.1	5.8	6.3	5.9	5.8	6.2
Neighborhood Attributes						
PP (in millions)	36.5	29.8	42.6	31.9	29.8	37.7
Share of Families	32.6	33.4	31.8	33.2	33.4	32.5
Unemployment Rate	5.4	5.8	5.1	5.8	5.8	5.6
Population per km^2	1,642.9	1,401.5	1,864.6	1,494.6	1,401.5	1,746.0
Rurality	25.5	30.0	21.5	28.6	30.0	25.1
Obs.	6,998,338	3,350,418	3,647,920	4,591,854	3,350,418	1,241,436

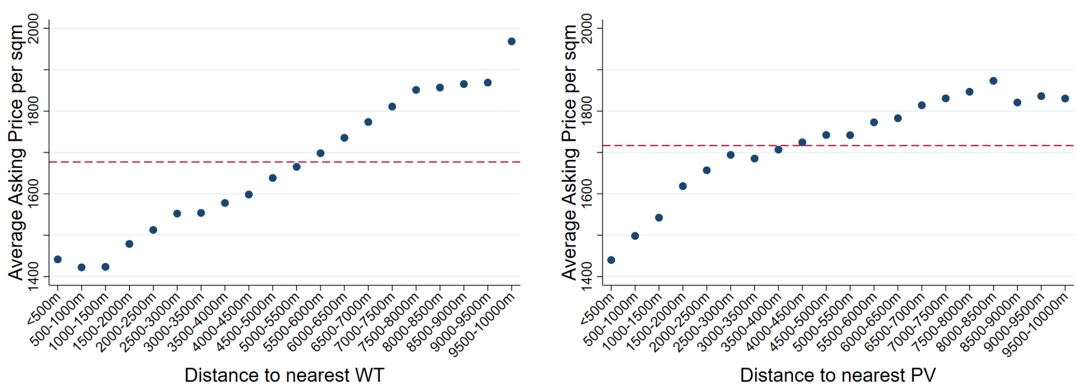
Note: The restricted sample excludes all properties beyond 8 km to the nearest wind turbine. The displayed values are average values. The mean of the binary variables single house, serial house, first occupancy, refurbished, clean, and work required are shown as percentage share of properties with the corresponding attribute. Neighborhood characteristics PP (annual purchasing power), share of families, unemployment rate, and population are on a 1 km^2 grid level. Rurality is on the municipality level and defined by the percentage share of inhabitants in a given municipality that live in a rural area with a population density of less than 150 inhabitants/km^2. The index is taken from the Federal Institute for Research on Building, Urban Affairs, and Spatial Development (BBSR, 2023). All differences between properties within and beyond a 6 km distance are statistically significant, with the exception of year of construction and last modernization.

[5] A visual inspection of the temporal differences in neighborhood characteristics is shown in Figure A4.

km distance tend to be listed at a lower price (per sqm), have a larger floor area and plot size, and are more likely to be detached properties. They are also located in more rural areas with lower average incomes and population densities. In the sample excluding properties located more than 8 km away, there are no sizeable differences based on observable property characteristics. However, properties within 6 km of PV farms are still located in slightly poorer and more rural areas, reflecting a higher concentration of PV farms outside cities and mainly in East Germany. As in the case of wind turbines, spatial differences are accounted for by including neighborhood characteristics and regional fixed effects in our analysis.[6]

Figure 2 illustrates the negative relationship between property prices and proximity to wind turbines and PV farms. On average, properties within a 10 km distance to the nearest wind turbine are listed for a price of €1,676 per square meter. The average property at a 0.5 to 1.5 km distance is listed for about €1,400 per sqm and the listing price increases gradually with distance to almost €2,000 per sqm for properties at a 9.5-10 km distance. Similarly, property prices increase with distance to the nearest PV farm at a diminishing rate, from about €1,440 per sqm at less than 500 m to more than €1,800 per sqm further than 6.5 km away. Differences in property prices by distance to the nearest wind turbines and PV farm can be explained by differences in the spatial distribution shown Figure 1.

Figure 2: Property Prices and Distance to Nearest Energy Facility



(a) Wind Turbines

(b) PV Farms

Notes: The figures display the average asking price for properties at different distances to the nearest wind turbine and PV farm, respectively. The horizontal dashed line represents the average asking price across all properties within a 10 km distance to the nearest wind turbine or PV farm.

[6]See Figure A5 for a graphical illustration of the differences over time.

2.3 Methodology

We employ a difference-in-differences (DiD) hedonic method to estimate the effect of energy facilities on property prices. To estimate property price effects based on both distance and number of facilities, we use two estimation strategies. Both estimation strategies are performed for both wind turbines and PV farms, respectively.

In a first step, we aim to identify the effect of installing energy facilities on property prices at distance d. To this end, we distinguish between energy facilities at distances d defined by 0-1 km, 1-2 km, 2-3 km, 3-4 km, 4-5 km, and 5-6 km. Distance-specific treatment dummies D_{itd} indicate at least one facility at distance d in the month t a property i is listed for sale. Properties beyond a distance of 6 km from any energy facility are considered untreated.[7] We choose this categorical definition of treatment instead of the continuous distance to the nearest wind turbine to estimate the relationship most flexibly and to explicitly account for the fact that energy facilities are not located on the green meadow. In other words, we are interested in the average property price effect of new installations at distance d conditional on other facilities at distance d'. Hence, we allow properties to be treated at different distances, which permits estimation of treatment effects for facilities other than the nearest one. Our estimates of property price effects of facilities at distance d are therefore an average effect over properties only affected facilities at distance d and properties affected by other facilities at distance $d' \neq d$ within a 6 km radius, both closer and further away. Using distance to the nearest facility as treatment does not allow for this differentiation, and the effect of the nearest facility absorbs the property price effects of all nearby facilities.

The two-way fixed-effects (TWFE) regression estimating distance specific treatment effects is defined as follows:

$$\log y_{irt} = \sum_{d=1}^{6} \beta_d D_{itd} + \lambda_r + \theta_t + \gamma_1 X_i + \gamma_2 X_{rt} + \sum_{s=t+1}^{t+4} \nu_{is} + \varepsilon_{irt} \qquad (1)$$

where y_{irt} is the offer price of property i located in location r listed in time period t, λ_r are location fixed effects based on 1 km^2 sized grid cells, and θ_t denotes year times month fixed

[7] Recall that the sample only includes within a 8 km distance to the nearest planned or installed wind turbine or PV farm location, respectively.

effects that capture seasonality and common property price developments, for instance due to economic fluctuations and inflation effects.[8] X_i and X_{rt} are vectors of property and time variant neighborhood specific control variables.[9] ν_{is} is a binary indicator equal to one for properties listed s years before a wind turbine is installed within a 3 km radius and captures anticipation effects. We choose the time window of 4 years based on the event study estimates shown in Figure A6 and the distance threshold based on the maximum distance up to which we detect significant treatment effects for wind turbines. We do not control for anticipation effects of PV farms as suggested by Figure A6(b).

Our parameters of interest are β_d, which identify the average property price effect of energy facilities at distance d relative to properties without an energy facility at distance d, that is, the conditional offer price differences between properties with and without wind turbines or PV farms at distance d located in the same grid cell.[10]For the interpretation of β_d it is important to bear in mind that they are conditional on treatment in other distance categories, that is, β_d estimate the average effect of energy facilities at distance d conditional on the existence of energy facilities at distance $d' \neq d$. Therefore, if a property is exposed to energy facilities at two distances, the two corresponding coefficients are estimated conditional on each other. In a robustness check, we estimate β_d separately for the cases were no other energy facility is present at $d' \neq d$, where another facility is present at $d' < d$ or $d' > d$, respectively. Finally, ϵ_i is an identically and independently distributed error term. We cluster our standard errors at the local labor market level to allow for serial correlation in the errors over time and spatial correlation in the development of property prices across grid cells. We use the definition by Kosfeld and Werner (2012), which comprises 141 local labor markets and are used as a measure for local housing markets.

In a second step, we are interested in treatment effects by treatment intensity and estimate the effect of different numbers of wind turbines (PV farms) located within a 3 km (2 km) radius.

[8]Singleton observations are omitted in the high-dimensional fixed effect regressions to avoid incorrect inference and an overestimation of significance levels in the presence of fixed effects nested in clusters. For a more detailed discussion on the effect of singleton observations in high-dimensional fixed effects regressions refer to Correia (2015).

[9]We control for (squared) floor space, (squared) plot size, property type FE, first occupancy and year of construction FE, and quality of facility FE at the property level. Grid cell controls include purchasing power (PP), share of foreigner, singles, and families, unemployment rate, and population.

[10]The effective number of treated units identifying distance-specific coefficients β_d, conditional on grid cell and month fixed effects are reported in Table A3.

We choose the threshold of 3 km (2 km) based on estimation results from equation (1) and the maximum distance $\bar{d}$ up to which wind turbines (PV farms) impact property prices significantly. To ensure the most flexible estimation of treatment intensity specific effects, we use a categorical definition of treatment intensity. In case of wind turbines, we use six categories ($J = 6$), namely 1, 2, 3, 4, 5-9, and 10≤ wind turbines, ensuring a sufficient number of observations for each level of treatment intensity. For PV farms, we differentiate between four categories ($J = 4$) due to a lower prevalence of PV farms at shorter distances, namely between 1, 2, 3, and 4≤.[11] The following regression model estimates the intensity specific treatment effects for each intensity category $j \in J$:

$$\log y_{irt} = \sum_{j=1}^{J} \beta_j D_{itj} + \gamma_1 X_i + \gamma_2 X_{rt} + \lambda_r + \theta_t + \sum_{s=t+1}^{t+4} \nu_{is} + \varepsilon_{irt} \tag{2}$$

with β_j identifying the average treatment effect of j wind turbines (PV farms) located within a 3 km (2 km) radius in the month in which a property is listed for sale. All the other variables are analogous to equation (1).

Last, we estimate distance specific effects for different treatment intensities. Yet, we only choose two intensity categories to ensure a sufficient number of observations at each distance for each intensity. In particular, we estimate distance specific property price effects of 1-4, and 5≤ wind turbines as well as 1 and 2≤ PV farms per distance band with the following regression:

$$\log y_{irt} = \sum_{j=1}^{2} \sum_{d=1}^{6} \beta_{jd} D_{itjd} + \gamma_1 X_i + \gamma_2 X_{rt} + \lambda_r + \theta_t + \sum_{s=t+1}^{t+4} \nu_{is} + \varepsilon_{irt} \tag{3}$$

where β_{jd} identifies the effect of j energy facilities at distance d.[12]

In all regression models (1)-(3), causal identification of the treatment effect requires that treatment, D, is uncorrelated with unobservables in the error term, i.e., unobserved factors that explain differences in property prices and make properties more or less likely to be near an energy facility in the month it is listed for sale. To address this threat to identification, we take the following steps to allow for causal interpretation. We restrict the full set of properties to those

[11] The effective number of treated units identifying intensity-specific coefficients β_j, conditional on grid cell and month fixed effects are reported in Table A5.

[12] The effective number of treated units identifying distance- and intensity-specific coefficients β_{jd}, conditional on grid cell and month fixed effects are reported in Table A6.

within a 8 km distance to the nearest wind turbine or PV farm location for the respective analysis, respectively.[13] As described in section 2.2, this reduces differences between treated and untreated properties and ensures a more homogeneous sample of properties based on observable property and neighborhood characteristics. Similar strategies to limit the risk of omitted variable bias are used by Dröes and Koster (2016, 2021) and Gaur and Lang (2023), who also limit their sample based on properties' proximity to wind turbine locations. Nevertheless, the sample might still comprise a large set of potentially different housing markets, heterogeneous price developments, and heterogeneous treatment probabilities across properties.

We address these concerns by controlling for time invariant differences between property locations across 1 km^2 sized grid cells (λ_r). Thereby, we capture selection effects and time-invariant factors that determine the exposure risk of a grid cell to wind turbines and PV farms. Due to the granular regional fixed effects, we are confident to be able to account for time invariant location specific factors. Key factors that determine placement of wind turbines are the degree of urbanization and income (Dröes and Koster, 2016) as well as topographic and meteorological conditions.

In addition, we control for several property and time variant grid cell characteristics to capture compositional shifts over time and differences in the probability of treatment between grid cells and property types. We discuss different robustness checks in section 3 to address additional threats to identification. For instance, we additionally (i) account for unobserved differences in treatment timing, (ii) use more conservative fixed effects specifications, and (iii) use different samples based on the maximum distance between property and energy facility.

3 Results for Wind Turbines

This section presents our estimation results. We first discuss the results for wind turbines and subsequently show the results for PV farms. As wind turbines are more prevalent, account for a higher share of the German electricity mix, and have been built for a longer period of time, we will concentrate on presenting the results for their implementation.

[13] We test the robustness or our results with respect to this threshold in section 3.

3.1 Distance specific effect

We begin our analysis by estimating the effect of wind turbines on property prices differentiated by distance and find a locally concentrated negative externality of wind turbines up to 3 km. The estimated effects based on equation (1) are shown in Table 3. In our main specification in column 1 the estimated coefficient for wind turbines less than 1 km away is 0.014% but is not statistically significant at conventional levels. The large standard errors are due to the small number of observations within such a short distance of the nearest wind turbine. Moreover, these properties are located in very rural areas with nearby wind turbines often installed before 2000, that is before the introduction of minimum distance requirements. Today, minimum distance requirements are implicitly regulated by noise protection regulations, which do not specify an exact distance in meters, but implicitly prohibit the installation of wind turbines within 1 km of residential areas. These regulations where first introduced in 1998 (Immission Control Law, 1998). For a detailed discussion of these regulations and minimum distance requirements, see Stede et al. (2021).

At 1-2 km and 2-3 km, wind turbines decrease property prices by 1.8% and 1.9%, respectively, which is equivalent to €48,330 and €51,015 based on the average asking price of properties between 2009 and 2021. Both effects are statistically significant at the 5 percent level. Beyond 3 km, we find no statistically significant effect of wind turbines on property prices, and the magnitude of the coefficients is virtually zero. In sum, our results thus show a locally concentrated negative effect of wind turbines on property prices within a radius of 3 km.

The estimates are robust to different sensitivity checks. First, our results are robust to unobserved differences in treatment timing, i.e., differences in property price effects of wind turbines installed at different points in time. In our baseline specification, month and grid cell fixed effects account for level differences in property price effects between properties exposed to wind turbines at different times. To account for differences in treatment timing at the property level, we additionally include years after or before first treatment fixed effects.[14] The estimated coefficients remain qualitatively and quantitatively unchanged, confirming a negative and significant effect of wind turbines at a distance of 1-3 km. (column 2).

[14]First treatment is defined by the installation year of the first energy facility within a 6 km radius of a property.

Second, we address the risk of omitted variable bias by controlling for different linear price trajectories between treated properties within a 6 km distance to the nearest wind turbine and properties without a proximate wind turbine by interacting the corresponding interaction term with a linear time trend. Again, our results remain robust, which suggests the absences of unobserved differences in price trends between treated and untreated properties (column 3). In fact, estimated property price effects tend to be slightly larger conditional on a differential linear price trend.

Third, the negative effect of wind turbines at a distance of 1-3 km is robust to different sample restrictions based on the maximum distance between properties and the nearest wind turbine. In particular, we estimate distance specific treatment effects based on properties within a 7 km

Table 3: Distance-Specific Property Price Effects of WT

Dependent Variable	ln(price)				
	(1)	(2)	(3)	(4)	(5)
WT at distance of (D_{itd})					
0-1 km	0.014	0.017	0.014	0.016	0.017
	(0.016)	(0.015)	(0.016)	(0.016)	(0.015)
1-2 km	-0.018**	-0.016*	-0.019**	-0.016*	-0.015*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
2-3 km	-0.019**	-0.017**	-0.020***	-0.017**	-0.015*
	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)
3-4 km	0.001	-0.001	-0.002	0.002	0.004
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
4-5 km	-0.005	-0.007	-0.009	-0.004	-0.002
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
5-6 km	-0.002	-0.006	-0.007	-0.000	0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Max. Distance to Nearest WT	8 km	8 km	8 km	7 km	6 km
Month × Year FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
1 km^2 Grid Cell FE	✓	✓	✓	✓	✓
4 Years Anticipation FE	✓	✓	✓	✓	✓
Years after/before 1^{st} WT FE	-	✓	-	-	-
Linear Price Trend Differences	-	-	✓	-	-
Observations	4,576,294	4,576,294	4,576,294	4,213,731	3,779,867
R-squared	0.718	0.718	0.718	0.716	0.712

Notes: Estimates are based on the restricted sample, i.e., properties within 8 km of the nearest wind turbine, following equation 1. The dependent variable is log listing prices per sqm in all specifications. Control variables include (squared) floor space, (squared) plot size, property type FE, first occupancy and year of construction FE, quality of facility FE at the property level. Time-varying controls at 1 km^2 grid cell level include purchasing power, share of foreigners, singles, and families, unemployment rate, and population. Standard errors clustered at the local labor market level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

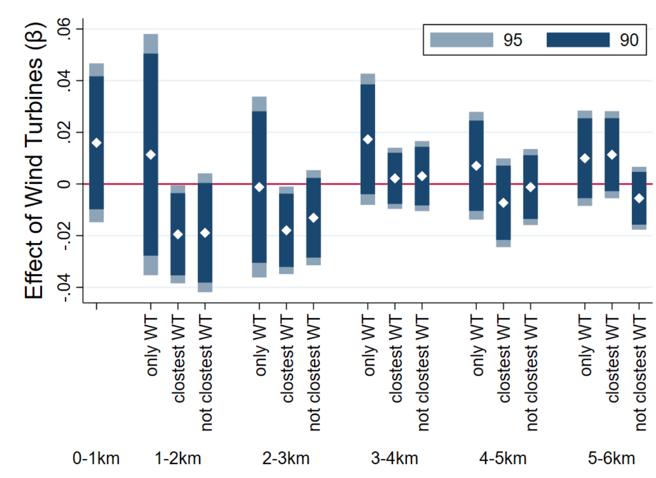
and 6 km distance to the nearest wind turbine, respectively. This reduces the size of our sample but improves the comparability of the properties in our sample by excluding properties located further away from wind turbines. The effects of wind turbines at 1-2 km and 2-3 only decrease marginally and remain statistically significant, respectively (column 4-5).

The fact that our estimates are robust to various robustness checks even in smaller, more homogeneous samples supports our claim that we identify the causal property price effect of wind turbines and supports a locally concentrated property price effect within a 3 km radius. So far, β_d, the estimated property price effect of wind turbines at distance d is conditional on wind turbines at other distances d' within a 6 km distance. However, one might expect different property price effects depending on whether (i) a property is not exposed to wind turbines at another distance d' (only at distance d), (ii) a property is also exposed to wind turbines at a shorter distance $d' < d$, or (iii) a property is also exposed to wind turbines at a further distance $d' > d$. To differentiate between these cases and to test if wind turbines other than the nearest have a significant impact on property prices, we interact treatment dummies D_{itd} in equation 1 with an indicator for each case. We do not differentiate between the three cases for wind turbines at a distance of less than 1 km due to the small number of observations. The corresponding estimates are presented in Figure 3.

In line with our baseline results (Table 3, column 1), we find no statistically significant treatment effects beyond a distance of 3 km. Moreover, property prices do not appear to be affected by wind turbines at distance d if there are no other wind turbines at distance d' within 6 km. The estimated effect size is close to zero or even positive, and the large standard errors are explained by a small number of properties with only one wind turbine in the respective radius (Table A4). For properties with wind turbines at multiple distances, estimated property price effects do not differ notably depending on whether there are additional wind turbines at shorter or further distances. Wind turbines at a distance of 1-2 km (2-3 km) reduce property prices by 1.9% (1.8%) conditional on other wind turbines at $d' > d$ within a 6 km radius. Both effects are statistically significant at the 5 percent level. Conditional on wind turbines at shorter distance, the estimated property price effect at a 1-2 km (2-3 km) distance is only marginally smaller and amounts to 1.9% (1.3%), yet forfeits statistical significant at the 10 percent level.

Our results suggest that property price effects may depend on the number of nearby wind

Figure 3: Distance-Specific Property Price Effects of (non) nearest WT



Notes: The regression results are reported in Table A7. Distance specific coefficients are based on equation (1) but differentiated by whether WT are present only at distance d (*"only WT"*), or whether other WT exists at shorter (*"non closest WT"*) or longer distances (*"closest WT"*). Standard errors are clustered at the local labor market level, the number of observations is 4,576,294 and the R^2 is 0.718.

turbines, as significant effects are only present when properties are exposed to wind turbines at multiple distances. We explore this in more detail in the following section. In addition, we find that also wind turbines other than the nearest have a significant impact on property prices.

3.2 Intensity effect

In a next step, we look at the importance of treatment intensity and differences in property price effects depending on the number of nearby wind turbines. In what follows, we refer to the number of wind turbines within a 3 km radius of properties as treatment intensity. We choose the distance threshold of 3 km because we do not observe statistically significant average effects beyond this threshold in Table 3. The corresponding estimates on property price effects by treatment intensity are based on equation (2) and are shown in Table 4.

Our intensity specific estimates exhibit two key features: First, the estimated effects of one, two, and four wind turbines within 3 km are quantitatively comparable and not statistically different. The estimated effect of three wind turbines is larger but also not statistically different at the ten percent level. This suggests that small differences in the number of nearby wind turbines do not affect the level of negative externalities.

Second, we find a larger negative externality for larger numbers of wind turbines, in line with the related literature (Gibbons, 2015; Dröes and Koster, 2016; Guo et al., 2024). While a single wind turbine reduces property prices by 2%, 5-9 (≥10) wind turbines exert a negative effect of 3.6% (4.8%), on average. Hence, our results show that treatment intensity does affect the local burden, however, only for large differences in the number of wind turbines.

3.3 Distance- and Intensity-Specific Property

So far, we have presented evidence of declining treatment effects with distance and increasing treatment effects with treatment intensity. Next, we explore the additional effects of adding wind turbines at different distances and how treatment intensity influences the maximum distance up to which externalities are identified. To this end, we estimate distance specific treatment effects for different treatment intensities based on equation 3. This allows us to differentiate between

Table 4: Intensity-Specific Property Price Effects of WT

Dependent Variable	ln(price) (1)
Treatment intensity dummy (≤ 3km) (D_{itj})	
1 WT	-0.020*
	(0.011)
2 WT	-0.018*
	(0.011)
3 WT	-0.028**
	(0.012)
4 WT	-0.019*
	(0.011)
5-9 WT	-0.036**
	(0.014)
≥10 WT	-0.048***
	(0.015)
Max. Distance to Nearest WT	8 km
Month × Year FE	✓
Controls	✓
1 km^2 Grid Cell FE	✓
4 Years Anticipation FE	✓
Observations	4,576,294
R-squared	0.718

Notes: Estimates are based on properties within an 8 km distance to the nearest WT and based on equation (2). The dependent variable is log listing prices per sqm. Control variables include (squared) floor space, (squared) plot size, property type FE, first occupancy and year of construction FE, quality of facility FE at the property level. Time-varying controls at the grid level are purchasing power, share of foreigners, singles, and families, unemployment rate, and population. Standard errors clustered at the local labor market level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Distance- and Intensity-Specific Property Price Effects of WT

Dependent Variable	ln(price) (1)	
WT at 0-1 km distance		
1-4	0.017	(0.015)
5≤	-0.031	(0.033)
WT at 1-2 km distance		
1-4	-0.016*	(0.010)
5≤	-0.020*	(0.010)
WT at 2-3 km distance		
1-4	-0.017**	(0.008)
5≤	-0.023**	(0.010)
WT at 3-4 km distance		
1-4	0.002	(0.006)
5≤	0.001	(0.008)
WT at 4-5 km distance		
1-4	-0.004	(0.006)
5≤	-0.011	(0.007)
WT at 5-6 km distance		
1-4	-0.001	(0.006)
5≤	-0.003	(0.008)
Max. Distance to Nearest WT	8 km	
4 Years Anticipation Effects	✓	
Controls	✓	
1 km^2 Grid Cell FE	✓	
Month × Year FE	✓	
4 Years Anticipation FE	✓	
Observations	4,576,294	
R-squared	0.718	

Notes: Estimates are based on the restricted sample, i.e., properties within 8 km of the nearest wind turbine, following equation (3). The dependent variable is log listing prices per sqm in all specifications. Control variables include (squared) floor space, (squared) plot size, property type FE, first occupancy and year of construction FE, quality of facility FE at the property level. Time-varying controls at 1 km^2 grid cell level include purchasing power, share of foreigners, singles, and families, unemployment rate, and population. Standard errors clustered at the local labor market level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

the effects of 1-4 and more than 4 wind turbines at different distances. Using two instead of five categories for treatment intensity ensures a larger number of observations for each distance and intensity category and increases estimation precision. Table 5 summarizes the corresponding estimates.

As before, we only find significant treatment effects up to 3 km distance also for higher treatment intensities. The estimated point estimates are notably smaller beyond a 3 km distance across all treatment intensities and statistically insignificant at conventional levels. This shows that also for higher treatment intensities the effect of wind turbines on property prices is locally concentrated within a 3 km radius. When looking at property price effects at a distance of less than 3 km by treatment intensity, our estimates show a larger property price effect of more wind turbines. Unsurprisingly, we find the largest point estimate of -3.1% for a high level of treatment intensity ($\geq$5) at a distance of less than 1 km. The large confidence intervals are likely due to the small number of observations, leading to reduced estimation imprecision. At 1-2 km and 2-3 km, one to four wind turbines reduce property prices by -1.6% and 1.7%, on average, while five and more wind turbines have an effect of -2% and -2.3%. respectively. In both cases, a higher number of wind turbines exert a larger negative effect on property prices but the effect sizes are not statistically different.

Taken together our distance and intensity specific results show that also for higher treatment intensity, local externalities from wind turbines are limited to a 3 km radius. Moreover, the estimates support evidence of a stronger negative property price effect of a higher number of wind turbines.

3.4 Heterogeneities

Last, we analyze different heterogeneities in the effect of wind turbines on property prices. For this purpose, we estimate the property price effects of wind turbines within a distance of 3 km and differentiate the treatment effect with respect to neighborhood and wind turbine characteristics. The threshold of 3 km marks the maximum distance up to which we observe significant treatment effects (section 3.1). For simplicity, we do not discuss heterogeneities in distance and intensity-specific effects.

First, we find notable differences in property price effects across turbine types, with larger effects for large, high capacity, and wide rotor turbines. However, in contrast to previous findings, e.g. by Dröes and Koster (2016, 2021), we find only small differences in effect sizes (Table A8). In particular, while low and medium capacity wind turbines appear not to have a statistically significant property prices, high capacity wind turbines with more than 1800 MW have an average effect of -2.5%. The differences in the estimated effects by height and rotor width are very similar, due to a high correlation between all three turbine characteristics. These findings suggest that wind turbine characteristics play an important role in terms of local externalities. Smaller wind turbines could reduce the local burden, but at the cost of lower energy production.

Second, we find a large heterogeneity in treatment effects across neighborhood characteristics (Table A9). In our baseline analysis, we control for 1 km^2 grid fixed effects. This is also the regional breakdown of our control variables, except for the degree of urbanity, which is at the municipality level, based on the Rurality Index developed by the Federal Institute for Research on Building, Urban Affairs, and Spatial Development (BBSR, 2023).[15] Therefore, variation in neighborhood characteristics only stems from temporal changes, which are generally quite small. Therefore, we use broader 2 km^2 grid cells fixed effects instead to allow for a higher degree of variation in observed neighborhood characteristics when estimating treatment effects, while maintaining the grid cell characteristics for each property at the 1 km^2 level. This allows for variation both within a 2 km^2 cell and over time and for a comparison of treatment effects by neighborhood characteristics.

With this setup, we find larger treatment effects in urban municipalities and in areas with lower population density. Property price effect only differ marginally by local income, measured by local purchasing power. The estimated heterogeneity of effects with respect to population density and the rurality of the municipality seems contradictory at first sight. On the one hand, we find no property price effect of wind turbines in rural municipalities, but a larger and statistically significant treatment effect of -13.2% in urban municipalities.

On the other hand, we only find statistically significant treatment effects in grid cells with lower population density, conditional on the rurality of the municipality. This suggests that the property price effects are larger in urban municipalities, but in grid cells with lower population density. This can mostly be explained by a higher prevalence of wind turbines in these areas. Our results show that the local costs of wind turbines vary notably across regions, with higher costs for rural and low-income neighborhoods.

[15]The index indicates the share of inhabitants in a given municipality living in a rural neighborhood with a population density of less than 150 inhabitants/km^2. Based on this index, we classify rural municipalities are those in which all residents live in neighborhoods with a population density of less than 150 inhabitants/km^2. In contrast, we classify urban municipalities as those in which all residents live in areas with a population density of more than 150 inhabitants/km^2. Mixed municipalities include both rural and urban neighborhoods.

4 Results for PV Farms

This section presents our findings on the estimated property price effect of PV farms. First, we estimate distance-specific property price effects and find treatment effects of similar size compared to wind turbines, but locally more concentrated (Table 6). We find a property price effect of -1.6% for PV farms 1-2 km (column 1) away which is statistically significant at the one percent level. Beyond a 2 km distance we do not find significant property price effects of PV farms. This finding is in line with the existing literature, but shows slightly smaller effects compared to previous estimates, for example by Dröes and Koster (2021). Compared to wind turbines, the negative impact of PV farms is more locally concentrated, but of similar magnitude.

Our estimates on distance specific property price effects of PV farms are robust to the set of sensitivity checks already discussed in section 3.1 (Table 6, columns 2-5). The estimated effect

Table 6: Distance-Specific Property Price Effects of PV Farms

Dependent Variable	ln(price)				
	(1)	(2)	(3)	(4)	(5)
PV at distance of (D_{itd})					
0-1 km	-0.007	-0.006	-0.006	-0.007	-0.007
	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)
1-2 km	-0.019***	-0.017***	-0.018***	-0.019***	-0.019***
	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)
2-3 km	-0.007	-0.005	-0.006	-0.007	-0.007
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
3-4 km	-0.009	-0.007	-0.008	-0.009	-0.009*
	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)
4-5 km	-0.005	-0.003	-0.004	-0.006	-0.006
	(0.005)	(0.005)	(0.007)	(0.005)	(0.005)
5-6 km	-0.004	-0.001	-0.003	-0.005	-0.005
	(0.005)	(0.005)	(0.007)	(0.005)	(0.005)
Max. Distance to Nearest WT	8 km	8 km	8 km	7 km	6 km
Month × Year FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
1 km^2 Grid Cell FE	✓	✓	✓	✓	✓
Years after/before 1st WT FE	-	✓	-	-	-
Linear Price Trend Differences	-	-	✓	-	-
Observations	4,456,857	4,456,857	4,456,857	4,038,519	3,529,849
R-squared	0.748	0.748	0.748	0.747	0.745

Notes: Estimates are based on properties within a 8km distance to the nearest PV farm following equation 1. The dependent variables is log listing prices per sqm in all specification. Control variables include (squared) floor space, (squared) plot size, property type FE, first occupancy and year of construction FE, quality of facility FE at the property level. Time varying control at grid level are purchasing power, share of foreigners, singles, and families, unemployment rate, and population. Standard errors clustered at local labor market level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Intensity-Specific Property Price Effects of PV Farms

Dependent Variable	ln(price) (1)
Treatment intensity dummy ($\leq$ 2km) (D_{itj})	
1 PV	-0.020***
	(0.006)
2 PV	-0.007
	(0.008)
3 PV	-0.028*
	(0.014)
$\geq$4 PV	-0.028*
	(0.015)
Max. Distance to Nearest WT	8 km
Month $\times$ Year FE	✓
Controls	✓
1 km^2 Grid Cell FE	✓
Observations	4,456,857
R-squared	0.746

Notes: Estimates are based on properties within an 8 km distance to the nearest PV farm and based on equation (2). The dependent variable is log listing prices per sqm. Control variables include (squared) floor space, (squared) plot size, property type FE, first occupancy and year of construction FE, quality of facility FE at the property level. Time-varying controls at the grid level are purchasing power, share of foreigners, singles, and families, unemployment rate, and population. Standard errors clustered at the local labor market level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

of PV farms 1-2 km away varies only slightly between -1.7% and -1.9% across all specifications and remains statistically significant at the one percent level. Thus, controlling for (i) years after or before the first treatment fixed effects (column 2), the differential linear time trend between properties within and beyond a 6 km distance to the nearest PV farms (column 3), and (iii) excluding properties beyond a 7 km or 6 km distance to the nearest PV farms (column 4&5) does not affect our results in a meaningful way. The robustness of our estimates gives us confidence that we are indeed estimating the causal effect of PV farms on property prices.

Table 7 shows that property price effects of PV farms only differ by a small extent by the number of PV farms. A single PV farm within a 2 km radius reduces property prices by 2%, while three or more PV farms reduce property prices by 2.8%. Yet, the estimated effects are not statistically different. Our results therefore suggest that the local burden of PV farms on property prices does not depend on the number of PV farms and associated differences in property price effects are only small.

Table 8 reports distance and treatment intensity specific coefficients based on equation (3), distinguishing between 1 and more than 2 PV farms for each distance. We do not differentiate at a distance of less than 1 km due to insufficient observations with more than one PV farm. Consistent with our previous findings, we find significant property price effects only at 1-2 km. This confirms the absence of negative externalities beyond 2 km, even at higher treatment intensities. However, a limited number of properties with more than one PV farm per distance category leads to lower estimation precision. Also at a distance of 1-2 km, the effect of two and more PV farms is statistically insignificant.

Finally, we assess differences in the impact of PV farms on property prices across different neighborhood and PV farm characteristics (Table A10 & A11). As in the case of wind turbines, we find a higher property price effects of PV farms in more urban municipalities and no significant effects in rural municipalities (column 1, Table A10). Within municipalities, however, property price effects are highest in grid cells with average population density (column 3, Table A10).

Table 8: Distance- and Intensity- Specific Property Price Effects of PV Farms

Dependent Variable	ln(price) (1)	
PV at 0-1 km distance	-0.007	(0.007)
PV at 1-2 km distance		
1	-0.020***	(0.006)
2≤	-0.015	(0.010)
PV at 2-3 km distance		
1	-0.008	(0.006)
2≤	-0.006	(0.008)
PV at 3-4 km distance		
1	-0.010	(0.006)
2≤	-0.007	(0.008)
PV at 4-5 km distance		
1	-0.007	(0.005)
2≤	-0.002	(0.007)
PV at 5-6 km distance		
1	-0.006	(0.005)
2≤	-0.001	(0.009)
Max. Distance to Nearest WT	8 km	
Month × Year FE	✓	
Controls	✓	
1 km^2 Grid Cell FE	✓	
Observations	4,456,857	
R-squared	0.748	

Notes: Estimates are based on properties within a 8 km distance to the nearest PV farm. The dependent variables is log listing prices per sqm in all specification. Control variables include (squared) floor space, (squared) plot size, property type FE, first occupancy and year of construction FE, quality of facility FE at the property level. Time varying control at grid level are purchasing power, share of foreigners, singles, and families, unemployment rate, and population. Standard errors clustered at local labor market level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

This reflects the higher prevalence of PV farms in semi-urban areas compared to wind turbines, which are present mostly in rural areas. We do not find significant property price effects of PV farms in low and high population density grid cells. With respect to income, we find the largest property price impact of PV farms in medium income grid cells of about -1.9% (column 2, Table A10. We find no property price effects in high income grid cells and the effect in low-income grid cells of -1.2% is only statistically significant at the ten percent level.

At last, we find only small differences in property price effects of PV farms by installed capacity (Table A11). PV farms with less than 1800 MW reduce nearby property prices by 2-2.3%. In contrast, the estimated effect of PV farms with larger capacity is slightly smaller and statistically insignificant. A potential reason might be that larger PV farms have a larger land use and are therefore more often located in more rural areas and possibly outside cities or built-up areas. As a result, they would have a lower impact on the nearby residence.

5 Conclusion

In this paper, we analyze the distance and intensity specific effect of wind turbines and PV farms on property prices. To this end, we exploit a spatial difference-in-differences setting with regional fixed effects at a one km^2 grid level and employ the universe of energy facilities and housing ads from Germany's largest online real estate platform between 2009 and 2021.

Our findings show that the installation of wind turbines and PV farms lowers property prices in the close proximity. A property with at least one wind turbine within a 1-3 km radius sells for roughly 2% less than a statistical equal property without a wind turbine at this distance. The effect for PV farms is similar in magnitude but more concentrated, as the negative impact is limited to a distance between 1-2km. Beyond these thresholds, we cannot detect further statistically significant effects. Moreover, we detect some evidence for cumulative effects of wind turbines but not for PV farms. While a single wind turbine within a 3km distance to a property reduces its asking price by 2%, the effect amounts to up to 5% for at least 10 wind turbines in that radius. The price effects seem to be particularly strong for higher wind turbines and increase with a decreasing population density.

Our analysis theoretically allows for both positive and negative effects of installing renewable energy facilities on property prices. It seems that locally the negative effects outdo potentially positive effects. While negative effects are very salient (e.g. noise, visual pollution, flickering), positive effects are more opaque and do not necessarily benefit the property directly (e.g. revenues for the facility operator). Yet, compared to other infrastructure investments like coal and gas plants (Davis, 2011), airports (Boes and Nüesch, 2011), and rail tracks (Thiel, 2022), the negative effects are comparable or smaller in magnitude.

Given that renewable energy generation is the major response to the threat of climate change, the society has to judge whether accepting local costs (in terms of lower property value) is worth providing the global benefit (in terms of green energy). Yet, as new capacity is required quickly to meet climate targets, this consideration has to be made timely. One possibility to accelerate this process could be by socializing the benefits that accrue by renewable energy, e.g. via partial ownership of the energy facilities, reduced electricity tariffs or lump-sum payments. Moreover, given that we only find small marginal effects of incrementing the number of wind turbines close to properties, it could be an accelerating factor to build wind turbines in small clusters rather than finding new locations.

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Appendix

A Tables and Figures

A.1 Tables

Table A1: Descriptive Statistics: Property Sample II

	Full Sample		Restricted Sample	
	Nearest WT			
	within 3 km	beyond 3 km	within 3 km	beyond 3 km
Property Attributes				
Price	244,415	313,879	244,415	279,473
Price per sqm	1,515	1,905	1,515	1,678
Year of Construction	1973	1974	1973	1972
Last Modernization	2006	2006	2006	2005
Living Space	169.6	171.1	169.6	174.3
Plot Area	727.3	643.5	727.3	686.7
Single House	55.6	47.9	55.6	54.3
Serial House	3.7	4.8	3.7	4.8
First Occupancy	15.7	16.5	15.7	16.0
Refurbished	11.1	12.9	11.1	12.1
Clean	15.8	17.4	15.8	16.5
Work Required	5.6	6.2	5.6	6.0
Neighborhood Characteristics				
PP (mio)	24.4	39.6	24.4	35.4
Share of Families	34.8	32.0	34.8	32.4
Unemployment Rate	5.7	5.4	5.7	5.8
Rurality	32.0	23.8	32.0	27.1
Population Density	1,159	1,769	1,159	1,649
Obs.	1,449,738	5,548,600	1,449,738	3,142,116

Note: The restricted sample excludes all properties beyond 8 km to the nearest wind turbine. The displayed values are average values. The mean of the binary variables single house, serial house, first occupancy, refurbished, clean, and work required are shown as percentage share of properties with the corresponding attribute. Neighborhood characteristics PP (annual purchasing power), share of families, unemployment rate, and population are on a 1 km^2 grid level. Rurality is on the municipality level and defined by the percentage share of inhabitants in a given municipality that live in a rural area with a population density of less than 150 inhabitants/km^2. The index is taken from the Federal Institute for Research on Building, Urban Affairs, and Spatial Development (BBSR, 2023). All differences between properties within and beyond a 6 km distance are statistically significant, with the exception of year of construction and last modernization.

Table A2: Descriptive Statistics: Property Sample III

	Full Sample				Restricted Sample			
	within 6 km	beyond 6 km	within 2 km	beyond 2 km	within 6 km	beyond 6 km	within 2 km	beyond 2 km
Property Attributes								
Price (€)	299,475	303,168	272,447	301,940	285,248	275,170	272,447	287,175
Price per sqm	1,824	1,857	1,667	1,839	1,718	1,654	1,667	1,726
Year of Construction	1974	1974	1973	1974	1973	1972	1973	1973
Last Modernization	2006	2005	2006	2006	2006	2005	2006	2005
Living Space (sqm)	174.1	168.9	173.6	170.5	173.2	172.0	173.6	173.1
Plot Area (sqm)	698.0	639.8	712.1	656.2	685.7	669.7	712.1	681.8
Single House	54.1	46.8	54.1	49.0	54.9	55.9	54.1	54.9
Serial House	4.6	4.8	3.5	4.7	4.4	4.7	3.5	4.6
First Occupancy	17.1	15.9	17.8	16.2	16.1	14.7	17.8	15.8
Refurbished	11.1	13.4	10.1	12.8	11.7	12.4	10.1	11.9
Clean	15.4	18.0	13.8	17.4	15.7	16.1	13.8	16.0
Work Required	5.8	6.2	5.4	6.1	5.8	5.9	5.4	5.9
Neighborhood Characteristics								
PP (mio)	36.5	38.9	29.3	37.1	32.6	33.2	29.3	33.1
Share of Families	32.1	32.7	31.1	32.7	32.3	33.0	31.1	33.3
Unemployment Rate	5.4	5.6	5.4	5.4	5.4	5.7	5.4	5.4
Rurality	32.1	21.7	37.8	24.4	32.3	29.5	37.8	29.5
Population Density	1,643	1,743	1,382	1,667	1,498	1,538	1,382	1,515
Obs.	2,533,158	4,466,738	585,049	6,414,847	2,533,158	1,939,095	585,049	3,887,204

Note: The restricted sample excludes all properties beyond 8 km to the nearest PV farm. The displayed values are average values. The mean of the binary variables single house, serial house, first occupancy, refurbished, clean, and work required are shown as percentage share of properties with the corresponding attribute. Neighborhood characteristics PP (annual purchasing power), share of families, unemployment rate, and population are on a 1 km^2 grid level. Rurality is on the municipality level and defined by the percentage share of inhabitants in a given municipality that live in a rural area with a population density of less than 150 inhabitants/km^2. The index is taken from the Federal Institute for Research on Building, Urban Affairs, and Spatial Development (BBSR, 2023). All differences between properties within and beyond a 6 km distance are statistically significant, with the exception of year of construction and last modernization.

Table A3: Effective number of treated units by distance

	Treated Properties	
	WT Sample	PV Sample
0-1 km	37,881	38,296
1-2 km	103,321	91,948
2-3 km	151,111	128,615
3-4 km	188,775	152,998
4-5 km	216,623	177,780
5-6 km	228,613	202,161

Note: Displayed values refer to the number of treated observations for each distance threshold conditional on month and 1 km^2 grid cell fixed effects.

Table A4: Effective number of treated units by distance & treatment type

	Treated Properties	
	WT Sample	PV Sample
0-1 km	37,881	38,296
1-2 km		
only WT	15,078	41,275
closest WT	107,395	70,408
not closest WT	21,497	20,594
2-3 km		
only WT	31,581	66,136
closest WT	170,441	74,816
not closest WT	84,370	40,836
3-4 km		
only WT	56,941	83,332
closest WT	161,003	60,763
not closest WT	123,379	58,968
4-5 km		
only WT	78,857	108,135
closest WT	131,328	44,911
not closest WT	145,043	79,026
5-6 km		
only WT	153,904	128,812
closest WT	71,462	26,617
not closest WT	158,148	93,553

Note: Displayed values refer to the number of treated observations for each distance threshold, differentiated by whether the wind turbine (WT) at distance d is the only WT within a 6 km radius, or whether other WTs are present at distances $d' < d$ (*"not closest WT"*) or $d' > d$ (*"closest WT"*), conditional on month and 1 km^2 grid cell fixed effects.

Table A5: Effective number of treated units by treatment intensity

Treated Properties			
WT Sample within 3km		PV Sample within 2km	
1	77,041	1	116,531
2	52,913	2	41,043
3	44,579	3	16,018
4	32,910	4≤	8,748
5-9	53,940		
10≤	19,383		

Note: Displayed values refer to the number of treated observations for each number of wind turbines (PV farms) within a 3km (2km) radius, i.e., treatment intensity category, conditional on month and 1 km^2 grid cell fixed effects.

Table A6: Effective number of treated units by distance & treatment intensity

Treated Properties			
WT Sample		PV Sample	
0-1 km			
1-4 WT	35,326	1 PV	31,829
5≤ WT	4,180	2≤	9,791
1-2 km			
1-4 WT	107,799	1 PV	83,328
5≤ WT	36,964	2≤	31,442
2-3 km			
1-4 WT	167,007	1 PV	120,225
5≤ WT	73,251	2≤	46,255
3-4 km			
1-4 WT	222,506	1 PV	142,474
5≤ WT	104,638	2≤	58,826
4-5 km			
1-4 WT	263,296	1 PV	164,642
5≤ WT	126,975	2≤	76,102
5-6 km			
1-4 WT	291,744	1 PV	183,220
5≤ WT	155,690	2≤	84,945

Note: Displayed values refer to the number of treated observations for each distance threshold and treatment intensity category conditional on month and 1 km^2 grid cell fixed effects.

Table A7: Distance-Specific Property Price Effects of (non) nearest WT

Dependent Variable	ln(price) (1)	
WT at 0-1 km distance	0.016	(0.016)
WT at 1-2 km distance		
only WT within 6 km	0.011	(0.024)
other WT at $d' > d$ within 6 km	-0.019**	(0.010)
other WT at $d' < d$ within 6 km	-0.019	(0.012)
WT at 2-3 km distance		
only WT within 6 km	-0.001	(0.018)
other WT at $d' > d$ within 6 km	-0.018**	(0.009)
other WT at $d' < d$ within 6 km	-0.013	(0.009)
WT at 3-4 km distance		
only WT within 6 km	0.017	(0.013)
other WT at $d' > d$ within 6 km	0.002	(0.006)
other WT at $d' < d$ within 6 km	0.003	(0.007)
WT at 4-5 km distance		
only WT within 6 km	0.007	(0.011)
other WT at $d' > d$ within 6 km	-0.007	(0.009)
other WT at $d' < d$ within 6 km	-0.001	(0.007)
WT at 5-6 km distance		
only WT within 6 km	0.010	(0.009)
other WT at $d' > d$ within 6 km	0.011	(0.009)
other WT at $d' < d$ within 6 km	-0.006	(0.006)
Max. Distance to Nearest WT	8 km	
Month × Year FE	✓	
Controls	✓	
1 km^2 Grid Cell FE	✓	
4 Years Anticipation FE	✓	
Observations	4,576,294	
R-squared	0.718	

Notes: Estimates are based on the restricted sample, i.e., properties within 8 km of the nearest wind turbine. The distance-specific effects following equation 1 are differentiated whether (i) WT are present only at distance d, (ii) whether other WT exists at shorter $d' < d$, or (iii) whether other WT exist at further longer distances $d' > d$. The dependent variable is log listing prices per sqm in all specifications. Control variables include (squared) floor space, (squared) plot size, property type FE, first occupancy and year of construction FE, quality of facility FE at the property level. Time-varying controls at 1 km^2 grid cell level include purchasing power, share of foreigners, singles, and families, unemployment rate, and population. Standard errors clustered at the local labor market level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A8: Regression Results - Heterogeneity WT Characteristics

Dependent Variable	ln(price)		
	(1)	(2)	(3)
WT within 3 km radius (D_{itj})			
× **Inst. Capacity**			
lower tercile ($\leq$ 945 MW)	-0.010		
	(0.013)		
middle tercile	-0.013		
	(0.014)		
upper tercile ($\geq$ 1800 MW)	-0.025**		
	(0.010)		
× **Hub Height**			
lower tercile ($\leq$ 54 m)		-0.012	
		(0.013)	
middle tercile		-0.015	
		(0.011)	
upper tercile ($\geq$ 77 m)		-0.025**	
		(0.008)	
× **Rotor Diameter**			
lower tercile ($\leq$ 68 m)			-0.001
			(0.008)
middle tercile			-0.017**
			(0.008)
upper tercile ($\geq$ 93 m)			-0.016**
			(0.009)
Max. Distance to Nearest WT	8 km	8 km	8 km
Controls	✓	✓	✓
Grid FE	✓	✓	✓
Month FE	✓	✓	✓
4 Years Anticipation Effects	✓	✓	✓
Observations	4,576,294	4,576,294	4,576,294
R-squared	0.718	0.718	0.718

Notes: Estimates are based on the restricted sample, i.e., properties within 8 km of the nearest wind turbine. The dependent variable is log listing prices per sqm in all specifications. Control variables include (squared) floor space, (squared) plot size, property type FE, first occupancy and year of construction FE, quality of facility FE at the property level. Time-varying controls at 1 km^2 grid cell level include purchasing power, share of foreigners, singles, and families, unemployment rate, and population. Standard errors clustered at the local labor market level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A9: Regression Results - Heterogeneity Area Characteristics WT Sample

Dependent Variable	ln(price)		
	(1)	(2)	(3)
WT within 3 km radius (D_{itj})			
× **Rurality**			
rural dummy	0.024		
	(0.022)		
mixed dummy	-0.018*		
	(0.005)		
urban dummy	-0.132**		
	(0.051)		
× **PP**			
lower tercile (≤ €10,8 mio)		-0.027***	
		(0.011)	
middle tercile		-0.020*	
		(0.012)	
upper tercile (≥ €33,9 mio)		-0.024*	
		(0.013)	
× **Population**			
lower tercile (≤ 504 inh./sqkm)			-0.038***
			(0.010)
middle tercile			-0.015
			(0.013)
upper tercile (≥ 1555 inh./sqkm)			-0.018
			(0.012)
Max. Distance to Nearest WT	8 km	8 km	8 km
Month × Year FE	✓	✓	✓
Controls	✓	✓	✓
1 km^2 Grid Cell FE	✓	✓	✓
4 Years Anticipation FE	✓	✓	✓
Observations	4,003,108	4,003,108	4,003,108
R-squared	0.704	0.704	0.704

Notes: Estimates are based on the restricted sample, i.e., properties within 8 km of the nearest wind turbine. The dependent variable is log listing prices per sqm in all specifications. The rural (urban) indicator is one for municipalities where all inhabitants live in neighborhoods with less (more) than 150 inhabitants/km^2 and zero otherwise. Control variables include (squared) floor space, (squared) plot size, property type FE, first occupancy and year of construction FE, quality of facility FE at the property level. Time-varying controls at 1 km^2 grid cell level include purchasing power, share of foreigners, singles, and families, unemployment rate, and population. Standard errors clustered at the local labor market level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A10: Regression Results - Heterogeneity Area Characteristics PV Sample

Dependent Variable	ln(price)		
	Rurality	PPP	Population
	(1)	(2)	(3)
PV within 2 km radius (D_{itj})			
× **Rurality**			
rural	-0.010		
	(0.028)		
mixed	-0.012*		
	(0.006)		
urban	-0.083**		
	(0.035)		
× **PP**			
lower tercile		-0.012*	
		(0.007)	
middle tercile		-0.019***	
		(0.007)	
upper tercile		-0.010	
		(0.009)	
× **Population**			
lower tercile			-0.009
			(0.007)
middle tercile			-0.017**
			(0.007)
upper tercile			-0.013
			(0.010)
Max. Distance to Nearest PV	8 km	8 km	8 km
Controls	✓	✓	✓
1 km^2 Grid Cell FE	✓	✓	✓
Month × Year FE	✓	✓	✓
Observations	4,456,857	4,441,093	4,441,093
R-squared	0.748	0.748	0.748

Notes: Estimates are based on the restricted sample, i.e., properties within 8 km of the nearest PV farm. The dependent variable is log listing prices per sqm in all specifications. The rural (urban) indicator is one for municipalities where all inhabitants live in neighborhoods with less (more) than 150 inhabitants/km^2 and zero otherwise. Control variables include (squared) floor space, (squared) plot size, property type FE, first occupancy and year of construction FE, quality of facility FE at the property level. Time-varying controls at 1 km^2 grid cell level include purchasing power, share of foreigners, singles, and families, unemployment rate, and population. Standard errors clustered at the local labor market level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

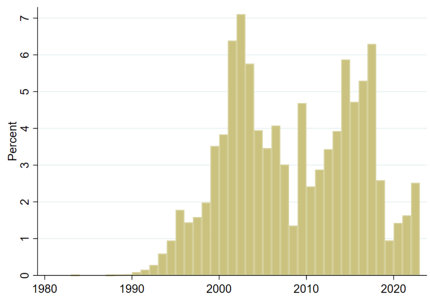
Table A11: Regression Results - Heterogeneity PV Characteristics

Dependent Variable	ln(price) (1)
PV within 2 km radius (D_{itj})	
× **Inst. Capacity**	
lower tercile ($\leq$ 757 MW)	-0.023**
	(0.009)
middle tercile	-0.020**
	(0.009)
upper tercile ($\geq$ 1800 MW)	-0.013
	(0.009)
Max. Distance to Nearest PV	8 km
Controls	✓
1 km^2 Grid Cell FE	✓
Month × Year FE	✓
Observations	4,456,857
R-squared	0.748

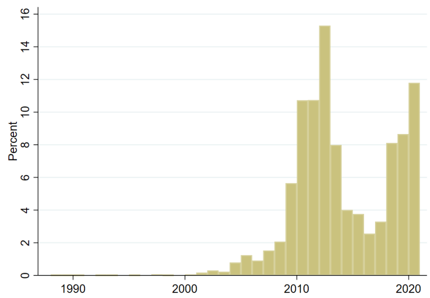
Notes: Estimates are based on the restricted sample, i.e., properties within 8 km of the nearest PV farm. The dependent variable is log listing prices per sqm in all specifications. Control variables include (squared) floor space, (squared) plot size, property type FE, first occupancy and year of construction FE, quality of facility FE at the property level. Time-varying controls at 1 km^2 grid cell level include purchasing power, share of foreigners, singles, and families, unemployment rate, and population. Standard errors clustered at the local labor market level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

A.2 Figures

Figure A1: Distribution of the Year of Installation of Energy Facilities



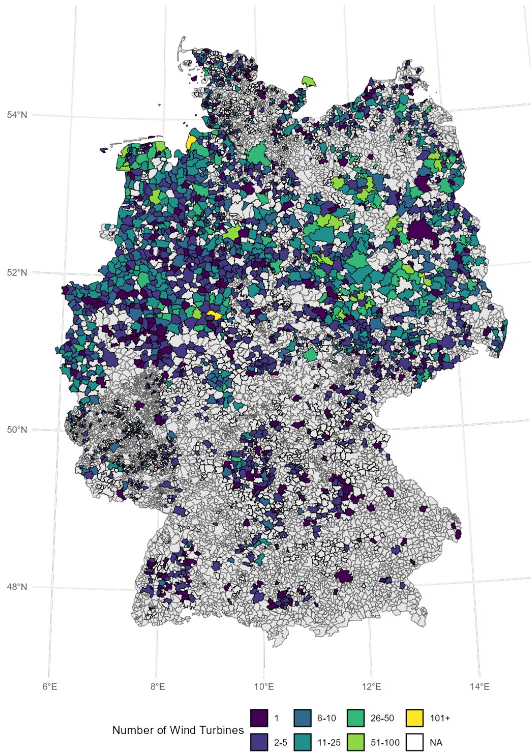
(a) Wind Turbines



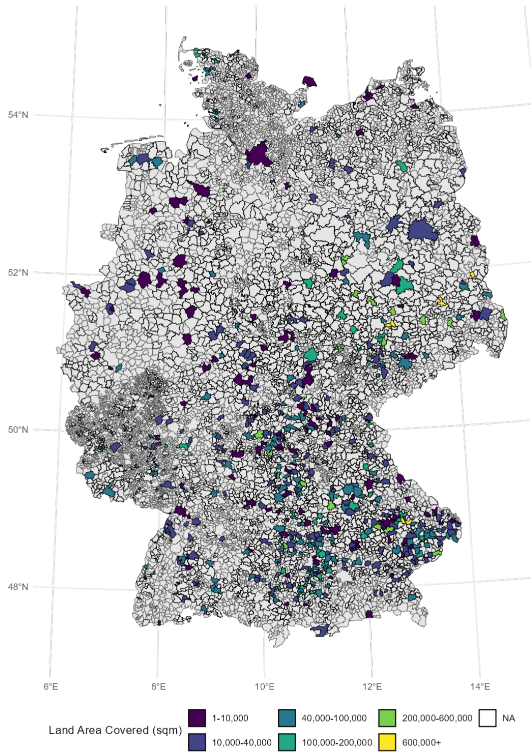
(b) PV farms

The histogram shows the distribution of the year of (planned) installment years of all wind turbines and PV farms.

Figure A2: Spatial Distribution of Wind Turbines and PV Farms 2009



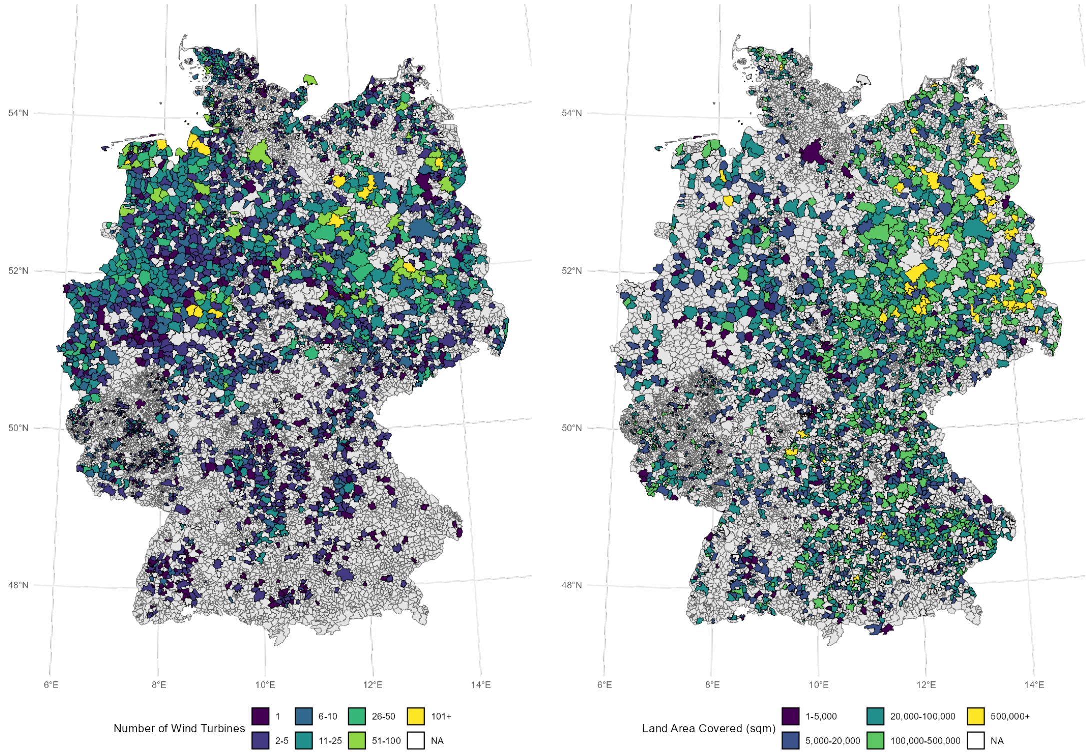
(a) Wind Turbines



(b) PV Farms

Notes: The maps show the number of installed wind turbines and the area covered by PV farms (in sqm) in each municipality in 2009. NAs refer to the absence of wind turbines or PV farms in a given municipality.

Figure A3: Changes in Spatial Distribution of Energy Facilities 2009-2022

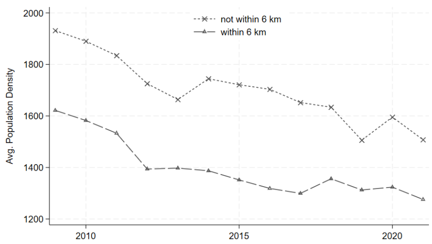


(a) Wind Turbines

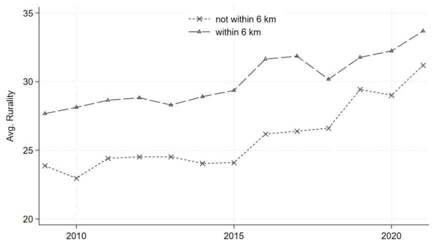
(b) PV Farms

Notes: The map illustrates the change in the number of installed wind turbines and the area covered by PV farms (in sqm) across municipality between 2009 and 2021. NAs refer to the absence of wind turbines or PV farms in a given municipality.

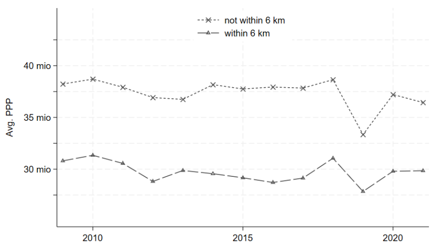
Figure A4: Temporal Differences in Neighborhood Characteristics - WT Sample



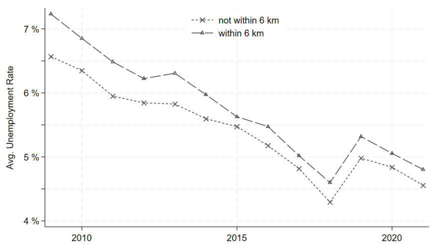
(a) Population



(b) Rurality



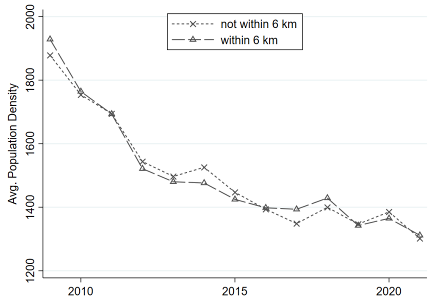
(c) PP



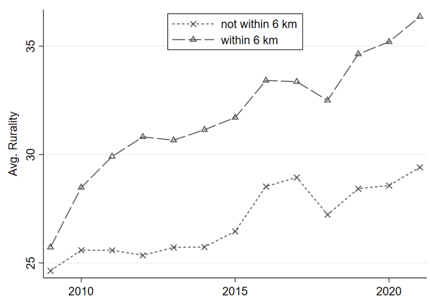
(d) Unemployment Rate

Notes: Each figure is based on properties within a 8 km distance to the nearest wind turbine and shows the difference in mean neighborhood characteristics of properties with and without a wind turbine within a 6 km radius over time. Rurality is defined by the share of inhabitants in a given municipality that live in an area with a population density of less than 150 inhabitants/km². All other variables are on the grid level.

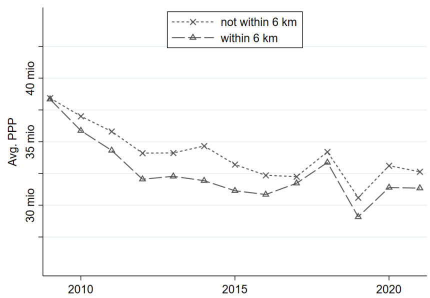
Figure A5: Temporal Differences in Neighborhood Characteristics - PV Sample



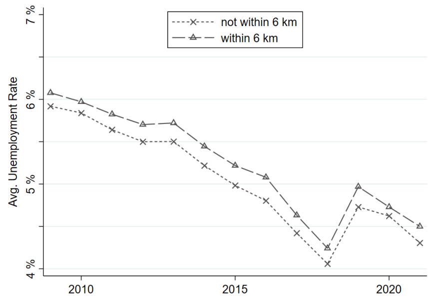
(a) Population



(b) Rurality



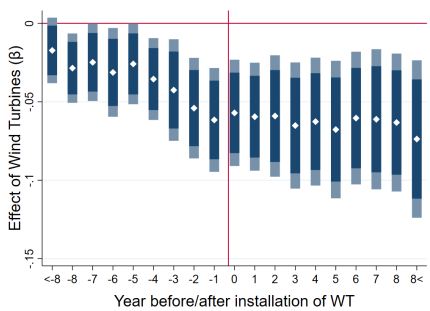
(c) PP



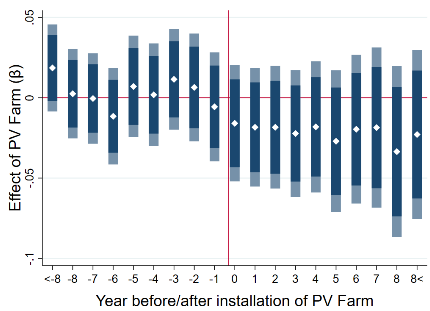
(d) Unemployment Rate

Notes: Each figure is based on properties within a 8 km distance to the nearest PV farm turbine and shows the difference in mean neighborhood characteristics of properties with and without a PV farm within a 6 km radius over time. Rurality is defined by the share of inhabitants in a given municipality that live in an area with a population density of less than 150 inhabitants/km². All other variables are on the grid level.

Figure A6: Event Study Estimates



(a) Wind Turbines



(b) PV farms

The figures display the event study estimates for both wind turbines and PV farms. based on the following regression: $\log y_{irt} = \sum_{s=t-1}^{t-9} \beta_s D_{it} + \sum_{s=t}^{t+9} \beta_s D_{it} + \lambda_r + \theta_t + \gamma_1 X_i + \gamma_2 X_{rt} + \varepsilon_{irt}$, where variables are analogous to equation (1).