Spin City: Local Externalities of Wind Turbines

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Abstract

Wind turbines offer significant environmental benefits but also create negative local externalities, such as noise and visual pollution, which can lead to local tensions and community resistance against the energy transition. This paper examines negative and positive externalities associated with wind turbine siting in Germany. Utilizing an instrumental variables approach, we find that wind turbine siting decreases house purchase prices by 1.9% in affected municipalities, with this adverse effect being most pronounced for the first turbines installed. Additionally, the siting of wind turbines reduces local tourism, apartment rents, and leads to fewer building permits being issued for apartments and houses, exacerbating existing housing shortages. On the positive side, each installed wind turbine increases a municipality's local tax capacity by 1.8% through higher commercial tax revenues. Our findings suggest that the negative externalities can be mitigated by investing the increased tax revenue into local amenities and public services, thereby compensating for the adverse effects of wind turbines.

Keywords: Wind power, externalities, hedonic pricing, NIMBY, local disamenities
JEL: D61, Q40, Q42, Q52

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1 Introduction

The transition from conventional thermal power plants to decentralized renewable energy sources is a key challenge in achieving the climate ambitions of developed countries. While most renewable energy technologies, including biomass, biogas, and hydropower, have limited deployment potential in Europe, wind and solar power offer much greater potential. However, unlike conventional large-scale power plants, wind and solar installations are significantly smaller and often sited in more remote areas.

Despite the significant benefits of abating greenhouse-gas emissions and local pollutants, the construction of wind turbines sometimes faces local opposition, commonly referred to as the 'Not In My BackYard' (NIMBY) syndrome (Van Der Horst, 2007). That is, people generally support the deployment of renewable energies, but within their vicinity, they do not want to endure the associated negative local externalities. In this regard, the literature documents adverse health effects related to living in proximity to wind turbines, via noise and visual pollution (Ata Teneler and Hassoy, 2023; Knopper and Ollson, 2011), which negatively influence households' well-being (Krekel and Zerrahn, 2017).

In this paper, we empirically assess these externalities by examining the induced variations in house prices and related outcomes in Germany. If local disamenities, such as noise and visual pollution of landscapes, are indeed perceived negatively by households, the deployment of new wind turbines should lead to a decrease in housing prices. Measuring this effect is particularly interesting because NIMBYism can hinder the deployment of wind turbines and, consequently, the replacement of polluting power plants. Quantifying the effect of wind turbines on house prices enables the implementation of targeted compensation measures to mitigate the impact on affected local communities. Additionally, assessing the heterogeneity of this effect can guide the strategic placement of future wind turbines. We focus on Germany, which serves as an excellent case study for an ex-post evaluation due to its leading and pioneering role in the deployment of wind energy.

We utilize a unique dataset combining house prices and the number and capacity of wind turbines in German municipalities between 2008 to 2017. A key challenge in identifying the causal effect of wind turbine proximity on house prices is the potential reverse causality, because property prices in a municipality may also determine wind turbine investments. This could be, for example, that investors may construct wind turbines in cheaper areas. To circumvent a potential endogeneity bias, our analysis leverages variation in the deployment of wind turbines, induced by changes in the government's incentive scheme, which determines the revenue of a wind turbine investment. Using this instrument, we can causally identify the effect of interest.

Our principal finding is that wind turbine placements negatively affect house prices within their proximity. We find that a wind turbine placement reduces the average house price in a municipality by 1.9%. However, the effect is not linear. Our estimates indicate that the initial wind turbine placements have a significantly large effect of -5.5% on house prices, whereas the effects of additional wind turbines in areas already populated with other wind turbines are statistically insignificant.

Moreover, we find that wind turbine siting not only depresses house prices but also affects apartment rents and hotel overnight stays, highlighting that the negative externalities extend to other outcomes as well. This latter effect suggests that the negative externalities of wind turbines are experienced not only by local residents but also by tourists. Additionally, we show that the number of building permits for apartments and houses issued by a municipality falls in response to wind turbine siting. This suggests a trade-off between allocating new land parcels for building new houses and apartments or for wind turbine siting. Therefore, policymakers should account for these negative impacts in their cost-benefit analyses when making decisions about wind power deployment.

Besides estimating the adverse effects of wind turbine investments, we also demonstrate that the number of wind turbines and the size of wind turbines significantly increase a municipality's tax income. Hence, in addition to their environmental benefits, wind turbines provide positive impacts on municipal finances, which help mitigate the negative externalities of visual and noise pollution. Municipalities may use the additional tax income to invest in local infrastructure, such as child care, medical and educational services, public transportation, and recreational facilities, to alleviate the local adverse effects of wind turbine sitings. Such targeted investments could help, ceteris paribus, increase housing prices and attract tourism.

This study contributes to the understanding of the local impacts of wind energy deployment. As we discuss in more detail in Sections 2.2 and 2.3, several studies investigated the effect of wind turbine deployment on land or housing prices. Among them are Jarvis (2025) and Gibbons (2015) for Great Britain, Dröes and Koster (2016) and Dröes and

Koster (2021) for the Netherlands, Sunak and Madlener (2016) and Sunak and Madlener (2017) for the German state North-Westphalia, and Quentel (2023) for Germany. These studies find negative effects of wind turbine proximity on housing or property prices, whereas the effects vary greatly. Yet, some papers find no significant effect or in some occasions even a positive effect, depending on the context, as summarized in a literature review by Parsons and Heintzelman (2022). Hence, an often made assumption that there is necessarily a negative effect of wind turbine deployment, regardless of the context, can lead to poor policy decisions.

In contrast to previous studies, this paper offers several new contributions. We combine multiple detailed datasets covering the entire country of Germany over a ten-year period (2008–2017), including crucial socioeconomic data. Beyond estimating the adverse effects of wind turbine proximity on house prices, we also examine impacts on apartment rents, hotel overnight stays, and building permits. Additionally, we show that wind turbines generate fiscal benefits for municipalities through increased commercial tax revenues. A key innovation is the estimation of a non-linear effect, whereby the first wind turbine imposes the greatest negative externality. Furthermore, we apply a credible instrumental variables approach to identify the effect of interest.

The rest of the paper is organized as follows. Section 2 provides a brief background on wind power promotion in Germany and local opposition. Section 3 describes our data. Section 4 outlines our empirical strategy. Section 5 presents the results and Section 5.3 provides robustness tests. Section 6 concludes.

2 Institutional background

In this section, we provide background information on the promotion and evolution of wind power in Germany over the past 20 years. We also discuss the dilemma between global benefits related to the reduction of greenhouse gas emissions and local disamenities, including visual and noise pollution. Finally, we review the literature assessing the costs to local residents of wind turbines and our contribution.

2.1 Wind energy expansion in Germany

From the early 2000s onward, Germany has pursued a rapid expansion of onshore wind power, driven by both its commitment to reduce CO_2 emissions in the electricity sector and its decision to phase out nuclear energy (*Atomausstieg*) first legislated in 2002 and reconfirmed in 2011 following Fukushima. Given Germany's comparatively high wind resources and relatively modest solar irradiation, wind energy emerged as the predominant renewable technology promoted under successive Renewable Energy Sources Acts (EEG) (Abrell et al., 2019).

Installed onshore capacity grew from just 6.1 GW in 2000 to 26.8 GW by 2010 and reached 61 GW in 2023. Over the same period, wind's share of gross electricity consumption climbed from 1.7 percent to 6.2 percent and ultimately to 22.4 percent in 2023 (Figure Ia–b).[1] This tenfold increase reflects an average annual capacity addition of approximately 2.5 GW, and continued growth is anticipated under the 2021 EEG amendment, which targets a 65 percent renewables share by 2030 to achieve carbon neutrality by 2050 (IEA, 2024).

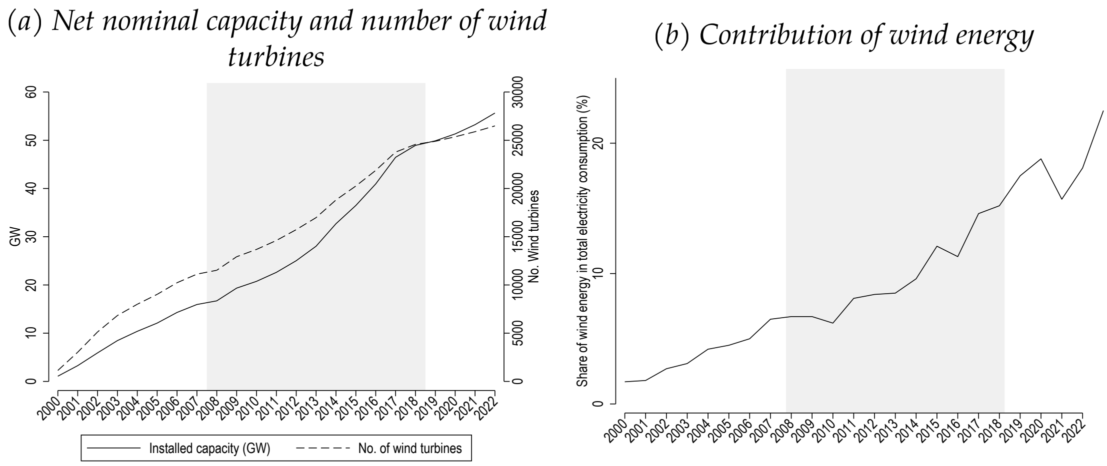

Figure I: *Development of wind energy in Germany, 2000–2022*

a) Aggregate installed wind power capacity and number of turbines based on the Market Master Data Register by the German Federal Network Agency (BNetzA, 2024). b) Wind's share in gross electricity consumption based on data from the German Federal Ministry for Economic Affairs and Energy (BMWK, 2025). The shaded area marks the sample period used in our analysis.

Much of this expansion has been attributed to government policies, in particular to subsidization of renewable systems through legislated feed-in tariffs (FIT). These tariffs

[1] Solar power was the second-largest renewable source in 2023, contributing 12.2 percent of gross electricity consumption (BMWK, 2025).

ensured that operators of renewable power plants received a fixed payment per MWh fed into the grid, irrespective of market conditions. Additionally, renewable generators were granted priority grid access, effectively shielding them from dispatch competition with conventional sources.

The level of the feed-in tariff during our study period varied by technology, plant size, and year of installation. FIT rates were administratively set based on estimated generation costs and were granted for a fixed duration of 20 years. Importantly, the tariff valid at the time of commissioning remained locked in for the full support period, making the installation year critical for determining expected revenues.

A central design element of Germany's FIT system was the *geographic differentiation* of support levels for wind power through the so-called *reference yield model*. This mechanism aimed to promote spatial diffusion of wind turbines beyond the most favorable sites, thereby alleviating regional grid congestion and smoothing aggregate output fluctuations. Under this model, each location's expected annual electricity output—calculated for a standardized reference turbine—was divided by the legislatively defined *reference yield*, which reflected the output at a benchmark site with average wind conditions (5.5 m/s at 30 m height, surface roughness 0.1 m). The resulting *yield ratio* determined the applicable tariff schedule.

The tariff schedule itself was composed of two phases: a high initial tariff and a lower base tariff. While the initial tariff was paid for at least five years, the duration of this phase was extended in low-wind locations. Specifically, the extension period decreased with the yield ratio, making projects in low-yield areas eligible for the higher payment for longer. This design mitigated differences in project profitability across space. Yield ratios in our data range from 0.3 to 2.2.

Until 2012, only sites with at least 60 percent of the reference yield were eligible for FITs. From 2012 onward, eligibility was expanded nationwide. The 2014 EEG amendment replaced fixed FITs with the *market premium model*, under which producers sell electricity directly on the spot market while receiving a premium to ensure minimum remuneration based on the location's yield ratio (Bundesministerium der Justiz und für Verbraucherschutz, 2014). Although this change marks a shift in design, the core principle of reference-yield-based compensation remained intact.

The 2017 EEG amendment marked a more fundamental reform by introducing competitive auctions for large-scale wind and solar projects. However, a transitional provision allowed projects with existing permits, and commissioned by the end of 2018, to remain eligible for the previous FIT regime (see Bundesministerium der Justiz und für Verbraucherschutz, 2017). As such, the reference yield system continued to determine expected returns for turbines built in our analysis period.

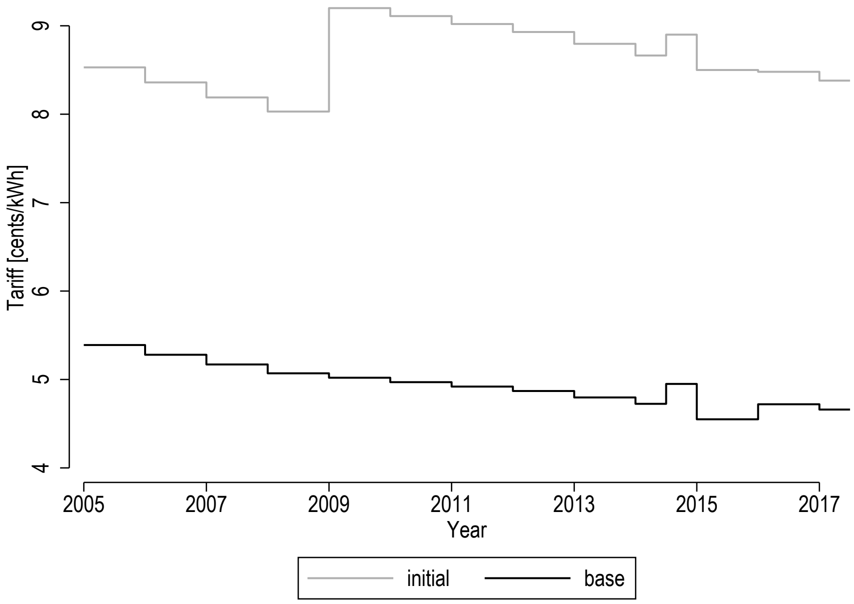

Figure II: *Development of feed-in tariffs for wind, 2005–2017*

Own illustration based on data from the German Transmission System Operators (2019). Figure also published in Germeshausen et al. (2023).

Figure II illustrates how both the initial and base FIT rates changed over time. Several EEG amendments between 2000 and 2017 adjusted tariff levels, with most introducing stepwise reductions. For example, the 2009 amendment temporarily raised the initial tariff by 17 percent to account for rising turbine costs due to increases in steel and copper prices (Böttcher, 2010). In years without amendments, automatic annual digression applied.

We exploit both the cross-sectional variation introduced by the reference yield model and the temporal variation arising from legislative and automatic changes to FIT rates for identification. It is important to note that these variations only apply to new installations: once a turbine is commissioned, its tariff remains fixed for 20 years. Thus, differences in FITs across years or locations affect the expected profitability of new projects but have no retrospective impact on previously installed turbines.

2.2 Benefits versus local opposition

The promotion of wind energy in Germany is motivated by environmental and nuclear safety concerns. By replacing thermal generation, wind power mitigates the emission of CO_2 and local pollutants such as SO_2, NO_x, and particulate matter (Cullen, 2013). This reduction in CO_2 emissions benefits the entire world, as a ton of CO_2 emitted anywhere contributes equally to climate change (Nordhaus, 2019).

However, this is not the case with local pollutants. Generating less electricity with conventional thermal power plants directly benefits populations living near these plants by reducing the likelihood of smog, haze, or respiratory illnesses and lung diseases (see, e.g., Deschenes et al., 2017; Holland et al., 2020; Jarvis et al., 2022). Thus, it is shown that phasing out coal has a significant impact on the local environment and health benefits that more than offset the costs of this phase-out in most regions of the world, even without considering the global benefits from slowing climate change (Rauner et al., 2020).

Moreover, the deployment of wind energy also serves to compensate for Germany's decision to phase out nuclear energy. In response to the Fukushima accident, the German Bundestag confirmed the decision to abandon this technology for safety reasons. The rationale is that the use of nuclear energy involves exposure to hazardous radioactive radiation for humans and the environment. The German society concluded that the risks of this technology outweigh its benefits and thus decided on the phase-out (Grossi et al., 2017). Hence, besides environmental value, wind turbines also mitigate citizens' perceived safety concerns related to nuclear energy.

The benefits of wind energy deployment stand against the negative local externalities, which have led to increasingly publicized opposition from local residents (as reported in popular media outlets, e.g., Spiegel, 2011; Financial Times, 2019; The Economist, 2021; The New York Times, 2022). The arguments advanced include visual pollution, noise, damage to biodiversity, and even a local loss of jobs in the conventional electricity producing industry. Zerrahn (2017) provides a comprehensive literature review on wind power and its negative local environmental externalities. Additionally, the massive deployment of decentralized renewables also requires the construction of many new high-voltage power lines, which themselves have adverse visual and biodiversity consequences.

In Germany, 97 percent of the 28,000 wind turbines installed are within two kilometers of a residential area. Resident resistance, often expressed through petitions with thousands of signatures against nearby projects (Spiegel, 2011), does not aim to halt the energy transition but to relocate it out of their sight. Polls even show that popular support for wind energy remains high in general, despite significant wind energy deployment in Germany (Financial Times, 2019). Thus, there is a tension between aggregate benefits and local costs.

It is crucial to understand the local costs of renewable energy infrastructures to prevent local opposition from hindering the achievement of climate goals. Highlighting this tension, environmental protection organizations such as Greenpeace are even signing petitions urging the government to relax animal protection laws to facilitate the installation of more wind turbines (Recharge, 2024).

Delays in project implementation due to administrative and legal challenges not only postpone deployment schedules but also escalate costs for developers. Such delays and increased expenses could jeopardize Germany's renewable energy goals. Industry stakeholders report that it can take 5 to 7 years to determine whether a wind turbine installation project is feasible (DPA, 2023), and that they are increasingly taken to court even when approved by the authorities (BDEW, 2019).

2.3 Valuing the costs to local residents

To implement appropriate policies to address these local objections, it is not only important to understand the benefits but also to credibly estimate the disamenities associated with wind energy deployment. The literature has highlighted several local externalities affecting households near wind turbines (Zerrahn, 2017)[2]. With an average height of around 100 meters during our study period, wind turbines can be visible from a significant distance depending on the topology. For instance, Gibbons (2015) demonstrated through a quasi-experimental research design in England and Wales that each additional wind turbine reduces house prices by 6.5 percent within 1 km and by 5.5 to 6 percent within 2 km if they are visible.

However, most studies do not differentiate between types of nuisances and use the hedonic pricing method to assess whether households value non-market amenities, assuming that the local impacts of wind projects are reflected in house prices. In a review

[2]The papers reviewed in Zerrahn (2017) describe and measure, among other things, the negative impact of wind turbines on wildlife, including a decrease in bird and bat populations, noise pollution—though no causally measured health effects—and landscape deterioration. Regarding positive externalities, there is some evidence of increased local employment and GDP.

of hedonic pricing studies, Parsons and Heintzelman (2022) highlight that most studies find a significantly negative effect of wind turbine deployment on property prices. However, the magnitude of this effect varies widely, underscoring the context-specific nature of these impacts. The literature also consistently shows that turbines tend to be sited in areas where land prices are lower, holding other factors constant. This supports the endogeneity problem described in detail in Section 4.

Key findings from the reviewed literature are as follows. Vyn and McCullough (2014) examine wind turbines in Southern Ontario, Canada, and find that an additional turbine within 1 km and in full view is associated with a 3–5% decrease in property values. The study reports large standard errors, attributed to a small sample size. In the Netherlands, Dröes and Koster (2016) apply a difference-in-differences methodology over the period 1985–2019 and find a 1.4% decrease in house prices within 2 km of a turbine, supported by a substantial observational dataset. In North Rhine-Westphalia, Germany, Sunak and Madlener (2016) report a 9–14% decrease in property prices. With a larger sample, they show for the same region a 12.5% decrease if the additional turbine is less than 1 km away and visible (Sunak and Madlener, 2017). This effect diminishes with distance and converges towards zero after 4–5 km.

In Denmark, Jensen et al. (2018) find that onshore wind turbines within 3 km lead to price reductions of 0.2–1.1% for primary residences and 1.1–2.1% for vacation homes. This disparity is likely due to a higher valuation of landscape views associated with secondary residences. Moreover, Jarvis (2025) report an average 4–5% reduction in residential property values at a 2 km distance from a wind project, with the effect diminishing as distance increases and becoming negligible beyond 4 km. The impact is notably more pronounced in wealthier neighborhoods. Closely related to our study is Quentel (2023), who estimates the impact of wind turbine proximity on German house prices. His main finding is that a wind turbine reduces house prices by 2.1%. He also applies an instrumental variables (IV) approach, exploiting variation in wind turbine height and wind conditions by altitude. This result aligns with our main estimate. However, our study differs in sample period, IV approach, highlighting a non-linear impact of wind turbine placements, using alternative outcome variables, and showing that municipalities earn tax income for wind turbines.

Overall, we contribute to the related literature in several ways. First, we employ an IV strategy that exploits variation in the expected revenue from wind turbines to address the endogeneity of treatment. Second, we combine multiple granular datasets covering all of Germany, enabling us to derive insights from a pioneering country in renewable energy deployment. Our results reveal a non-linear impact of wind turbine placement, with the first turbine exerting the strongest adverse effect on house sale prices. In addition to the housing market, we find that wind turbines reduce apartment rental prices and negatively affect tourism by lowering the number of hotel overnight stays. Moreover, municipalities appear to issue fewer building permits for housing in favor of wind turbine sitings, which is consistent with our finding that they generate more tax revenue from larger wind turbine investments within their jurisdiction. Finally, several robustness tests support our primary estimates.

3 Data

This section describes the dataset underpinning our empirical analysis. In summary, it includes house prices, the number of wind turbines and their capacity, as well as local socioeconomic characteristics like population density, unemployment, and citizens' average age at the municipality level ('Gemeindeverband', corresponding to the European LAU 1-level) during the period from 2008 to 2017.[3] Table I summarizes the primary data employed in our analysis.

[3]Germany has 4,639 municipalities (Gemeindeverband, corresponding to the European LAU 1-level) in total, of which we observe 3,430 in our data, because house prices are not reported for municipalities with less than 50 house transactions per year. The median size of a municipality is 47 km^2, which corresponds to a radius of approximately 3.8 km.

Table I: *Summary statistics of main variables*

	Mean	SD	Min	Max	Obs.
Dependent variable					
ln(house price index)	-0.10	0.43	-2.63	1.94	26,657
Variables of interest					
Number of wind turbines:					
Full sample	5.65	14.02	0.00	257.00	26,657
Always-eligible (pre-2012)	6.29	12.31	0.00	154.00	6,343
Initially ineligible (pre-2012)	1.77	7.80	0.00	123.00	4,874
Always-eligible (2012–2017)	9.00	18.04	0.00	257.00	9,238
Initially ineligible (2012–2017)	3.04	11.04	0.00	156.00	6,202
Net wind turbine capacity (MW):					
Full sample	8.88	25.34	0.00	689.24	26,657
Always-eligible (pre-2012)	8.46	18.03	0.00	236.89	6,343
Initially ineligible (pre-2012)	2.71	12.54	0.00	184.90	4,874
Always-eligible (2012–2017)	14.84	35.03	0.00	689.24	9,238
Initially ineligible (2012–2017)	5.26	19.50	0.00	284.43	6,202
Control variables					
Age	44.05	2.17	36.29	53.71	26,657
Employment	55.97	5.28	20.36	77.35	26,657
Population density	364.77	441.63	14.99	4708.36	26,657
Instrumental variables					
Expected revenue of a WT (k€/m^2):					
Full sample	0.72	0.45	0.00	2.25	26,657
Always-eligible (all years)	1.00	0.29	0.07	2.25	15,581
Initially ineligible (all years)	0.33	0.31	0.00	1.39	11,076
Initially ineligible (2012–2017)	0.58	0.15	0.27	1.39	6,202
Always-eligible (2012–2017)	0.95	0.30	0.46	2.18	9,238
Eligible municipality-years	0.90	0.31	0.27	2.25	21,808
Ineligible	0.18	0.38	0.00	1.00	26,657
Wind potential (MWh/m^2)	2.81	0.78	1.23	9.28	26,657
Ineligible $\times$ Wind potential	0.38	0.83	0.00	2.59	26,657

Notes: Descriptive statistics for municipality-level data. Annual data for 2008–2017. Wind potential denotes the Reference Yield (Referenzertrag), i.e., the expected annual electricity output in MWh per m^2 of rotor area at a given location (source: DWD)."Always-eligible" refers to municipalities with wind potential $\geq$60% of the reference site (i.e., $\geq$2.59 MWh/m^2), which were eligible for FIT throughout the sample period. "Initially ineligible" refers to municipalities below this threshold that became eligible following the 2012 reform. "Eligible municipality-years" includes all observations from always-eligible municipalities (2008–2017) plus post-2011 observations from initially ineligible municipalities.

3.1 House prices

We employ an index of house purchase prices per German municipality, developed by Klick and Schaffner (2021), which uses the RWI-GEO-REDX dataset (Boelmann et al., 2019) on house sale offers from the largest real estate internet platform in Germany, 'Im-

a) Mean house price index, 2008–2017 *b) Within municipality house price variation, 2008–2017*

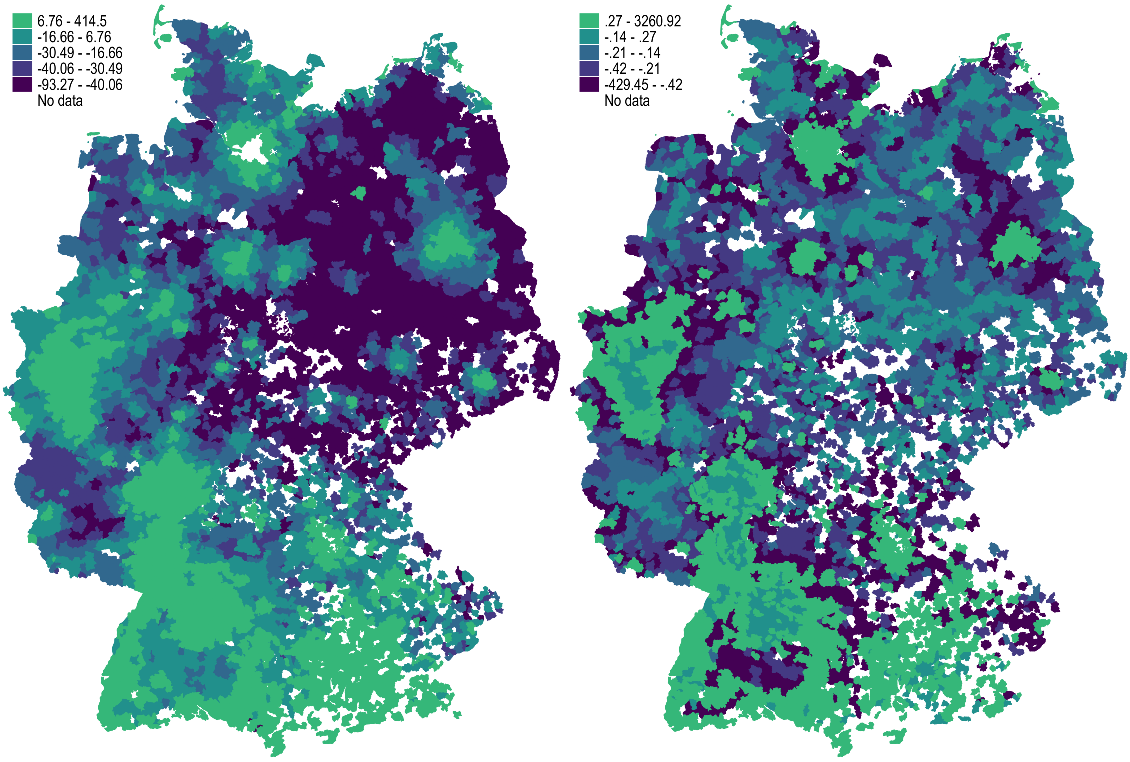

Figure III: *Means and within municipality variation of the house price index 2008–2017*

The graph shows a) the mean and the within variation b) of the house price index per municipality. The white areas represent missing data, i.e. municipalities with less than 50 house transactions per year

mobilienScout24'. The index is created via annual cross-sectional hedonic price regressions, which control for typical house properties, such as size, rooms, floors, vintage, type of house, furnishing, energy consumption, etc., and characteristics of the property, such as property size and location.

The underlying model is:

$$ln(y_{igt_0}) = \theta X_{igt_0} + u_{gt_0} + \epsilon_{igt_0}, \quad (1)$$

where i denotes the individual house, g the municipality, and t_0 is the respective year of the cross sectional regression. X captures house and property characteristics. u are municipality fixed effects, and ϵ is the error term. Variation at the municipality level of the index is derived from the municipality fixed effects u of the regressions. The house price index is only available for municipalities with at least 50 house purchases in a given year. Otherwise, the data is removed from the sample for data protection reasons. Thus, out of the 4,654 municipalities in Germany, we are left with an average of 2,742 municipalities per year.

Figure IIIa shows that there are significant regional disparities with higher prices in the southwest, west, and northwest. These regions correspond to former West Germany. Besides higher land parcel prices, other variables remain significantly different between the former German Democratic Republic and West Germany: in the West, the population is younger, wealthier, and less rural. Figure IIIb shows the within variation of house prices. It is calculated as the ratio of within and between standard deviations and expressed as a percentage. The figure shows that prices also varied within zip codes with an average variation of about 10 percent.

3.2 Wind Deployment

Data regarding the number and capacity of wind turbines within each municipality were sourced from the Marktstammdatenregister (Market Master Data Register) by the German Federal Network Agency (BNetzA, 2024). The Marktstammdatenregister contains, as a central register, data on all generation plants that are connected via the electricity and gas networks. For each wind turbine it contains information on the turbine's net capacity, geo-coordinates, commissioning date, height, rotor diameter. During the sample period 2008 to 2017, the average number of wind turbines is 5.65 and the average aggregate net capacity is 8.88 MW. Over the decade we study, the number of wind turbines in Germany increased sharply from 14,167 in 2008 to 26,344 in 2017, and the installed capacity rose from 18.8GW to 48.6GW. Figure IV shows the geographical distribution of wind turbines across Germany in 2008 and 2017. The turbines are predominantly located in the north of the country, where wind potential is highest (Figure V).

3.3 Expected revenue

During the sample period 2008–2017, the remuneration per unit of electricity produced by wind turbines was not uniform across Germany. The applied feed-in tariff aimed to encourage deployment across the entire territory to limit congestion problems and smooth the temporal profile of intermittent non-dispatchable wind production. As already outlined in more detail in Section 2.1, the regional distribution of feed-in tariffs was set according to a 'reference yield model'.

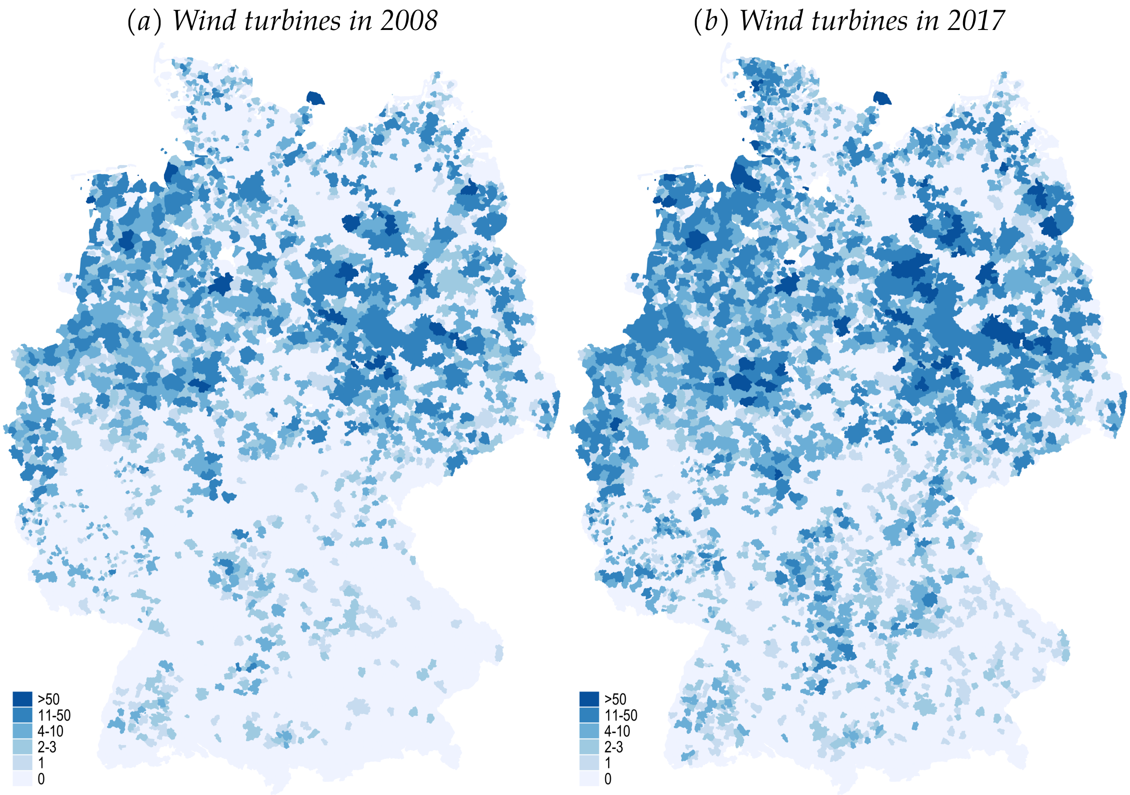

Figure IV: *Development of wind turbines in Germany between 2008 and 2017*

This graphs show the number of turbines per municipality in 2008 (a) and 2017 (b). The average number of turbines per municipality is 5.7, but the graph displays significant regional heterogeneity, with some municipalities in the north having more than 50 turbines. Panel (b) also published in Germeshausen et al. (2023).

This remuneration scheme implies larger payments per megawatt-hour (MWh) of electricity output for wind turbines placed in locations with lower wind profiles (i.e., where the wind blows less strongly and regularly). The key variable determining these payments is the wind potential, formally known as the Reference Yield (*Referenzertrag*), which we denote $POTENTIAL_i$. This is the expected annual electricity output in MWh per m^2 of rotor area at municipality i, calculated by the German Meteorological Office (DWD) based on local wind conditions.

The EEG legislation defines a standardized "reference site" with a wind potential of 4.32 MWh/m^2, corresponding to mean wind speed of 5.5 m/s at 30m hub height and surface roughness of 0.1m. Each location's wind potential is compared to this benchmark to determine the applicable tariff schedule. Figure V displays the wind potential across Germany. Prior to 2012, only locations with at least 60% of the reference site's wind potential (i.e., $\geq$2.59 MWh/m^2) were eligible for FIT support.

We calculate the expected revenue (ER) per wind turbine using the wind potential and the applicable tariff schedules obtained from the German TSOs:

$$ER_{i,t} = (FIT_{init,t} \times n_{init,i} + FIT_{base,t} \times n_{base,i}) \times POTENTIAL_i, \tag{2}$$

where $FIT_{init,t}$ represents the initial tariff for year t, $n_{init,i}$ the duration of the initial tariff period for municipality i, $FIT_{base,t}$ the base tariff for year t, and $n_{base,i}$ the duration of the base tariff period. $FIT_{init,t}$ is always higher than $FIT_{base,t}$ and varies over time with successive reforms, introducing temporal variation to expected revenue.

The tariff rates are fixed for each wind turbine at commissioning and remain constant for 20 years, hence $n_{init,i} + n_{base,i} = 20$ years. Crucially, the duration of the higher initial tariff depends on local wind potential: low-yield locations receive the initial tariff for longer than high-yield locations, partially compensating for differences in natural wind resources. Expected revenues are measured in €1,000 per m^2 of rotor surface. For eligible municipality-years, the sample average is approximately €900 per m^2, ranging from €270 to €2,250. Expected revenue is set to zero for initially ineligible municipalities prior to the 2012 reform. Appendix Figure A1 illustrates the spatial distribution of expected revenue in 2008 and 2015, highlighting both the cross-sectional variation and the expansion of eligibility following the 2012 reform.

3.4 Control variables

As socioeconomic control variables, we collected data on municipalities' average age of the residents, population density, and the local employment rate from `www.inkar.de`, a database on spatial and urban development in Germany, provided by the German Federal Institute for Research on Building, Urban Affairs, and Spatial Development (BBSR, 2024).

4 Identification strategy

This section details our baseline estimates for the effect of wind turbine construction on house prices. We model this relationship using the following regression equation:

$$log(P_{i,t}) = \beta \cdot WT_{i,t} + \gamma \cdot \mathbf{X_{i,t}} + \xi_i + \phi_t + \varepsilon_{i,t}, \tag{3}$$

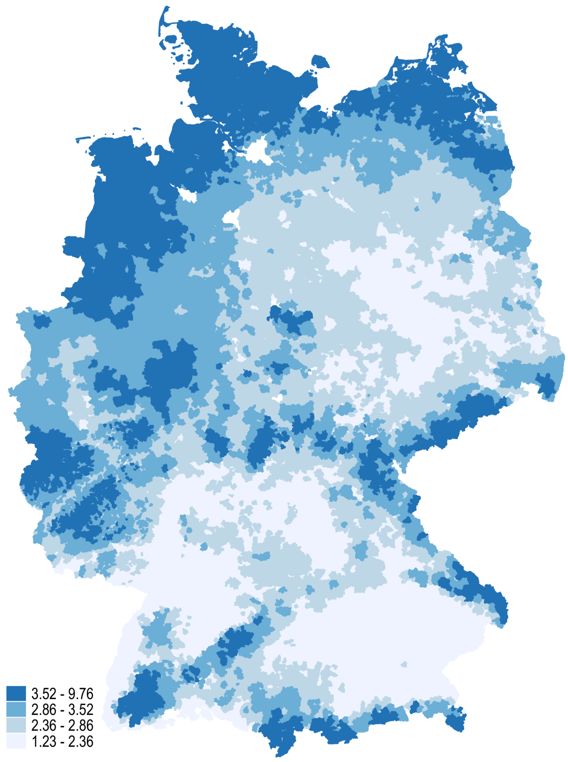

Figure V: *Wind potential in Germany*

This map shows the wind potential (Reference Yield, Referenzertrag) in MWh per m^2 of rotor area across German municipalities. The reference site defined in the EEG has a wind potential of 4.32 MWh/m^2. Prior to 2012, locations with less than 60% of this value (i.e., below 2.59 MWh/m^2) were ineligible for FIT support. Figure also published in Germeshausen et al. (2023).

where the dependent variable $log(P_{i,t})$ represents the logarithm of the average house price in municipality i in year t. WT_{it} measures the number of wind turbines within the municipality and β is the parameter of interest.

The vector of control variables $\mathbf{X}_{i,t}$ encapsulates time-varying socioeconomic characteristics, specifically average local employment rate, population density, and the average age of the population. The municipality fixed effects ξ_i absorb any time-invariant characteristics specific to each municipality, such as local preferences and profitability. Moreover, the year fixed effects ϕ_t control for annual aggregate shocks that influence both house prices and wind turbine deployment. To account for correlation in the error term, we cluster the standard errors $u_{i,t}$ at the municipality level in all specifications.

Although time and municipality fixed effects can effectively control for constant time and municipality-specific characteristics, concerns about potential endogeneity between the outcome variable and the variable of interest persist. This may lead to estimation bias of the parameter of interest $\hat{\beta}$ if we estimate equation 3 by OLS. Several reasons underpin this concern. Firstly, property prices likely influence the siting decisions for new wind turbines. Developers aiming to maximize expected revenue may prefer less expensive areas, all else being equal, leading to reverse causality. If this were the case, the OLS estimates would be biased toward zero.

Additionally, unobserved preferences for wind turbines might not be stable over time, as households could change their views on the technology's presence in their vicinity, for example, due to media coverage. There may also be other unobserved changes over time that affect wind turbine deployment and preferences. For instance, if wind turbines generate monetary benefits for the municipality, which are then used to improve local infrastructure, this could increase the value of houses. We will discuss this in more detail later. Lastly, the variable $WT_{i,t}$ serves as a proxy for the population's actual exposure to wind turbine disamenities (e.g., noise, visual impact). Since it does not capture the precise proximity of turbines to housing, it potentially introduces measurement error, which would bias OLS estimates toward zero.

To address these potential sources of endogeneity bias, we adopt the instrumental variables strategy of Germeshausen et al. (2023), leveraging quasi-experimental spatial and year-to-year variations in variables determining the expected local revenues for wind turbines.

As discussed in Section 3.3, the reference yield model introduces exogenous variation on the revenues wind turbines expect to receive across municipalities and years. This is because both the cross-sectional variation in the feed-in tariff, which depends on local wind potential, and the yearly adjustments to the feed-in tariff scheme, which are based on policy targets for distributing wind turbines across Germany, are plausibly independent of other local characteristic changes, such as house prices. Another source of exogenous variation is introduced by a policy change in the coverage of the reference yield model. While before 2012, only wind turbines in locations exceeding a certain wind potential (i.e., $\geq 60\%$ of the reference yield) were eligible for feed-in tariffs, from 2012 on, all locations were covered by the subsidy scheme. The reduction of the eligibility threshold concerned a large part of the German land area and led to significant revenue increases.

Thus, we are confident that the profitability of wind turbines based on feed-in tariffs set by the reference yield scheme is uncorrelated with shocks to house prices. The key identifying assumption is that expected FIT revenue affects house prices (and other out-

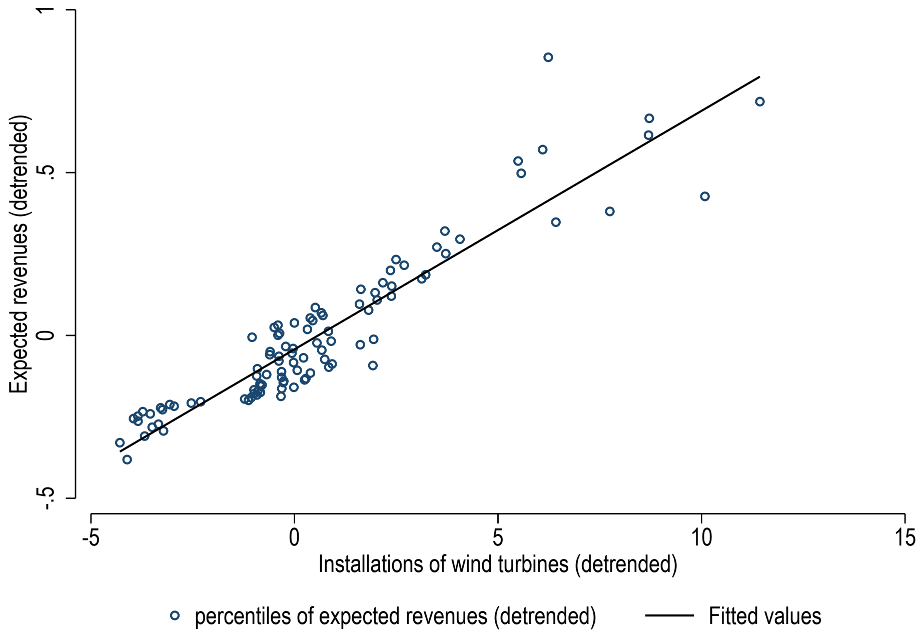

Figure VI: *Expected revenues and wind turbine installations correlation*

The figure plots expected revenues from the reference yield scheme (defined in eq. 2) against the number of newly installed wind turbines, after residualizing both variables with respect to year dummies. This procedure corrects for both cost reductions in wind turbine construction and reductions in the feed-in tariffs over time.

come variables we consider) only through its effect on wind turbine deployment. Under this exclusion restriction, our instrumental variables strategy identifies the total causal effect of wind turbine deployment on the outcome variable, regardless of the specific mechanism through which turbines affect outcomes. For instance, wind turbines may affect house prices directly through visual and noise disamenities, or indirectly through effects on local infrastructure investment funded by turbine-related revenues. Our IV estimates capture the combined effect operating through all such channels, which is the policy-relevant parameter for evaluating the local welfare consequences of wind turbine deployment.

The other condition that needs to hold for the IV is that our instrument is relevant. In our case this means that anticipated revenues according to the reference yield scheme shift the siting decisions of new wind turbines. This assumption is testable and holds as we will show in the result section. The plot of the two variables, expected revenues and wind turbines, in Figure VI also demonstrates a strong positive correlation between the number of wind turbines in a municipality and the expected revenue there according to the reference yield scheme.

Thus, to implement this IV strategy, we estimate a first-stage equation of the form

$$\begin{aligned} WT_{i,t} = \gamma_1 \times ER_{i,t} + \gamma_2 \times INELIGIBLE_{i,t} + \gamma_3 \times INELIGIBLE_{i,t} \\ \times POTENTIAL_i + \Gamma \mathbf{X_{i,t}} + \mu_i + \nu_t + \epsilon_{i,t} \end{aligned} \tag{4}$$

$ER_{i,t}$ represents the expected revenue for wind turbines located in municipality i for year t. As detailed in section 3.3, locations with a yield ratio below 60 percent became eligible for the feed-in tariff only since the year 2012. For these municipalities, $ER_{i,t} = 0$ before 2012. Hence, $INELIGIBLE_{i,t}$ is a dummy equal to 1 before 2012 when $ER_{i,t} = 0$ and 0 otherwise. Moreover, $INELIGIBLE_{i,t} \times POTENTIAL_{i,t}$ captures heterogeneous investment incentives in ineligible locations.

5 Results

We apply a GMM estimator for our IV regressions. This is similar to a two-stage least squares approach, but has the beneficial feature that GMM applies a weighting matrix for our three instrumental variables. Local variations in the expected revenue of a wind turbine serve as a strong predictor of both the number and capacity of wind turbines installed within a municipality. Table II presents the outcomes of the first-stage regression.

Table II: *First-stage regression estimates*

Dependent variable is *No. wind turbines*	
Expected revenue of a WT (k€/m^2 of rotor surface)	3.503***
	(0.654)
Ineligible	4.269***
	(0.499)
Ineligible × Wind potential	-0.096
	(0.317)
Year FE	y
Municipality FE	y
Socioeconomic controls	y
Obs.	26,657

First stage estimates. Standard errors clustered at the municipality level in parenthesis. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

We find that higher expected revenue per square meter of rotor surface significantly increases the number of wind turbines. The coefficient on the 'Ineligible' dummy is positive and statistically significant.[4] Furthermore, although the coefficient on the interaction term 'Ineligible × Wind potential' is statistically insignificant, it improves the overall performance of the instrumentation by increasing the first-stage F statistic, thereby strengthening the predictive power of our instruments.

Table III presents the primary OLS and IV estimates for the impact of the number of wind turbines on house prices. Columns (1) and (3) omit socioeconomic control variables, while columns (2) and (4) include them. Evidently, the IV estimates yield significantly more pronounced effects (i.e., difference about 35%–40%) than the OLS estimates. This is expected and indicates that neglecting the endogeneity bias results in estimates biased toward zero. Hence, neglecting endogeneity would significantly underestimate the true impact of wind turbines on house prices.

Table III: *Effect of wind turbine deployment on house prices*

	Dependent variable is *ln*(*house price index*)			
	IV-GMM		OLS	
	(1)	(2)	(3)	(4)
No. wind turbines	-0.0295***	-0.0191***	-0.0009***	-0.0004*
	(0.0030)	(0.0029)	(0.0003)	(0.0002)
Year FE	y	y	y	y
Municipality FE	y	y	y	y
Socioeconomic controls		y		y
Durbin-Wu-Hausman test	0.00	0.00		
First stage F stat.	59.72	43.63		
Obs.	27,016	26,657	27,077	26,660

The dependent variable is the logged municipality level house price index. The adoption of wind turbines is instrumented for with the expected revenue according to the reference yield subsidy scheme in Columns (1) and (2). The IV estimator is two-step feasible GMM. Columns (3) and (4) give the corresponding OLS estimates. Standard errors clustered at the municipality level in parenthesis. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

The first-stage F-statistic of 60 and 44 for the two IV specifications suggest that weak instruments are not a concern in this analysis. Moreover, the Durbin-Wu-Hausman test rejects exogeneity of WT, substantiating our decision to employ an instrumental variable

[4]We note that the relatively large magnitude of the coefficient on the ineligibility indicator is a mechanical consequence of the model structure rather than an indication that ineligible areas are intrinsically more attractive. Since expected revenue is high in the early sample years, the first-stage year fixed effects take on negative values to fit the data for eligible municipalities. For ineligible municipalities (where expected revenue is zero), the ineligibility dummy must effectively offset these negative year fixed effects. This is confirmed by the first-stage fitted values, which correctly predict substantially fewer turbines in ineligible areas (mean predicted: 1.8) compared to eligible ones (mean predicted: 6.3) in the pre-2012 period, consistent with the observed averages in our sample (mean actual: 1.5 vs. 5.0).

approach. Consequently, our interpretations of the results rely on the IV estimates for the remainder of the paper.

The IV estimates, both excluding (column (1)) and including socioeconomic control variables (column (2)), are reasonably close. Our preferred baseline specification is the fully specified model in column (2), which shows that the placement of a wind turbine decreases house prices in a municipality by 1.9%, indicating a significant negative externality on nearby house owners.

To contextualize the magnitude of our findings, we compare them with existing literature. Quentel (2023) also found a 2.1 percent decrease in German house prices for each additional wind turbine within a 3 km radius using an alternative instrumental variable. Although our study varies in the dependent variable, location, time horizon, and IV strategy, it is noteworthy that our results align with this study. Moreover, Sunak and Madlener (2016) and Sunak and Madlener (2017), focusing on a single German state, North Rhine-Westphalia, estimated a 9% to 14% reduction in house prices per additional wind turbine, also indicating a negative, yet more pronounced effect of wind turbines. Our findings also align with Parsons and Heintzelman (2022)'s review of studies on the effect of of wind power projects on property values, which generally find a negative impact.

5.1 Effect of first vs. additional wind turbines

One concern with the aforementioned estimate is that the first wind turbines might have a significantly more pronounced adverse effect on house prices than subsequent turbines. For example, the impact of increasing the number of wind turbines from four to five might be less substantial compared to installing the first turbine in an area previously free of such structures. A natural way to test this hypothesis would be to include a squared term in the model or to interact the number of turbines with an indicator for the first year of deployment to assess potential non-linearities. However, these approaches are challenging in our IV framework. Both a squared term and an interaction term would be endogenous and require appropriate instrumentation. We attempted to instrument these terms using interactions of the original instruments, but they proved too weak for identification.

To address this concern, we adopt an alternative strategy. We restrict our model to compare municipalities with no wind turbines in 2007 to those that already had at least one wind turbine sited in 2007. While this does not strictly isolate the marginal effect of the very first turbine, it allows us to compare the effect of the *expansion* of wind power into previously unaffected locations against the *intensification* of wind power in locations where residents are already accustomed to their presence.

Columns (1) and (2) of Table IV present the respective estimates. We find a pronounced negative effect of adding wind turbines in a municipality that initially had no wind turbines. In such cases, the marginal effect of a wind turbine reduces house prices in the neighborhood by 5.5%. This is a significant effect in economic terms. However, in municipalities that already had installed wind turbines at the start of the period, the placement of an additional turbine has no statistically significant effect on house prices.

Given that the first-stage F statistic of the model in column (1) is 7.99, which is below the generally accepted rule of thumb value of 10, the estimates may be suffering from weak instrumentation. Hence, we re-estimate the model using the continuously updating GMM estimator (CUE) (Hansen et al., 1996) which is more robust to weak instruments. Columns (3) and (4) of Table IV report the GMM-CUE estimates. The estimates remain robust, confirming that introducing wind turbines to new areas reduces house prices by 5.6%, whereas additional wind turbines in established areas do not significantly alter house prices.

Table IV: *Effect of WTs in new vs. established areas*

	Dependent variable is $ln(house\ price\ index)$			
	IV-GMM		IV-GMM-CUE	
	(1) No WTs in 2007	(2) WTs in 2007	(3) No WTs in 2007	(4) WTs in 2007
No. wind turbines	-0.0546*** (0.0177)	0.0025 (0.0034)	-0.0560*** (0.0174)	0.0026 (0.0034)
Year FE	y	y	y	y
Municipality FE	y	y	y	y
Socioeconomic controls	y	y	y	y
Durbin-Wu-Hausman test	0.00	0.48	0.00	0.48
First stage F stat.	7.99	8.97	7.99	8.97
Obs.	2,985	10,700	2,985	10,700

The dependent variable is the logged municipality level house price index. The adoption of wind turbines is instrumented for with the expected revenue according to the reference yield subsidy scheme. The IV estimator in Columns (1) and (2) is two-step feasible GMM. In Columns (3) and (4) the continuously updating GMM estimator (CUE) is applied which is more robust to weak instruments. Standard errors clustered at the municipality level in parenthesis. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

There are several potential explanations for this finding. Once the visual landscape is adversely impacted or noise becomes noticeable, each additional turbine likely has a diminishing marginal impact. It may also be the case that residents become accustomed to wind turbines, finding additional ones less disturbing.

An alternative interpretation is that municipalities without turbines in 2007 have systematically different preferences toward wind energy, leading to stronger house price reactions. However, our empirical design addresses this concern in several ways. First, municipality fixed effects absorb all time-invariant differences between municipalities, including any persistent differences in resident preferences. Second, year fixed effects control for common temporal shifts in attitudes toward wind energy. Third, identification in both subsamples comes from the same source of exogenous variation – expected FIT revenue determined by national policy and local wind conditions – rather than from variation in local preferences. For preference heterogeneity to explain our results, there would need to be systematic differences in how municipalities respond to new turbines that operate beyond these controls. The more parsimonious explanation is that the samples differ in their baseline turbine stock: the "expansion" sample includes transitions starting from zero, while the "intensification" sample does not, consistent with diminishing marginal disamenities.

These findings generate some useful information for policymakers, which we discuss in Section 6.

5.2 Heterogeneous effects by turbine size

We next examine whether the capitalization of wind turbine externalities varies with turbine size. Larger turbines are likely to be more visible and generate more noise, potentially leading to stronger negative price effects. To test this, we disaggregate the count of wind turbines into three categories based on their capacity: small (below the 10th percentile), medium (10th–90th percentile), and large (above the 90th percentile).

We define these thresholds using the *year-specific* nationwide distribution. This is necessary because wind turbines have grown substantially over our sample period, with average capacity increasing from approximately 2 MW in 2008 to 3 MW by 2017 (see Figure VII). Using a fixed threshold for the entire sample would mechanically categorize most recent additions as “large” and older ones as “small,” thereby conflating the effect of physical size with turbine vintage. Our year-specific approach ensures that we capture the effect of being large *relative* to the contemporary technology standard. To address endogeneity, we interact our instruments with these size-specific indicators.

Appendix Table A1 reports the results. We find that all three coefficients are negative and statistically significant, but the magnitude increases with turbine size. Municipalities with the largest turbines (above the 90th percentile) experience a price decline of 2.8% per additional turbine, compared to 1.8% for medium-sized turbines and 1.5% for the smallest turbines. While the joint test of coefficient equality cannot reject that all three coefficients are equal ($p = 0.15$), pairwise comparisons suggest that the effect of the largest turbines is marginally significantly different from both medium-sized ($p = 0.08$) and small turbines ($p = 0.07$). These results provide suggestive evidence that larger turbines impose greater negative externalities on local housing markets. This finding is particularly important against the background of steadily increasing turbine sizes, as it implies that the local disamenity costs of wind energy may rise as the technology continues to scale up.

5.3 Robustness

To assess the robustness and plausibility of our findings on the impact of wind turbine installations on house prices, we conduct several tests, which are presented in the following three subsections.

5.3.1 Effect of future wind turbine placements on contemporaneous house prices

A potential concern of our IV strategy may be that the areas that received subsidies were also the ones building turbines for other reasons. To address this concern, we first conduct a placebo test. We estimate the effect of wind turbines built in the year after next on the current house price index. The idea is that the siting of wind turbines should have no effect on house prices before they were actually built.

Column (1) of Appendix Table A2 provides the estimates of this placebo test. Indeed, the coefficient estimate is statistically not different from zero, as expected. Since the two-periods lag reduces the number of observations, we further check in column (2) of Appendix Table A2 if the sample selection potentially drives this result. We thus re-estimate our original, contemporaneous model for the same sample, as in column (1). It turns out that we still find a significantly negative impact of wind turbine placement on house price and that the magnitude of the effect (-1.6%) remains similar to the baseline estimate (-1.9%). Thus, this placebo test supports the notion that our findings are causal.

5.3.2 Randomized siting of wind turbines

We further conduct another placebo test in the form of random treatment assignment. We randomly assign the number of wind turbines in a given municipality i to another municipality j and re-estimate our main regression specification, as introduced in equation 3. The instruments are also assigned to municipality j. We replicate this random assignment 1,000 times.

The left-hand side of Appendix Figure A2 displays the density function of the obtained coefficients. They are normally distributed and centered around zero. For comparison, the red line indicates our primary estimate (-0.0191), which does not overlap with the coefficients from the placebo estimations. Moreover, the right-hand side of Appendix Figure A2 provides a distribution of the p-values, showing that the lion's share of the point estimates are statistically insignificant at conventional levels. By contrast, our primary estimate is statistically significant with a p-value less than 0.00. This placebo test suggests that our primary estimate is not driven by chance.

5.3.3 Alternative time periods

A a third robustness check, we test if our findings may be driven by the the specific time period we analyze. For this purpose, we restrict the initial sample period 2008–2017 to alternative periods by excluding one or two years from each end. Appendix Table A3 presents the estimates for the period 2009–2016 (column (1)) and 2010–2015 (column(2)).

In both specifications, the estimates effect of wind turbine placement on house prices stays similar in magnitude: -1.7% during the period 2009–2016 and -1.6% during the period 2010–2015. These estimates support the notion that our main results are not driven by a specific circumstance in time.

5.3.4 Always eligible vs. initially ineligible areas

Prior to 2012, municipalities with wind potential below a statutory minimum threshold were ineligible for remuneration under the reference yield scheme. The 2012 EEG amendment removed this threshold, allowing all locations—including those previously considered too low in wind potential—to benefit from wind power subsidies.

Since our observation period includes this policy change, we can assess whether the Local Average Treatment Effect (LATE) identified by our IV strategy primarily reflects the impact in newly eligible locations or whether it also applies to areas that were always eligible for feed-in tariffs. If the effect were concentrated in the formerly ineligible group, this would raise concerns about the generalizability of our findings.

To explore this, we extend the baseline model by estimating separate treatment effects for locations that were initially eligible and those that were not. The former is identified solely through variation in expected revenues, while the latter additionally exploits the time variation introduced by the policy reform.

Appendix Table A4 shows that the estimated effect is slightly larger in the group of newly eligible municipalities than in the always-eligible group, but the difference is not statistically significant (Wald test p = 0.39).[5]

We therefore cannot reject the hypothesis that wind turbines have a similar effect on house prices in always-eligible and newly eligible locations. This alleviates concerns that our LATE may be specific to the policy change and strengthens the external validity of our results.

5.3.5 Discounting expected revenue

Our baseline specification uses undiscounted expected revenue as the instrument, summing feed-in tariff payments over the 20-year support period. However, developers likely calculate the present value of future revenue streams when making investment decisions. To assess whether discounting affects our results, we re-estimate our main specification using discounted expected revenue at various discount rates.

Appendix Table A5 reports the results using discount rates of 3%, 5%, 7%, and 10%, which span the range of estimated capital costs for wind projects with guaranteed feed-in tariffs in Germany (Egli et al., 2018; Steffen, 2020). The estimates remain negative and highly significant across all specifications, with point estimates ranging from -2.1% to -2.7%. The first-stage F-statistics remain stable around 43–44, indicating that instrument

[5]The high values of both first-stage F-statistics and also the Kleibergen-Paap rk Wald F-statistic on joint significance confirm that the instruments are sufficiently strong to identify both interaction terms.

strength is unaffected by discounting. These results confirm that our main finding is robust to alternative assumptions about how developers value future revenue streams.

5.3.6 Differential trends

Our baseline specification already removes time-invariant municipal heterogeneity and common year shocks through municipality and year fixed effects. To check whether unobserved developments that differ across states (Bundesländer) could still confound the estimates, Appendix Table A6 introduces richer time controls. Column (1) adds state-by-year fixed effects to account for unobserved state-level shocks that vary over time, while Column (2) includes state-specific linear time trends to capture gradual, region-specific developments. In both cases, the estimated effect of wind turbine installations remains stable and statistically significant, indicating that our main findings are not driven by omitted regional time trends.

5.3.7 Spatial correlation

If error terms exhibit spatial correlation, statistical inference from our baseline estimates may be invalid. To address this concern, we follow Conley (1999) and compute standard errors using a spatial HAC estimator. This approach applies a weighting function based on the product of kernels in two dimensions (north-south and east-west), where the kernel weight equals one at zero distance and declines linearly to zero at a specified cutoff distance. We report results for cutoff distances of 10, 25, and 50 kilometers. A limitation of existing implementations is that the Conley (1999) estimator cannot be combined with efficient two-step GMM estimation. We therefore estimate the IV model using standard two-stage least squares when computing Conley standard errors. For comparability, we also report our baseline IV specification estimated via 2SLS rather than GMM. Table A7 in the appendix presents the results. The estimated treatment effects remain statistically significant across all distance cutoffs, indicating that our findings are robust to allowing for spatial correlation in the error terms beyond the boundaries of our cross-sectional units.

5.4 Different outcome variables

Besides investigating the effect of wind turbine placements on house prices, we also employ alternative outcome variables in the regressions. As discussed in Section 4, our instrumental variables strategy identifies the total causal effect of wind turbine deployment on each outcome, capturing all channels through which turbines may operate. Table V provides estimates on apartment rental prices (column (1)), the number of overnight stays in hotels (column (2)), and the number of building permits for apartments and houses (column (3)). All outcome variables are introduced in logarithms to allow for percentage interpretations of the coefficient estimates.

We find that wind turbines have a statistically significant and adverse economic effect on all three outcome variables. Column (1) indicates that a wind turbine placement reduces apartment rents in its neighborhood by 2.1%. This effect is consistent with the hedonic pricing framework: the rent decline reflects renters' valuation of the disamenities associated with wind turbines, such as noise and visual pollution. A renter who pays lower rent after turbine installation receives compensation for reduced quality of life. While substitution between housing tenures could also contribute – if falling house prices induce some renters to become homeowners, reducing demand for apartments – the welfare interpretation remains similar, as both renters and new homeowners in turbine-affected areas accept lower prices in exchange for tolerating the disamenity.

Column (2) shows that a wind turbine reduces hotel overnight stays by 1.5%, suggesting that wind turbines exert a negative externality on tourism. One might hypothesize that tourists substitute toward vacation rentals rather than reducing visits altogether. However, vacation rentals in turbine-affected areas are subject to the same disamenities as hotels, so such substitution would not represent an unambiguous welfare gain for tourists. We therefore interpret this result as reflecting the disamenity associated with wind turbines, while acknowledging that we cannot fully decompose changes in tourism demand from substitution across accommodation types.

Finally, column (3) indicates that the number of building permits falls by 2.2% in response to a wind turbine placement. This effect may operate through direct land-use trade-offs, as municipalities allocate land to turbines rather than housing, or through reduced developer demand in response to lower house prices. Our instrumental variables approach captures the total causal effect operating through all such channels.

Altogether, our empirical results indicate significant adverse effects of wind turbines on local housing markets, rental markets, tourism, and construction activity. Policymakers must consider these externalities in their cost-benefit calculations when deciding on wind power deployment.

Table V: *Alternative outcome variables*

	(1) Apartment rent	(2) Hotel accommodation	(3) Building permits
No. wind turbines	-0.0213***	-0.0152**	-0.0216**
	(0.0030)	(0.0076)	(0.0085)
Year FE	y	y	y
Municipality FE	y	y	y
Socioeconomic controls	y	y	y
Durbin-Wu-Hausman test	0.00	0.03	0.00
First stage F stat.	28.37	40.03	74.16
Obs.	16,316	28,563	43,445

The dependent variable in Column (1) is the log apartment rent price index, in Column (2) the log number of guest overnight stays in accommodation establishments, in Column (3) the log number of building permits for apartments and houses. The observation unit is the municipality level in all columns. The adoption of wind turbines is instrumented for with the expected revenue according to the reference yield subsidy scheme. The IV estimator is two-step feasible GMM. Standard errors clustered at the municipality level in parenthesis. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

5.5 Commercial taxes

Despite the adverse effects we found so far, wind power deployment can also be financially beneficial for German municipalities through increased commercial tax income. The commercial taxes depend on the number and capacity of wind turbines. Column (1) of Table VI provides estimates on the impact of wind turbine placements in a municipality on the logarithm of commercial tax income, showing that for each additional wind turbine, commercial taxes increase by 2%. Since commercial taxes constitute the bulk of a municipality's total tax capacity, we observe an effect of similar magnitude when total tax capacity is used as the dependent variable as shown in Column (3) of Table VI.

Table VI: *WTs and commercial taxes*

	Commercial taxes		Total tax capacity	
	(1)	(2)	(3)	(4)
No. wind turbines	0.0201***		0.0181***	
	(0.0058)		(0.0055)	
Net wind turbine capacity (MW)		0.0083***		0.0072***
		(0.0023)		(0.0021)
Year FE	y	y	y	y
Municipality FE	y	y	y	y
Socioeconomic controls	y	y	y	y
Durbin-Wu-Hausman test	0.00	0.00	0.00	0.00
First stage F stat.	74.03	69.27	74.19	69.44
Obs.	43,355	43,355	43,424	43,424

The dependent variable is log municipality level commercial taxes in columns 1 and 2 and the total tax capacity in columns 3 and 4. The adoption of wind turbines is instrumented for with the expected revenue according to the reference yield subsidy scheme. The IV estimator is two-step feasible GMM. Standard errors clustered at the municipality level in parenthesis. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$..

Notably, wind turbines have become significantly larger over time. While the average wind turbine had a capacity of 1 MW in 2000, it grew to almost 4 MW by 2022, as shown in Figure VIIa. During the sample period from 2008 to 2017, the average wind turbine capacity increased from about 2 MW to about 3 MW. Similarly, Figure VIIb depicts trends in wind turbines' hub height and rotor diameter, both of which have grown substantially. In 2000, the average hub height was about 70 meters and the average rotor diameter was about 60 meters. By 2022, these metrics increased to nearly 130 meters and 125 meters, respectively. These increases in size have a significant impact on municipal tax income.

To account for this, we also estimate the effect per MW of installed net capacity of wind turbines in a municipality on commercial taxes, as shown in columns (2) and (4) of Table VI. The estimates indicate that commercial taxes increase by 0.8% per additional MW of net turbine capacity. For instance, a wind turbine built in 2017 has a 50% greater effect on a municipality's commercial tax income than one built in 2008.

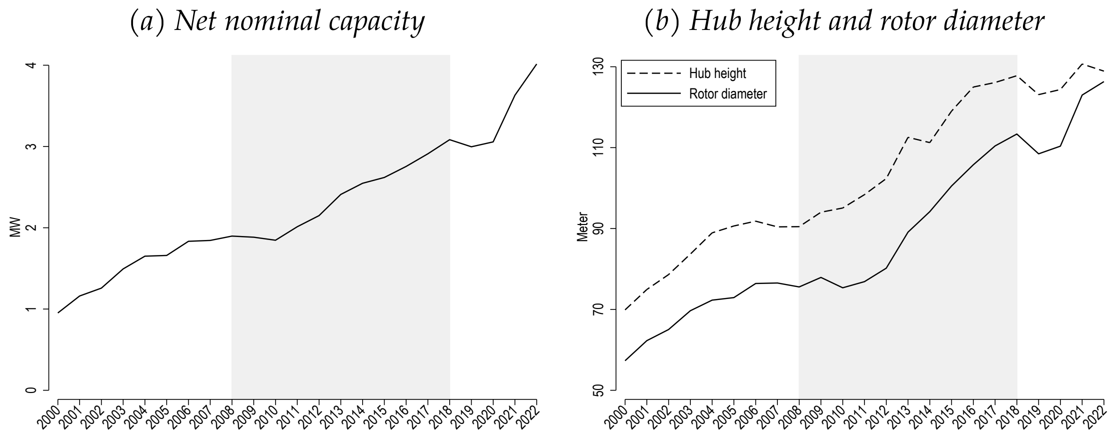

Figure VII: *Development of wind turbine characteristics over time*

Notes: The shaded area indicates the sample period of the econometric analysis.

6 Discussion and Policy Recommendations

Germany is a global leader in renewable energy deployment, particularly wind energy, with investments in wind turbines expected to accelerate in the coming years according to government goals. With over 28,000 wind turbines installed across the country, 97 percent of which are within two kilometers of a residential area, understanding the local economic consequences of wind energy deployment is crucial. Despite strong promotion by national and European authorities, as well as international institutions advocating for climate change mitigation, negative perceptions among local populations may hinder the expansion of wind turbines. Our findings demonstrate that these perceptions are grounded in real economic costs that policymakers must address.

Our results indicate that new wind turbine installations in a municipality reduce house purchase prices by 1.9%. However, this effect is strongly non-linear: expanding wind power into municipalities that previously had no turbines leads to a pronounced price drop of 5.5%, while adding turbines to municipalities that already host wind farms has no statistically significant impact. We also find that wind turbines negatively affect apartment rents, tourism, and building permits, each by roughly 2% on average. Moreover, larger turbines appear to exert stronger negative effects on house prices than smaller ones. In contrast, wind turbines increase local tax capacity by 1.8%, due to their contribution to commercial tax revenues. These findings reveal that wind turbine deployment creates both winners and losers within local communities: homeowners face reduced property values, renters face lower rents, local tourism shrinks, and construction activity declines, while municipalities benefit from increased tax revenues.

This distributional tension suggests several policy responses. First, the additional tax income from wind turbines could be explicitly hypothecated for compensating affected homeowners or improving local amenities, rather than absorbed into general municipal budgets. Making this link between wind turbine revenues and local benefits explicit could help build community acceptance for new projects.

Second, our finding that expanding wind power into previously unaffected areas has a substantially larger negative impact than adding turbines to existing locations suggests a strategic approach to siting. Clustering wind turbines in locations with existing installations would minimize aggregate welfare losses while also taking advantage of existing grid infrastructure.

Third, for communities where new wind turbines are built, a formal compensation mechanism for nearby homeowners deserves consideration. Denmark's value-loss scheme may serve as a model (Jørgensen et al., 2020): eligible homeowners file claims before construction, a neutral valuer estimates property value losses, and the developer reimburses verified losses at commissioning. Such a scheme would ensure that those who bear the costs are compensated by those who reap the benefits.

In conclusion, the energy transition requires continued expansion of wind power capacity, but achieving climate goals sustainably requires addressing the legitimate economic concerns of local communities. Our findings provide an empirical foundation for designing compensation and siting policies that share both the costs and benefits of wind energy deployment more equitably.

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Appendix

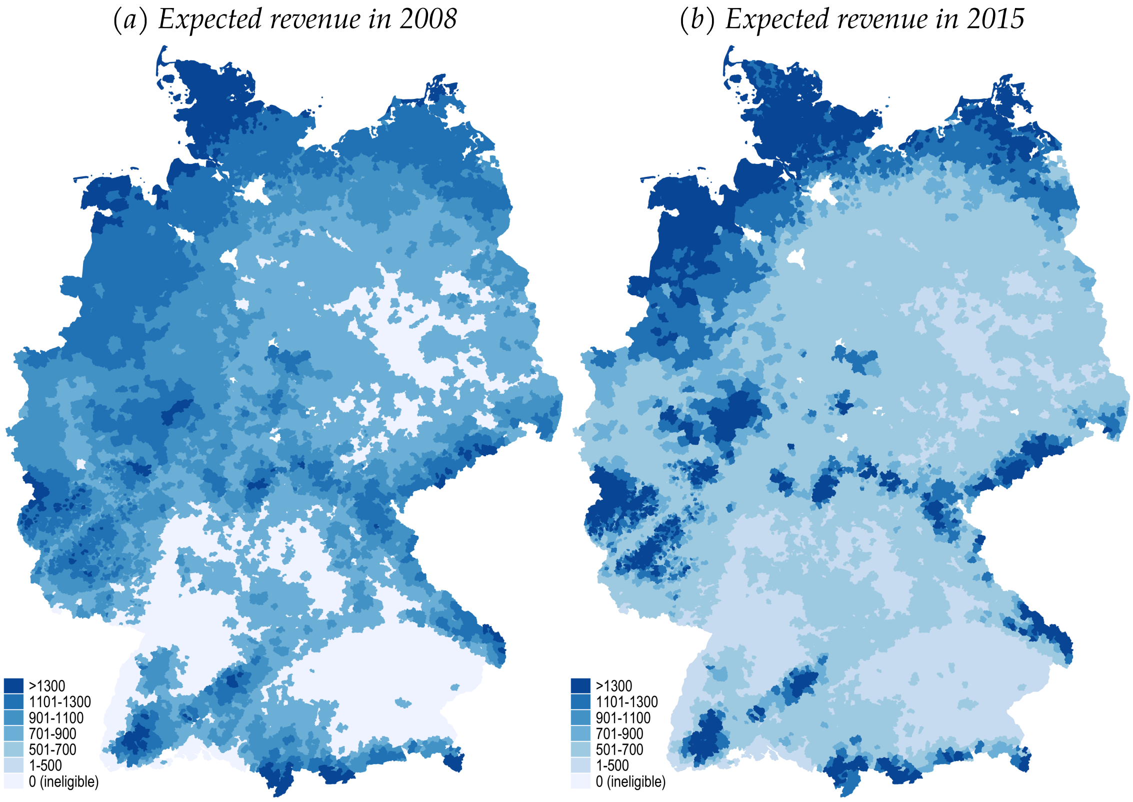

Figure A1: *Expected revenue from wind turbines in Germany*

These maps show the expected revenue per m^2 of rotor surface (in €/m^2) for a wind turbine installed in each municipality in 2008 (a) and 2015 (b). Expected revenue is calculated based on the reference yield model described in Section 3.3. In 2008, municipalities with wind potential below 60% of the reference site (shown in the lightest shade) were ineligible for FIT support and thus have expected revenue of zero. Following the 2012 reform, all municipalities became eligible, as shown in panel (b).

Table A1: *Heterogeneous effects by average turbine size*

Dependent variable is *ln*(*house price index*)	
No. WT in municipality × average WT size<p10	-0.015**
	(0.006)
No. WT in municipality × average WT size p10–p90	-0.018***
	(0.003)
No. WT in municipality × average WT size>p90	-0.028***
	(0.007)
Year FE	y
Municipality FE	y
Socioeconomic controls	y
Durbin-Wu-Hausman test	0.00
First stage F stat. <p10	25.64
First stage F stat. p10–p90	24.25
First stage F stat. >p90	3.58
Kleibergen Paap F stat.	20.36
Obs.	26,657

The dependent variable is the log municipality-level house price index. The number of wind turbines is interacted with indicators for whether the average turbine size in the municipality falls below the 10th percentile, between the 10th and 90th percentile, or above the 90th percentile of the year-specific size distribution. All three interaction terms are treated as endogenous and instrumented with expected revenue interacted with the same size indicators. Standard errors clustered at the municipality level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A2: *Placebo test with lagged dependent variable*

	(1) Lagged ln(house price index)	(2) ln(house price index)
No. wind turbines	-0.0029	-0.0158***
	(0.0026)	(0.0031)
Year FE	y	y
Municipality FE	y	y
Socioeconomic controls	y	y
Durbin-Wu-Hausman test	0.29	0.00
First stage F stat.	33.35	33.35
Obs.	18,442	18,442

The dependent variable in Column (1) is the log municipality level house price index lagged by two periods. The dependent variable in Column (2) is also the log municipality level house price index but without lags, but the same sample as in Column (1) is applied in order to allow for a better comparison. In both columns the adoption of wind turbines is instrumented for with the expected revenue according to the reference yield subsidy scheme. The IV estimator in both columns is two-step feasible GMM. Standard errors clustered at the municipality level in parenthesis. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

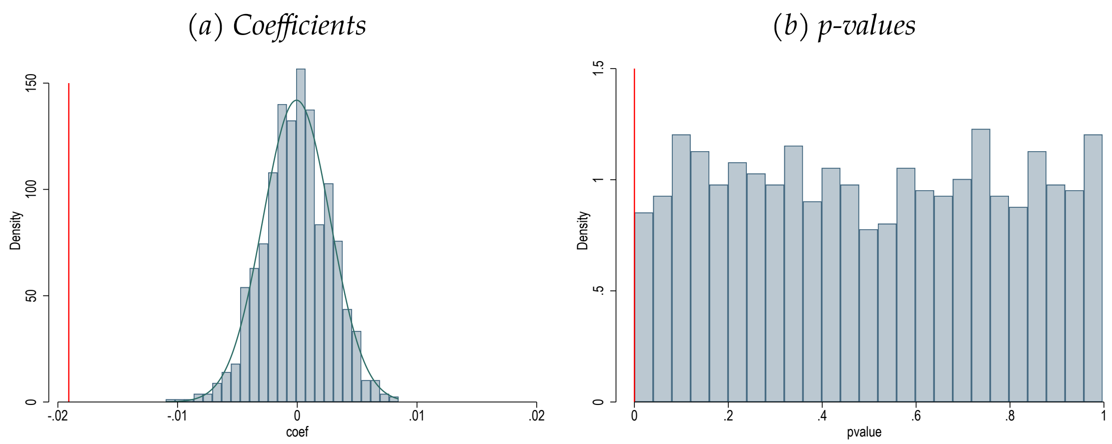

Figure A2: *Placebo test*

The red vertical lines indicate estimation results from Column (2) in Table III, with a point estimate of -0.0191 ($p = 0.00$). The black line presents a normal distribution. The Durbin-Wu-Hausman's p-value in the placebo test is $p = 0.50$ (not shown here).

Table A3: *Alternative sample periods*

	Dependent variable is *ln*(*house price index*)	
	(1) 2009 – 2016	(2) 2010 – 2015
No. wind turbines	-0.0170*** (0.0035)	-0.0160*** (0.0045)
Year FE	y	y
Municipality FE	y	y
Socioeconomic controls	y	y
Durbin-Wu-Hausman test	0.00	0.00
First stage F stat.	40.13	37.37
Obs.	21,156	15,688

The dependent variable is the log municipality level house price index. In Column (1) the observation period is shortened to 2009–2016 and in Column (2) it is shortened to 2010–2015. The adoption of wind turbines is instrumented for with the expected revenue according to the reference yield subsidy scheme. The IV estimator is two-step feasible GMM. Standard errors clustered at the municipality level in parenthesis. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A4: *Eligible vs. non-eligible locations*

Dependent variable is *ln*(*house price*)	
No. WT in municipality × always eligible	-0.018*** (0.003)
No. WT in municipality × initially ineligible	-0.024*** (0.009)
Year FE	y
Zip code FE	y
Socioeconomic controls	y
Durbin-Wu-Hausman test	0.00
First stage F stat. *Always eligible*	41.55
First stage F stat. *Initially ineligible*	24.70
Kleibergen Paap F stat.	21.53
Obs.	26,657

The dependent variable is the logged municipality-level house-price index. The turbine count is interacted with dummies indicating whether a location was always eligible for the reference-yield scheme. Both interaction terms are treated as endogenous and instrumented with expected turbine revenues (from the reference-yield formula) interacted with the same eligibility dummies. Standard errors clustered at the municipality level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A5: *Robustness to discounting expected revenue*

	Dependent variable is *ln*(*house price index*)			
	(1)	(2)	(3)	(4)
	3%	5%	7%	10%
No. wind turbines	-0.0211***	-0.0219***	-0.0246***	-0.0273***
	(0.0030)	(0.0031)	(0.0033)	(0.0035)
Year FE	y	y	y	y
Municipality FE	y	y	y	y
Socioeconomic controls	y	y	y	y
Durbin-Wu-Hausman test	0.00	0.00	0.00	0.00
First stage F stat.	43.71	43.47	43.68	43.70
Obs.	26,657	26,657	26,657	26,657

Notes: The dependent variable is the logged municipality-level house price index. Expected revenue is calculated as the present value of feed-in tariff payments over 20 years, discounted at 3%, 5%, 7%, or 10% annually. Discount rates in this range are consistent with estimates of the weighted average cost of capital for wind projects with guaranteed feed-in tariffs (Egli et al., 2018; Steffen, 2020). The IV estimator is two-step feasible GMM. Standard errors clustered at the municipality level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A6: *Controlling for differential trends*

	Dependent variable is *ln*(*house price index*)	
	(1)	(2)
No. wind turbines	-0.016***	-0.025***
	(0.006)	(0.006)
Year FE	y	y
Municipality FE	y	y
State×Year FE	y	
State specific trend		y
Socioeconomic controls	y	y
Durbin-Wu-Hausman test	0.01	0.00
First stage F stat.	10.69	13.84
Obs.	26,657	26,637

The dependent variable is the logged municipality level house price index. The adoption of wind turbines is instrumented for with the expected revenue according to the reference yield subsidy scheme. The IV estimator is two-step feasible GMM. Standard errors clustered at the municipality level in parenthesis. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A7: *Conley standard errors with spatial correction*

	Dependent variable is $ln(house\ price\ index)$			
	(1)	(2)	(3)	(4)
No. wind turbines	-0.015***	-0.015***	-0.015***	-0.015***
	(0.003)	(0.002)	(0.003)	(0.004)
Year FE	y	y	y	y
Municipality FE	y	y	y	y
Socioeconomic controls	y	y	y	y
Conley cluster distance	-	10km	25km	50km
First stage F stat.	43.67	165.38	65.14	34.04
Obs.	26,637	26,968	26,968	26,968

The dependent variable is the logged municipality level house price index. The adoption of wind turbines is instrumented for with the expected revenue according to the reference yield subsidy scheme. Standard errors adjusted for spatial correlation (Conley, 1999) within different thresholds. Estimation by 2SLS. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.