Renewable Energy Infrastructure, Welfare, and Redistribution*

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Abstract

Renewable energy has vast potential, yet adoption remains slow as residents oppose construction. I leverage technology-induced changes in wind energy suitability, data at 1-by-1 km resolution, and a quantitative spatial model to estimate preferences against wind turbines in Germany. Emissions abatement implies large benefits from wind energy, but the incentives for host communities remain mixed. As generation costs continue to fall, slow and costly development threatens to forfeit annual welfare gains of $32.1 billion by 2045. As an alternative, I propose a set of turbine locations and transfers that halves welfare costs and makes development incentive-compatible.

JEL Codes: D62, Q42, Q51, Q58, R13, R23

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1 Introduction

Electricity generation causes almost a quarter of global emissions (IPCC 2021), increasing projected climate damages by an estimated $4.5 trillion each year. Renewable energy mitigates such damages. As costs fall, wind and solar energy could rise to power most of the world by 2040 (Arkolakis and Walsh 2023). Still, adoption lags far behind its potential as local residents view renewable infrastructure as a nuisance (Dröes and Koster 2021) and often resist its development.

Indeed, concerns about redistribution threaten public support for climate policy more broadly (Dechezleprêtre et al. 2025). While compensation is straightforward in principle if local costs are known, eliciting true costs is often difficult. I develop a framework that combines quasi-experimental variation and a quantitative spatial model to measure local preferences against nuisance infrastructure. The model highlights the distributional consequences of renewable energy and yields compensatory transfers sufficient to incentivize future adoption.

I apply the framework to evaluate wind energy policy in Germany. Wind power is Germany's largest source of electricity, and the Renewable Energy Sources Act (2023) mandates a 2.5-fold expansion by 2045. However, modern turbines reach heights of up to 225 m, imposing substantial visual and noise disamenities on nearby residents. As a consequence, construction is frequently met with opposition, and net development in Germany has nearly come to a halt (see figure 1). More generally, sluggish development threatens to erode the potential welfare gains from renewable energy worldwide.[1] As opposition rises, how can policy reconcile the diverging interests in the energy transition? The case of Germany offers insights for a global debate.

To answer the question, I begin by documenting the impact of turbines on nearby communities. Locations exposed to renewable energy infrastructure differ from potential control areas on many characteristics, and isolating the long-term effect of development is therefore difficult. I propose a novel strategy that leverages changes in turbine technology, which increase wind energy suitability heterogeneously across space but are plausibly unrelated to confounding changes in neighborhood charac-

[1] Indeed, protests are nearly ubiquitous in high-income countries and typically span wind turbines, solar parks, power lines, and battery energy storage systems, as I document in appendix A.

teristics. Over time, installed wind turbines become taller. This benefits primarily locations with large vertical wind shear, a meteorological phenomenon that arises because rugged topography outside the neighborhood slows down winds close to the surface but not at higher altitudes (see figure 2). I find that the technology-induced changes in suitability do not predict pre-treatment differences in neighborhood characteristics or trends. However, from the year 2000 onward, changes in suitability increase turbine development, reduce house prices, and decrease the share of high-skilled residents. Measuring these impacts at a resolution of 1-by-1 km grid cells allows me to control for rich geographic characteristics and fine spatial fixed effects. In addition, I show that the effects are absent in placebo locations where development is prohibited. Further, they are unlikely to arise from alternative explanations, which I confirm through a series of robustness checks.

The results indicate that neighborhoods near wind turbines become less attractive, particularly for high-skilled residents. To quantify the preferences against construction, I interpret the observed neighborhood changes through the lens of a quantitative spatial model in the spirit of Ahlfeldt et al. (2015). I extend the model to flexibly capture the impact of wind turbines on amenities, which I estimate separately for high- and low-skilled residents. As before, estimation leverages technology-induced changes in the suitability for wind energy. Consistent with the reduced form results, I find that residents have strong preferences to avoid living close to any wind turbine, amounting to 3.9 and 1.1 percent of their income for high- and low-skilled residents, respectively. The marginal cost decreases with each additional turbine and becomes negligible beyond a 3 km radius. Given preferences, I quantify the welfare effects in general equilibrium. I take into account that residents adapt to construction by relocating to more desirable neighborhoods, and the endogenous responses of housing and labor markets, which I calibrate drawing on novel shift-share designs.

Using the model, I evaluate Germany's present and future wind energy development through a series of counterfactuals. For the period 2000 to 2024, the analysis yields four main insights. First, wind energy development in Germany increases net welfare. Although development creates large welfare costs for residents, which amount to 0.60 percent of welfare or an annual equivalent variation of $8.89 billion, the welfare benefits outweigh the costs by about three to one. Benefits accrue primarily from emissions abatement, and optimal policy thus depends on the extent to which

the planner internalizes the global benefits of climate change mitigation.

Second, while wind energy is overall beneficial, the incidence of costs varies sharply. Development concentrates turbines in few places, and local costs exceed benefits in about one third of affected neighborhoods if residents internalize global climate damages and in all affected neighborhoods if they don't. Exceeding local costs discourage development, consistent with the observed slowdown in construction rates.

Third, I use the model to calculate monetary transfers that compensate residents for the cost of turbines, and thereby encourage turbine development. Transfers vary substantially across space and amount to \$89,829 per turbine-year for the median municipality. Adequate compensation is about an order of magnitude higher than existing schemes and likely politically infeasible.

Fourth, to make adequate compensation more feasible, I propose an alternative turbine allocation that generates the same electricity capacity, respects spatial constraints in wind resources, land use, and transmission infrastructure, and reduces welfare costs for residents sixfold. The alternative allocates turbines further from residents, and especially from high-skilled residents, so that the planner faces an equity-efficiency trade-off. Inequality before redistribution increases, but adequate compensation becomes much cheaper and thus more likely to be politically feasible.

Building on these insights, I evaluate Germany's prospective wind energy policy through 2045. Current development is sluggish and costly. Projecting construction trends forward, Germany is set to fall short of its wind energy targets in every reference year. Missing targets entails large welfare costs because falling generation costs make wind increasingly competitive, even if the planner ignores climate damages. Since compensating residents and incentivizing development is costly under existing policies, I propose a path for wind energy development that achieves targets while reducing the costs to residents. Relative to business-as-usual, I show that this path reduces annual emissions by 9 percent or $0.06\,\mathrm{GtCO_2}$ while annual welfare benefits of wind energy increase by 29 percent or \$32.1 billion by 2045.

My main contribution is to quantify the unequal costs of climate change mitigation and to provide transfers that incentivize adoption in an important context. Misaligned incentives between global beneficiaries and local stakeholders limit environmental

regulation, especially in the case of climate change (Hardin 1968, Oates 1972, Portney 1994, Stern 2007). Countries can mitigate unilaterally (Bilal and Känzig 2024, 2025) or form climate clubs (Nordhaus 2015, Farrokhi and Lashkaripour 2025, Hsiao 2025a) but both require political support and may not always be feasible. As an alternative, renewable energy increasingly pays for itself (Arkolakis and Walsh 2023), but creates local costs marked by reduced house prices (Gibbons 2015, Dröes and Koster 2016, 2021), which slow down adoption (Jarvis 2025). I provide the first theory-consistent estimates of the welfare costs and compute transfers that incentivize adoption.[2]

Methodologically, I build on revealed preference approaches in the tradition of Rosen (1974) and Roback (1982), which motivate the central role of house prices to evaluate environmental disamenities (Chay and Greenstone 2005, Greenstone and Gallagher 2008, Currie et al. 2015). Building on Ahlfeldt et al. (2015), I show that, in addition to house prices, local costs are informed by skill-specific population and income changes. Ignoring these responses biases preferences by 60 and 22 percent for high- and low-skilled residents, respectively. I complement work on disamenities and sorting (Heblich et al. 2021, Redding and Sturm 2024, Bagagli 2025) by highlighting a context in which skill differences in preferences create an equity-efficiency trade-off for the planner with important implications for environmental justice (Banzhaf et al. 2019). Computationally, I show that reasonable commuting restrictions permit solving the model for 133,332 neighborhoods, thereby allowing me to study sorting across and within cities at granular level.

More broadly, I connect to a literature on the spatial implications of climate change (Conte et al. 2021, Bilal and Rossi-Hansberg 2023, Balboni et al. 2024, Castro-Vincenzi 2024, Cruz and Rossi-Hansberg 2024, Conte 2025, Nath 2025). Emphasizing adaptation, an important strand highlights how infrastructure and land use policy lessen or amplify the damages of climate change (Ospital 2023, Ostriker and Russo 2024, Balboni 2025, Hsiao 2025b). I focus on renewable energy infrastructure, which mitigates emissions and helps limit climate damages before they arise.

[2]Subsequent work by Kashner (2026) estimates the welfare cost of turbines in the United States. Estimation relies on comparing exposed and non-exposed locations over time, while I use a new IV design that leverages location-specific shocks to suitability generated by technological change. For counterfactuals, I benefit from legislation in the Renewable Energy Sources Act (2023), permitting me to quantify the welfare losses from sluggish relative to desired development until 2045.

2 Background and data

2.1 Background

Fossil-fuel energy production is a major cause of climate change. Electricity generation from coal, oil, and gas accounts for 23 percent of global greenhouse gas emissions (IPCC 2021). Using the German Environment Agency's (2024) estimate of the social cost of carbon, \$325/tCO_2, annual emissions imply climate damages of \$4.5 trillion, equivalent to about four percent of global GDP. Renewable energy sources offer low-emission alternatives. In Germany, wind power primarily replaces coal-fired generation and avoids an estimated 758 gCO_2/kWh on average (UBA 2025).[3]

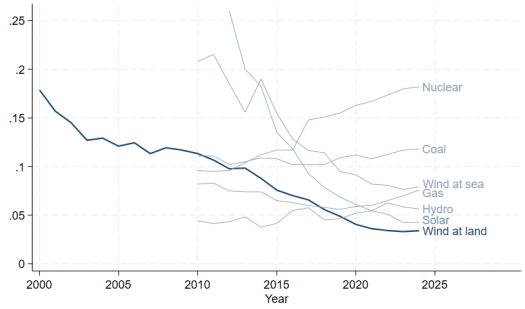
Despite historically high costs, decades of technological progress have made wind and solar energy remarkably inexpensive (Arkolakis and Walsh 2023). For wind power in particular, advances in materials and engineering have enabled taller towers and larger rotor diameters, allowing turbines to access stronger winds at higher altitudes. These improvements have steadily reduced generation costs. Today, newly installed wind turbines produce electricity at a lower cost than any other source (see figure 1a).

While wind energy provides cheap and sustainable electricity, it also generates visual and noise disamenities for nearby residents. Modern turbines are up to 225 m tall and even a small number can greatly alter the character of the landscape. Several studies find that visible turbines reduce house prices (Gibbons 2015, Dröes and Koster 2016, Dröes and Koster 2021), with shadow flicker cast by rotor blades causing particularly large declines (Andersen and Hener 2025). In addition, turbines emit intermittent noise and low-frequency vibrations, which some residents link to sleep disturbance and stress, though empirical evidence for physiological harm remains limited (Knopper et al. 2014, Krekel et al. 2023). Despite the costs, host communities capture almost no benefits. Most importantly, turbines create only small transitory employment effects (Fabra et al. 2024) and, during the study period, residents are not compensated through direct payments or lower electricity prices.

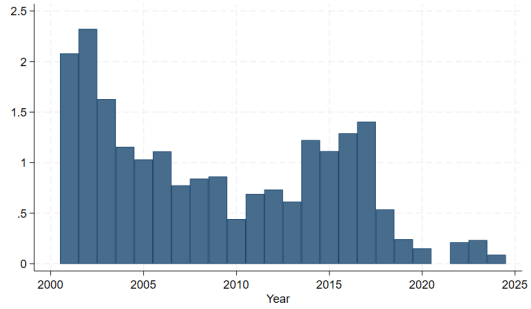
[3] Throughout the paper, I use *wind energy* as shorthand for wind energy at land. All statistics reported hereafter therefore refer to onshore wind energy. Offshore wind energy accounts for only 15 percent of wind capacity in Germany and is about twice as expensive as onshore wind (IRENA 2025).

Figure 1: Wind energy in Germany, 2000-2024

(a) Generation cost ($/kWh)



(b) Net turbine development (1000s)



The left figure compares generation cost of electricity across technologies and over time. The measure reflects the global cost of electricity averaged over the lifetime of a plant installed in the respective year. Costs are measured in inflation-adjusted, year-2024 USD per kilowatt-hour. The right figure shows turbine development net of decommissioning in Germany. In 2021 net development was negative and the year is omitted. Appendix A details the data sources.

Wind energy development in Germany began in 1991 with the Electricity Feed-in Act. Construction accelerated especially in the early 2000s, when Germany introduced subsidies for renewable energy, and the country has since become the world's third-largest producer of wind power, after China and the United States. In 2024, wind energy generated roughly one quarter of German electricity production, more than any other source.

Despite the early success, development has markedly slowed down in recent years. Annual net construction is down from several thousand in the early 2000s to only 89 in 2024 (figure 1b), when 635 new turbines were barely enough to replace 546 old ones that were decommissioned. Several factors contribute to this decline. Older turbines lose eligibility for feed-in subsidies after 20 years and are gradually phased out (FA Wind 2025). Modern turbines are much larger, require greater minimum spacing, and often cannot be installed on the small sites previously occupied by older turbines (Unnewehr et al. 2021). Meanwhile, local opposition has intensified. There are now hundreds of organized groups that use information requests, procedural objections, and lawsuits to delay the permitting process. As a result, average project completion times have risen from about five years a decade ago to nearly eight years today (FA Wind 2023). Finally, in response to growing resident concerns, state governments have enacted stricter minimum-distance requirements, further exacerbating land scarcity.

Recent legislation in the form of the Renewable Energy Sources Act (2023) ac-

knowledges the concerns and encourages turbine operators to compensate affected municipalities at a rate of \$0.002/kWh, although transfers are voluntary and it remains uncertain they provide adequate compensation. At the same time, the act mandates a rapid expansion of wind energy from 63 GW in 2024 to 115 GW in 2030, and ultimately to 160 GW in 2045. Meeting the 2030 target would require the construction of 2,218 turbines per year, three to four times the number installed in 2024.

Targets appear increasingly out of reach, and among policymakers skepticism is growing. Chancellor Friedrich Merz, for instance, has expressed doubts about the long-term viability of wind power, stating that turbines are "ugly and don't belong in the landscape" (Handelsblatt 2024). In the US, President Donald Trump has voiced similar concerns and suggested halting wind turbine development altogether (Bloomberg 2025). Meanwhile, as generation costs continue to fall, wind energy is booming in China. The case of Germany, a country that is increasingly torn between wind energy's societal benefits and local costs, therefore informs a global debate.

2.2 Data

I divide contiguous Germany into 360,479 square-kilometer cells and construct a panel data set with information on suitability for wind energy, turbine development, and neighborhood characteristics spanning the years 2000 to 2017.

Wind power density. I obtain cross-sectional information on local wind conditions from the *Global Wind Atlas* (2023). The atlas combines data on regional wind patterns and local topography with wind flow modeling to simulate wind conditions at 250 m resolution (Davis et al. 2023). I calculate average wind power density for each grid cell at the heights of 50, 100, 150, and 200 m and obtain values for intermediate heights by linear interpolation. Wind power density is measured in watts per square meter and reflects the potential power output available at a given location and height, independent of the area swept by the rotor blades.

Wind turbines. Data on wind turbines come from Eichhorn et al. (2019), who compile turbine coordinates and construction years from state authorities. Because their dataset covers only turbines built through 2015, I supplement it with information

from the wind energy intelligence firm *The Wind Power* (2025), which systematizes industry and media reports to track construction in real time. Appendix A shows that year-to-year construction in the combined data closely matches national statistics. Between 2000 and 2017, the number of turbines increases from 5,343 to 27,723, and the increase accounts for about four-fifths of turbines operating today. Owing to Germany's high population density, 98.8 percent of turbines lie within 3 km of residential population, with an average of 915 residents in that radius. At the same time, wind parks in Germany are comparatively small. Conditional on any development, the median neighborhood in 2017 is exposed to four turbines within 3 km.

House prices. I construct a quality-adjusted house price index using object-level data from Germany's largest online real estate platform *ImmobilienScout24*. Due to the website's launch year, data is only available from 2007. Over the sample period, the website lists on average 3.2 million houses and flats per year. Each listing comes with information on the asking price, the date of the ad, the object's location, and a rich set of object characteristics. Following Diamond (2016), I translate sales to rental prices assuming a discount rate of 7.85 percent. Then, I calculate the rental price per square meter and residualize it on non-parametric functions of the object type, year of construction, number of rooms, and plot area. Since for smaller neighborhoods there is not a listing in every year, I take a three-year rolling average, which allows me to increase the sample size and calculate house price changes for 79,815 grid cells.

Neighborhood characteristics. I collect information on population, employment, income, and workplace wages by skill from social security data hosted by the Institute for Employment Research in Germany. The data encompasses nearly the entire labor force, including all employees subject to social insurance or on unemployment benefits. I group workers into high- and low-skilled based on college attainment and compute all variables separately by type. By the end of the sample period, the data covers 5.5 million high- and 22.2 million low-skilled residents. To protect sensitive information, the data excludes neighborhoods that have fewer than ten residents or workers. The final sample contains 128,300 residential and 67,231 workplace neighborhoods, which overlap and span 133,332 grid cells in total.

Auxiliary data. As control variables, I measure the altitude, terrain ruggedness, and slope in each neighborhood from the elevation model provided by Germany's *Fed-*

eral Agency for Cartography and Geodesy. I also obtain information on land cover in 1990 from *Copernicus* and measure the share of the neighborhood covered by buildings, agricultural land, forests, and water. In placebo exercises, I test for pre-effects and trends using data from the *Establishment History Panel*, which allows me to measure municipality-level workplace population going back to 1975. In a second placebo check, I also use maps on conservation zones that restrict wind turbine development from the *German Federal Agency for Nature Conservation*. Estimation of the quantitative spatial model draws on various data sets, which I describe in the respective section. Evaluating wind energy development counterfactuals for 2000 to 2045, I further draw on turbine and capacity development statistics from the *German Wind Energy Association*, land use scenarios from the think tank *Agora Energiewende*, and electricity transmission maps from *Infrageomatics*. Grid cells aggregate to 11,203 municipalities (*Gemeinden*), 401 districts (*Kreise*), and 16 states (*Länder*). Appendix A documents all sources and provides additional details.

3 Quasi-experimental evidence

3.1 Empirical strategy

Objective. The goal of this section is to estimate the impact of wind turbine development on the surrounding neighborhoods. I focus on house prices and residential sorting, two key variables used to measure environmental disamenities and neighborhood decline (for example, Chay and Greenstone 2005, Banzhaf and Walsh 2008, Heblich et al. 2021). Since households may face short-term migration frictions, I am interested in the long-run response given by

$$\Delta y_n = \Delta f(\mathcal{T}_n) + \varepsilon_n \tag{1}$$

where Δy_n is the change in the outcome variable in neighborhood n and $\Delta f(\mathcal{T}_n)$ captures the impact of turbine development. Three observations complicate estimation. First, the effect may depend on turbines at different distance bands d from the

neighborhood, such that $\mathcal{T}_n(T_n^1, \ldots, T_n^d)$. Second, the effect may decline with each additional turbine, so that $f(\mathcal{T}_n)$ is nonlinear. Third, unobserved trends ε_n may be correlated with turbine development and confound estimation. I focus on the challenge of establishing causality first. To simplify, I assume that effects are linear in the number of turbines and limited to 3 km from the turbine.[4] Formally, $f(\mathcal{T}_n) = \beta T_n$ and equation 1 simplifies to

$$\Delta y_n = \beta \Delta T_n + \varepsilon_n. \tag{2}$$

The identification concern is that turbine development may correlate with unobserved trends in the outcome variables. For instance, policymakers might steer development to regions where they anticipate rising electricity demand, or developers may avoid locations where they expect increasing public resistance, and both may correlate with trends in house prices or sorting. To address this challenge, I develop a strategy that leverages technology-induced variation in wind energy suitability.

IV strategy. The power output P of a wind turbine depends on local wind power density w, the area swept by the rotor blades A, and conversion efficiency ζ.

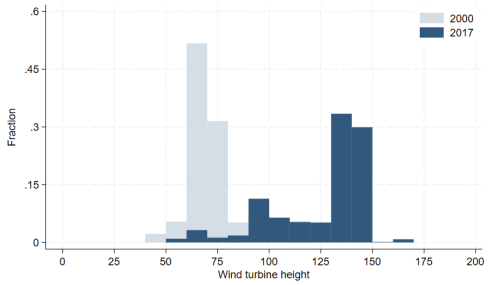
$$P = wA\zeta \tag{3}$$

While developers choose the rotor area and conversion efficiency from a set of available technologies, wind power density is determined by the location and height of the turbine. Over time, advances in materials and engineering enable the construction of taller turbines. For turbines installed in each year, the average hub height increases from 68 m to 126 m between 2000 and 2017 (figure 2a). Winds are typically stronger at higher altitudes and the rise in turbine heights implies that wind power density increases by 59 percent for the average neighborhood (figure 2b).

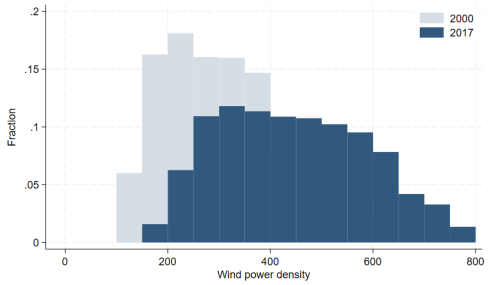
[4] Ex ante, both assumptions are reasonable approximations. The house price effects of turbines typically fade out quickly over distance (Gibbons 2015, Dröes and Koster 2016, Andersen and Hener 2025), and specifically after 3 km as estimated for Germany by Heuer and Sommer (2025). House price effects also typically increase in the number of turbines (Gibbons 2015, Guo et al. 2024, Heuer and Sommer 2025), though not always linearly, which I document in the appendix in figure B.2. I revisit both assumptions in section 3.4, and take potential nonlinearities into account when evaluating welfare costs.

Figure 2: Instrumental variable strategy

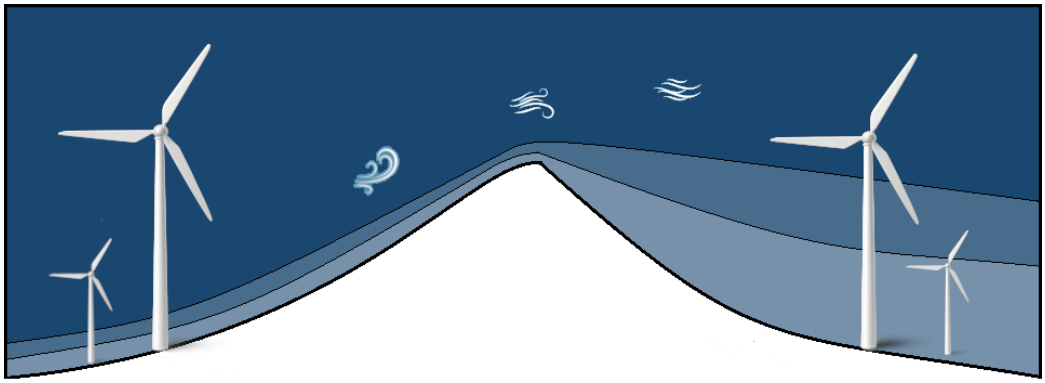
(a) Wind turbine heights



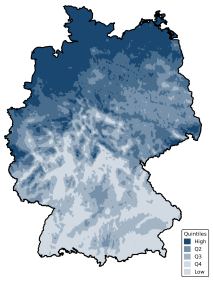
(b) Wind power density



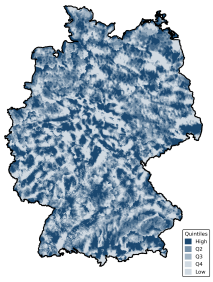
(c) Changes in wind power density vary due to wind flows and terrain



(d) Raw variation



(e) Residual variation



(f) First-stage

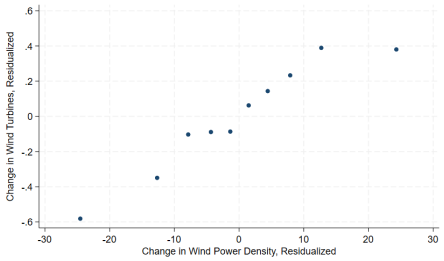


Figure 2a shows the height distribution of turbines installed in 2000 and 2017. Height increases over time, which in turn raises wind power density. 2b shows the wind power density distribution of neighborhoods at the average turbine height. Gains depend on vertical wind shear, which is shaped by wind flows and topography, see 2c. Hills block winds at lower heights, inducing stronger vertical wind shear downwind of the hill. 2d shows the raw changes in wind power density implied by changes in turbine heights, while 2e shows the same variation after residualizing on geographic controls and district fixed effects as detailed in equation 6. Finally, 2f plots residualized changes in wind power density against residualized turbine construction in a binscatter plot.

As taller turbines become the norm, suitability for wind energy shifts across space. Locations benefit disproportionately if local wind power density rises quickly with altitude. The strength of the so-called vertical wind shear is determined by wind flows and their interaction with the topography outside the location (figure 2c). In particular, rugged terrain such as hills blocks winds at lower heights and thereby generates larger vertical wind shear for up to ten kilometers downwind of the obstacle (Global Wind Atlas 2023, Davis et al. 2023). I measure the technology-implied change in wind power density as the difference across turbine heights

$$\Delta w_n = w_{n,126} - w_{n,68} \tag{4}$$

where $w_{n,h}$ denotes wind power density of location n at height h, which I evaluate for the years 2017 and 2000, respectively. Consistent with wind turbine development, I calculate the average change in wind power density within 3 km (figure 2d).

Main specification. I estimate the intention-to-treat specification

$$\Delta y_n = \beta \Delta w_n + \gamma X_n + \delta_{d(n)} + \varepsilon_n \tag{5}$$

where Δy_n is the change in an outcome variable and Δw_n is the change in wind power density. I control for all local geographic characteristics X_n that according to the data provider (Davis et al. 2023) affect vertical wind shear, including altitude, ruggedness, slope, and the share of land used for buildings, agriculture, forests, and water (omitted category). The district fixed effects $\delta_{d(n)}$ ensure that I only compare neighborhoods that are relatively close. In addition, I estimate

$$\Delta y_n = \beta \Delta T_n + \gamma X_n + \delta_{d(n)} + \varepsilon_n \tag{6}$$

where I instrument wind turbine development with changes in wind power density. For all specifications except house prices, changes in wind power density and turbine development are calculated between 2000 and 2017. For house prices, data availability is restricted, and I calculate all changes, including changes in turbine heights and wind

Table 1: Balance checks

	Δ Turbines	Population	Skilled	Income	Δ Share High-Skilled	
	2000-17	1992	1992	1992	1975-92	2000-17
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Wind power density	1.102***	2.152	-0.002	0.212	0.002	-0.009**
	(0.210)	(5.468)	(0.003)	(1.189)	(0.004)	(0.004)
Observations	8,578	8,578	8,578	8,578	7,892	7,892

Each column reports a separate regression based on equation 5. Due to data availability, all outcomes and the instrument are aggregated at the municipality level. Changes in wind power density are calculated between 2000 and 2017. Outcomes in 1992 measure population density, the share of high-skilled residents, and income per capita. Trends measure the change in the share of high-skilled residents between 1975 and 1992, and between 2000 and 2017, respectively. The last two columns do not control for land use, which is measured in 1990, and restrict the sample to West Germany. Standard errors clustered at the district level are reported in parentheses.

power density, between 2007 and 2017 accordingly. In all specifications, I cluster standard errors at the district level.

3.2 Main results

Instrument validity. Unbiased estimation requires that, conditional on controls, changes in wind power density are not related to unobserved trends in the outcome variable, so that $E[\Delta w_n \varepsilon_n | X_n, \delta_{d(n)}] = 0$. I offer five arguments in support of the assumption. First, a priori, it is not evident that vertical wind shear should be related to changes in house prices or sorting, other than through its effect on wind turbine development. I consider a series of plausible alternative explanations in section 3.3 and find that none of them can explain the observed effects. Second, I residualize the instrument on the controls and plot the remaining, identifying variation (figure 2e). There is no visual indication that the instrument should correlate with unobserved economic determinants of changes in house prices or sorting.

Third, in the first four columns of table 1 I show that the instrument is not correlated with pre-treatment characteristics. Historic data is only available at the municipality level. I report correlations for 1992, which is the first year after the Electricity Feed-in Act enabled systematic wind energy development, as well as the first year for which data on the unified Germany is available. While changes in wind power density predict contemporaneous turbine development, they are not related to pre-treatment population density, the share of high-skilled residents, or income.

Fourth, in the last two columns of table 1 I show that the instrument is not correlated with pre-trends in the outcomes. Since geographically disaggregated information on house prices is not available, I focus on pre-trends in residential sorting. I consider changes between 1975, which is the first year for which data is available, and 1992. Reassuringly, I find that contemporaneous changes in wind power density affect only contemporaneous but not past residential sorting.

Fifth, in the spirit of Altonji et al. (2005), I test if changes in wind power density affect outcomes in neighborhoods where turbine development is prohibited. To the extent that I can correctly identify such neighborhoods, they serve as a placebo group since any correlation with the outcome could not arise through the proposed wind turbine mechanism. Given historic land use data, I calculate the share of land within 3 km of the neighborhood that can in principle be used for development. I exclude urban areas and a 400 m buffer around them (FA Wind 2022), industrial sites, other urban infrastructure, water bodies, and conservation zones where development is forbidden (UBA 2013), see appendix A for details. Then, I estimate

$$\Delta y_n = \alpha \Delta w_n + \beta \Delta w_n s_n + \gamma X_n + \delta_{d(n)} + \varepsilon_n \tag{7}$$

where Δw_n is the change in wind power density and s_n is the share of land available for wind energy development. The top panel of table 2 compares the first-stage and intention-to-treat specifications estimated in equations 5 and 7. Reassuringly, the interaction terms show that changes in wind power density affect turbine development, house prices and sorting exclusively in neighborhoods where land for development is available, while the effects in placebo neighborhoods are economically small and statistically insignificant. Taken together, the five arguments provide evidence that wind power density affects house prices and sorting only through the proposed channel of turbine development.

Finally, I show that the instrument strongly predicts turbine development at the neighborhood level (figure 2f). Moving a neighborhood from the 25th to the 75th percentile in the instrument distribution increases the change in wind power density from 120 to 199 $\mathrm{W/m^2}$ and raises expected construction by 1.56 turbines, see table 2. To formally test instrument relevance, I calculate and report the Effective F-statistic

Table 2: Wind turbines, house prices, and residential sorting

	Δ Wind turbines		Δ Log house prices		Δ Share high-skilled	
	(1)	(2)	(3)	(4)	(5)	(6)
	First-stage		Intention-to-treat			
Δ Wind power density	1.969***	0.105	-0.029*	-0.006	-0.012***	-0.002
	(0.279)	(0.236)	(0.017)	(0.018)	(0.003)	(0.002)
Δ Wind power density		2.462***		-0.030***		-0.013***
x Share land available		(0.187)		(0.008)		(0.001)
			Instrumental variable			
Δ Wind turbines			-0.021*	-0.019***	-0.006***	-0.005***
			(0.013)	(0.005)	(0.002)	(0.001)
Instrument(s)			Wind	Wind + interaction	Wind	Wind + interaction
Effective F-statistic			33	70	50	129
Observations	133,332	133,332	79,815	79,815	128,448	128,448

Each column within a panel reports a separate regression. The top panel estimates the first-stage and intention-to-treat specification in equation 5, the bottom panel estimates the IV specification in 6. All changes are measured between 2000 and 2017, except in the third and fourth columns, which measure changes between 2007 and 2017 due to data availability. Odd columns report the base specification, even columns add the interaction between changes in wind power density and the share of land available for wind energy as an independent or instrumental variable. Standard errors clustered at the district level are reported in parentheses.

(Montiel and Pflueger 2013), which remains valid under clustered standard errors. Across samples, the statistic varies between 33 and 50, indicating that the instrument is sufficiently strong.

Effect on house prices. The bottom panel of table 2 reports the IV estimates from equation 6. My preferred specification in column 3 suggests that each additional wind turbine reduces house prices by 0.021 log points or about 2.1 percent. For the median treated neighborhood, which receives three wind turbines between 2007 and 2017, the coefficient implies a total house price decline of 6.1 percent.[5]

A growing literature on the house price effects of turbine development allows me to benchmark the IV strategy against previous difference-in-differences methodologies (Gibbons 2015, Dröes and Koster 2016, Dröes and Koster 2021, Andersen and Hener 2025, Heuer and Sommer 2025). Figure B.2a in the appendix compares magnitudes across studies, adjusting for the height of turbines in the sample. I find the IV estimates in this paper to be 0.7 percentage points or 13 percent larger than expected given the literature. Previous studies identify house price impacts by comparing houses near and far from turbines or with more and less visible turbines. Both

[5] I translate effects in log points to percentage changes using $\%\Delta = 100(e^{\beta T_n} - 1)$.

designs may slightly attenuate estimates if the control group is also affected, and it is thus reasonable that the effects in this study are slightly larger.

Effect on residential sorting. High- and low-skilled residents may respond differently to wind turbines, for example because they have heterogeneous preferences or react differently to changes in house prices (Diamond and Gaubert 2022). I find that wind turbine development induces substantial residential sorting. As shown in table 2, each additional wind turbine reduces the share of high-skilled residents by 0.6 percentage points. An increase of four turbines, the median development between 2000 and 2017, corresponds to a 2.4 percentage point decrease.

Table B.4 in the appendix reports population responses by worker type. High-skilled population declines by 1.5 percent per turbine, while low-skilled population rises by 1.8 percent. The difference is not statistically significant, and the results imply that low-skilled residents replace high-skilled residents nearly one-for-one.

The magnitudes are similar to sorting behavior observed in other contexts. For comparison, Heblich et al. (2021) find that a one standard deviation increase in air pollution during the British Industrial Revolution increased the share of low-skilled workers by 3.4 percentage points. Similarly, Redding and Sturm (2024) report that housing blocks in London that were destroyed during World War II experienced house price declines between 11 and 18 percent and a 4 percentage point reduction in the share of high-income residents. Perhaps most closely, Bagagli (2025) shows that the development of expressways in the US decreased house prices by an average of 9.69 percent and the share of high-skilled residents by 3 percentage points.

Together, the reduction in house prices and the share of high-skilled residents suggest that wind turbine development makes neighborhoods less attractive. The welfare consequences for residents, however, remain ambiguous. First, preferences against renewable energy infrastructure cannot be inferred from observed changes in house price and sorting alone. For example, the increase in low-skilled residents could reflect a lower disamenity from turbines or a higher migration elasticity with respect to housing costs. Second, migration responses may themselves affect house prices and wages, which in turn shape welfare. Section 4 quantifies these forces and subsumes the discussion of the welfare consequences of wind energy development.

Compensation. While wind turbine development reduces house prices and the share of high-skilled residents, it is possible that residents also benefit from turbine development. In appendix B, I use a combination of systematic and anecdotal evidence to rule out the relevance of four channels: labor demand, electricity prices, compensation for farmers, and compensation for local municipalities.

I find no evidence that turbine development increases local labor demand. Firms that design, assemble, and maintain turbines concentrate in cities outside of the immediate turbine neighborhood, and employment during construction is limited (Fabra et al. 2024). Firms do not buy electricity directly from local providers, and are unlikely to benefit from local energy infrastructure (WindEurope 2018). Residential consumers do not benefit since wholesale electricity prices are determined at the national level and regional surcharges are if anything higher in regions with wind development (Agora 2016). Farmers benefit from renting out their land for turbine development (Haan and Simmler 2018) but I find no evidence that income spills over to residents, see table B.4. Finally, over the sample period there were no federal compensation schemes for residents. Turbines generate potential business tax income approximately between $3,250 and $9,700 per turbine per year, a share of which is received by the local municipality (Meier et al. 2025). These payments are modest and considerably lower than the compensatory transfers that I estimate in the next sections. Overall, compensation for residents remains limited over the study period.

3.3 Robustness

I consider several alternative explanations. A first concern is that vertical wind shear may be shaped by geographic characteristics that also correlate with changes in economic outcomes. The baseline specification already accounts for geographic neighborhood characteristics, including altitude, ruggedness, slope, and land use. Table B.5 tests the robustness to geographic remoteness, which I measure using the distance to the next river (a proxy for being located in a valley), the orientation of the slope of the neighborhood (north-, east-, south-, or west-facing), and the distance to the next city. I find that the coefficients remain stable and conclude that remoteness does not explain the results.

Second, technology-induced changes in wind power density are particularly strong in coastal regions, see figure 2d, which may follow different economic trends. Controlling for district fixed effects in the baseline specification ensures that all effects are identified from within-district variation. In addition, I show that controlling directly for the distance to the coast in table B.5 leaves the results unchanged.

Third, Heblich et al. (2021) document that historic pollution can have persistent effects on house prices and sorting. A potential concern is that neighborhoods with higher vertical wind shear may have been more attractive locations for polluting industries, for example because they rely on tall chimneys to disperse emissions. To address this, table B.5 also controls for the industrial composition at baseline. The results remain robust, indicating that differences in polluting economic activity are unlikely to drive results.

Fourth, the instrument could influence not only the number of turbines built but also their size. If treated neighborhoods receive both more and taller turbines than control neighborhoods, the estimated effect would conflate differences in turbine numbers with differences in turbine heights. Because taller turbines tend to have stronger impacts on nearby neighborhoods (Dröes and Koster 2021, Andersen and Hener 2025, Heuer and Sommer 2025), this would bias the estimates upward. In table B.6, however, I show that while changes in wind power density predict the number of turbines, they do not predict their size. This is consistent with the evidence in figure 2a, which shows that the technological shift toward taller turbines was essentially uniform.

Fifth, I consider violations of the stable unit treatment value assumption. Equation 6 estimates the effect of turbine development using within-district variation. If residents primarily relocate to control neighborhoods in the same district, house prices and the share of high-skilled there may increase, biasing estimates upwards. To test for such concerns, I follow Borusyak et al. (2023) and control for distance- and population-weighted treatment intensity in the region. Intuitively, controlling for treatment intensity absorbs the indirect effect that may arise from migration spillovers from nearby treated locations. Formally, I predict $\Delta\hat{T}_k$ given changes in wind power density Δw_k for all neighborhoods k, and calculate the treatment intensity outside of neighborhood n as

$$\Delta\hat{T}^{dist}_{\neg n} \equiv \frac{\sum_{k\neq n} R_k dist^{\zeta}_{nk} \Delta\hat{T}_k}{\sum_{k\neq n} R_k dist^{\zeta}_{nk}} \tag{8}$$

where $dist_{nk}$ measures the distance from n to k, and I set the distance elasticity to $\zeta = -1.25$ following Borusyak et al. (2023). Column 7 of table B.5 re-estimates equation 6 controlling for treatment intensity. I find that the estimates are slightly smaller, though the difference is not statistically significant. To be conservative, I include the treatment intensity when estimating preferences against wind turbines in the next section.

3.4 Heterogeneity

Effects by distance. I revisit the assumptions taken in section 3.1. First, I estimate effects separately by distance band

$$\Delta y_n = \sum_{d=1}^{D} \beta^d \Delta T^d_n + \gamma X_n + \delta_{d(n)} + \varepsilon_n \tag{9}$$

where ΔT^d_n is wind turbine development in distance band d. I consider the distance bands 0-3, 3-6, 6-9, 9-12, and 12-15 km.[6] Beyond 15 km turbines can still be perceived but their visual impact is considered negligible (Gibbons 2015). Since the correlation of wind power density changes in adjacent distance bands is high, the main instrument alone is not sufficient to separately estimate the effect of turbines in each band. I add the interaction with the share of area available in distance band d, which breaks the spatial correlation. Formally, I instrument $\{\Delta T^d_n\}_d$ in 9 with $\{\Delta w^d_n, \Delta w^d_n s^d_n\}_d$. As figure B.3 in the appendix shows, the interacted instrument predicts turbine development in the respective distance band but not in other distance bands. Figure B.4 reports the IV estimates. Wind turbine development decreases house prices and the share of high-skilled residents primarily for neighborhoods within 3 km. Beyond the threshold, the estimates become small and mostly insignificant.

[6] I also consider distance bands of one kilometer width, but find that the spatial correlation in the instrument across distance bands is too high to separately estimate the effect for narrow bands.

Effects by number of turbines. Second, I relax the assumption that $f(\mathcal{T}_n)$ is linear. A priori it is likely that the marginal impact decreases with the total number of turbines, for example because the first turbines have a higher visual impact on the landscape. Indeed, previous house price studies find that the first wind turbine decreases house prices most strongly (Gibbons 2015, Dröes and Koster 2016, Guo et al. 2024, Heuer and Sommer 2025). I estimate the marginal impact of new wind turbines separately by the number of turbines at baseline

$$\Delta y_n = \sum_{b=1}^{B} \beta^b \Delta T_n \delta_n^b + \gamma X_n + \delta_{d(n)} + \varepsilon_n \tag{10}$$

where δ_n^b is an indicator equal to one if neighborhood n is in group b. Groups partition neighborhoods based on the number of turbines at baseline. I define groups as neighborhoods with 0, 1, 2-5, 6-10, or more than 10 wind turbines at baseline. To predict turbine development in each group, I interact the instrument with the group indicator. Formally, I instrument $\{\Delta T_n \delta_n^b\}_b$ in 10 with $\{\Delta w_n \delta_n^b\}_b$. Figure B.5 reports the results. Marginal effects are largest for the first turbine and decrease as area become more saturated with turbines. For house prices, the first turbine yields a decrease of 4.4 percent, which declines to 0.6 percent after ten turbines. For the share of high-skilled residents, the first turbine yields a decrease of 0.8 percentage points, which declines to 0.2 percentage points. The results indicate that preferences are likely nonlinear in the number of turbines, an observation that I will take into account when estimating the cumulative impact $f(\mathcal{T}_n)$ on amenities in the next section.

4 Using theory to infer the implied welfare costs

Objective. The quasi-experimental evidence suggests that neighborhoods become less livable but remains silent on the welfare consequences. In this section, I combine a revealed preference approach with the IV strategy to estimate preferences against wind turbine development and quantify the welfare costs in general equilibrium.

4.1 Model

In the model, L workers live and work in N neighborhoods. Each worker ω is high- or low-skilled, denoted by superscript $\theta \in \{h, l\}$.

Residence and workplace choice. Extending Ahlfeldt et al. (2015) to include high- and low-skilled workers, individuals choose a residential neighborhood n and a workplace i based on residential amenities A_n^θ, workplace amenities E_i^θ, workplace wages w_i^θ, the cost of commuting d_{ni}^θ, local house prices Q_n, the share of income spent on housing α^θ, and a taste shock $\varepsilon_{ni}^\theta(\omega)$, which yields the indirect utility

$$u_{ni}^\theta(\omega) = \frac{A_n^\theta E_i^\theta w_i^\theta}{d_{ni}^\theta Q_n^{\alpha^\theta}} \varepsilon_{ni}^\theta(\omega). \tag{11}$$

Amenities depend on turbines at distance d from the neighborhood $f^\theta(T_n^1, \ldots, T_n^d)$ and an exogenous component a_n^θ that captures general preferences for neighborhoods. I allow the marginal cost of turbines to decline over distance and with each additional turbine. Both gradients are allowed to be type-specific.

$$ln(A_n^\theta) = f^\theta(T_n^1, \ldots, T_n^d) + a_n^\theta \tag{12}$$

Individuals hold idiosyncratic preferences over neighborhoods and workplaces. Taste shocks are Fréchet-distributed with shape parameter κ^θ, which controls the dispersion of taste shocks and thus the labor supply elasticity across space. Using the properties of the Frechet distribution, the share of individuals that live in n and work in i is

$$\lambda_{ni}^\theta = \frac{\left(\frac{A_n^\theta \tilde{w}_i^\theta}{d_{ni}^\theta Q_n^{\alpha^\theta}}\right)^{\kappa^\theta}}{\sum_{r=1}^N \sum_{s=1}^N \left(\frac{A_r^\theta \tilde{w}_s^\theta}{d_{rs}^\theta Q_r^{\alpha^\theta}}\right)^{\kappa^\theta}} \equiv \frac{\phi_{ni}^\theta}{\phi^\theta} \tag{13}$$

where I denote workplace-amenity-adjusted wages $\tilde{w}_i^\theta \equiv E_i^\theta w_i^\theta$. Multiplying commuting shares by the total number of workers in the economy and aggregating over

workplaces and residences yields the number of residents and workers, respectively.

$$R_n^\theta = L^\theta \sum_{i \in N} \lambda_{ni}^\theta, \qquad L_i^\theta = L^\theta \sum_{n \in N} \lambda_{ni}^\theta \tag{14}$$

Labor market. Labor supply is given by L_i^θ in 14. I model inverse labor demand as a log-linear function of high- and low-skilled workers (Diamond 2016).

$$ln(w_i^h) = \gamma^{hh} ln(L_i^h) + \gamma^{lh} ln(L_i^l) + z_i^h \tag{15}$$

$$ln(w_i^l) = \gamma^{hl} ln(L_i^h) + \gamma^{ll} ln(L_i^l) + z_i^l \tag{16}$$

The labor demand parameters γ^{hh}, γ^{hl}, γ^{lh}, and γ^{ll} capture labor substitution and productivity spillovers without imposing additional functional form assumptions on the structure of production and the embedded agglomeration externalities. Employment across workplaces aggregates to the total number of workers.

$$L^\theta = \sum_{n \in N} R_n^\theta = \sum_{n \in N} L_n^\theta \tag{17}$$

Housing market. Housing demand depends on average income in the neighborhood, which is calculated over wages in the surrounding neighborhoods i weighted by the probability that a resident of n commutes to i.

$$\bar{v}_n^\theta = \sum_{i \in N} \lambda_{ni|n}^\theta w_i^\theta = \sum_{i \in N} \frac{\left(\tilde{w}_i^\theta / d_{ni}^\theta\right)^{\kappa^\theta}}{\sum_{s \in N} \left(\tilde{w}_s^\theta / d_{ns}^\theta\right)^{\kappa^\theta}} w_i^\theta \tag{18}$$

The demand for housing units equals total income spent on housing divided by the price. Housing supply depends on the fundamental housing stock H_n and the location-specific elasticity η_n. The market clearing yields

$$\bar{H}_n Q_n^{\eta_n} = \left(R_n^h \bar{v}_n^h \alpha^h + R_n^l \bar{v}_n^l \alpha^l\right) / Q_n. \tag{19}$$

Welfare. The expected utility of a resident is

$$\bar{U}^\theta = E\left[u_{ni}^\theta(\omega)\right] = \Gamma\left(\frac{\kappa^\theta - 1}{\kappa^\theta}\right)\left[\sum_{n\in N}\sum_{i\in N}\left(A_n^\theta \tilde{w}_i^\theta\right)^{\kappa^\theta}\left(d_{ni}^\theta Q_n^{\alpha^\theta}\right)^{-\kappa^\theta}\right]^{\frac{1}{\kappa^\theta}} \tag{20}$$

where Γ is the Gamma function and I assume $\kappa^\theta > 1$. Because residents are free to move expected utility equalizes across locations.

Equilibrium. An equilibrium is a vector $\left\{R_n^\theta, L_n^\theta, w_n^\theta, \bar{v}_n^\theta, Q_n\right\}$ and scalars $\bar{U}^\theta$ such that the number of residents R_n^θ and workers L_n^θ are determined by the location choice in equations 13 and 14, wages w_n^θ are determined by firms' labor demand given in 15 and 16, average income $\bar{v}_n^\theta$ is calculated as in 18, the housing market clearing 19 pins down the rental price Q_n, and the labor market clearing 17 pins down $\bar{U}^\theta$.

4.2 Estimation

4.2.1 Preferences against wind energy development

Equation 12 determines the impact of wind turbines on amenities, and thus characterizes how much residents are willing to pay to avoid turbines near their neighborhood. Estimation requires an instrument that shifts turbine development but is not correlated with other determinants of amenities. I follow the strategy established in section 3 and instrument development with technology-induced changes in wind power density. Rewriting amenity supply in changes yields

$$\Delta ln(A_n^\theta) = \Delta f^\theta(T_n^1, \ldots, T_n^d) + \Delta a_n^\theta. \tag{21}$$

Estimation requires information on amenity changes, which are not observed in the data. I leverage the structure of the model and solve for the revealed preference

change in amenities that rationalizes changes in location choices in the data. Solving equation 13 for amenities and writing it in changes yields

$$\Delta ln\left(A_n^\theta\right) = \frac{1}{\kappa^\theta}\Delta ln\left(R_n^\theta\right) + \alpha^\theta \Delta ln\left(Q_n\right) - \Delta ln\left(\left(\sum_{i=1}^{N}\left(\tilde{w}_i^\theta / d_{ni}^\theta\right)^{\kappa^\theta}\right)^{1/\kappa^\theta}\right) + \frac{1}{\kappa^\theta}\Delta ln(\phi^\theta / L^\theta). \quad (22)$$

All else equal, amenities decrease if a neighborhood loses residents. The decline is larger if many people leave (mediated by the cost of moving), if house prices decrease (mediated by the share of consumption spent on housing), and if wages in nearby workplaces increase (mediated by the cost of commuting).

I quantify 22 using a set of baseline parameters. Appendix C shows that amenity changes and the subsequent estimation of preferences and welfare costs are robust to alternative choices. Population and house prices are observed in the data. Following recent evidence for Germany, I set κ^θ to be 4.56 (Krebs and Pflüger 2023).[7] From the German Microcensus I compute the share of income spent on housing α^θ to be 0.25 and 0.29 for high- and low-skilled residents, respectively. For commuting, I use a routing algorithm to calculate travel times and estimate the commuting elasticities from the model-implied commuting gravity equation, see appendix C for details. I find that each additional minute decreases commuting by 3.8 percent for high-skilled and by 6.2 percent for low-skilled workers.[8] Since the high spatial resolution implies a prohibitively large choice set of about 10 billion commutes, I divide Germany into 257 labor market regions (BBSR 2025) and assume that residents can only commute to workplaces in the labor market of their residence. With the restriction bilateral location choices reduce to a block-diagonal matrix, and I use the commuter market clearing to solve for adjusted wages, see appendix C for details. Given the parameters, I compute the amenity changes between 2007 and 2017 per equation 22.

[7] Choosing a uniform labor supply elasticity has the obvious disadvantage that it may misattribute skill differences in mobility as amenity differences. I take 4.56 as a baseline value and conduct a series of robustness checks to confirm that amenity and welfare are not meaningfully affected by other sensible parameter choices.

[8] The commuting semi-elasticities are consistent with evidence in Tsivanidis (2023) who also finds high-skilled workers to respond less to travel time than low-skilled workers. In terms of magnitude, estimates are comparable but slightly smaller than in the closest context, Berlin in 2008 (semi-elasticity of -0.07, Ahlfeldt et al. 2015), possibly because commuting has become easier over time or is more draining in cities.

Table 3: Wind turbines and amenities

	High-skilled		Low-skilled	
	(1)	(2)	(3)	(4)
Δ Wind turbines	-0.013**	-0.012***	-0.005	-0.006***
	(0.005)	(0.002)	(0.005)	(0.002)
Instrument(s)	Wind	Wind + interaction	Wind	Wind + interaction
Effective F-statistic	39	94	39	94
Observations	111,148	111,148	111,148	111,148

Each column reports a separate regression based on equation 23. The dependent variables are changes in log amenities by skill. I instrument turbine development with changes in wind power density and, in even columns, its interaction with available land. All changes are measured between 2007 and 2017. Controls include altitude, ruggedness, slope, land use, and district fixed effects. Standard errors clustered at the district level are reported in parentheses.

Main effects. I proceed as in section 3 and first assume that turbines matter only within 3 km and that the effect is linear in the number of turbines. I estimate

$$\Delta ln\left(A_n^\theta\right) = \beta^\theta \Delta T_n + \gamma X_n + \delta_{d(n)} + \varepsilon_n \tag{23}$$

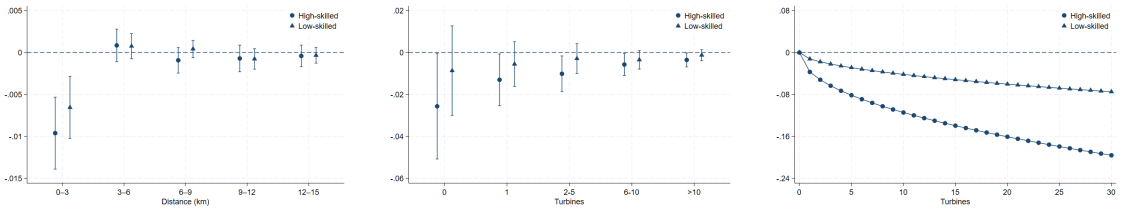
where I instrument turbine development with changes in wind power density. Since house prices are only available between 2007 and 2017, I calculate changes in amenities, wind power density, and turbines over the restricted time horizon. In addition to $\{\Delta w_n\}$, I also show the estimates using $\{\Delta w_n, \Delta w_n s_n\}$ as instruments. Table 3 reports the results. My preferred specification implies that each additional wind turbine reduces high- and low-skilled amenities by 1.3 and 0.5 percent, respectively. The effect for low-skilled residents is imprecise, but becomes significant when using both wind power density and its interaction with the share of land available for turbines as instruments. I find that the effects are robust to the controlling for the additional variables discussed in section 3.3, see table C.8, and to calculating amenity changes under a wide range of parameter choices, see table C.9.

Effects by distance. I estimate

$$\Delta ln\left(A_n^\theta\right) = \sum_{d=1}^{D} \beta^{\theta,d} \Delta T_n^d + \gamma X_n + \delta_{d(n)} + \varepsilon_n \tag{24}$$

Figure 3: Wind turbines and amenities

(a) By distance (b) By turbines (c) Cumulative



The left and middle figures report amenity effects by distance and number of turbines at baseline. Each figure reports two separate regressions. The dependent variables are changes in log amenities by skill. The left figure estimates equation 24. Wind turbines are measured within 0-3, 3-6, 6-9, 9-12, and 12-15 km and instrumented with changes in wind power density and its interaction with the share of land available by distance band. The middle figure estimates equation 25. Wind turbines are measured separately for neighborhoods with 0, 1, 2-5, 6-10, or more than 10 wind turbines at baseline and instrumented with changes in wind power density and its interaction with an indicator for each group. Standard errors are clustered at the district level and bars indicate 95 percent confidence intervals. The right figure simulates the implied cumulative impact of turbines on amenities. I assume that cumulative impact follows a power law and estimate the scale and curvature of the function using nonlinear least squares and moment conditions that I derive from the estimates in the middle figure and report in table C.10 in the appendix.

where I use 3 km distance bands and instrument $\{\Delta T_n^d\}_d$ with $\{\Delta w_n^d, \Delta w_n^d s_n^d\}_d$. Figure 3a shows the results. Amenities decrease significantly when wind turbines are developed within 3 km. For larger distances, I find a precise zero effect. I conclude that amenities are exclusively affected by turbines in the first distance band.

Effects by number of turbines. I estimate

$$\Delta ln\left(A_n^\theta\right) = \sum_{b=1}^{B} \beta^{\theta,b} \Delta T_n \delta_n^b + \gamma X_n + \delta_{d(n)} + \varepsilon_n \tag{25}$$

where I choose groups as in equation 10 and instrument $\{\Delta T_n \delta_n^b\}_b$ with $\{\Delta w_n \delta_n^b\}_b$. Figure 3b shows the results. In neighborhoods that have no wind turbines at baseline the impact of an additional turbine is large, decreasing amenities by 2.7 percent for high-skilled and 0.8 percent for low-skilled. As the number of turbines at baseline increases, the effect gradually decreases. For neighborhoods that already have ten or more turbines the marginal decrease reduces to 0.4 and 0.1 percent, respectively.

Cumulative impact. I assume that the cumulative impact takes the form

$$f^{\theta}(T_n) = \sigma_1^{\theta} \left(T_n\right)^{\sigma_2^{\theta}}. \tag{26}$$

The functional form ensures that the amenity impact is zero at the origin and, for $\sigma_2^{\theta} < 1$, decreases smoothly in the number of turbines, including when evaluating out-of-sample counterfactuals. In appendix B, I document that the functional form closely matches the non-parametric estimates in the literature (Gibbons 2015, Guo et al. 2024, Heuer and Sommer 2025). To parametrize 26 I derive moment conditions

$$\beta^{\theta,b} = \frac{f^{\theta}(\tilde{T}_n^{b,17}) - f^{\theta}(\tilde{T}_n^{b,07})}{\tilde{T}_n^{b,17} - \tilde{T}_n^{b,07}} \tag{27}$$

where I use $\beta^{\theta,b}$ estimated in 25. $\tilde{T}_n^{b,t}$ denotes the median number of wind turbines in group b in year t. Appendix C reports all group-specific estimates and medians. Estimation via nonlinear least squares yields $(\sigma_1^{\theta}, \sigma_2^{\theta})$ of about (-0.04, 0.49) for high-skilled and (-0.01, 0.54) for low-skilled residents. Figure 3c plots the implied cumulative amenity impact. For both skill types, the first turbine has by far the largest impact, reducing amenities by 3.9 and 1.1 percent, respectively. Moving from one to two turbines decreases amenities by 1.5 and 0.5 percent, and after ten turbines the marginal drop declines to 0.6 and 0.2 percent, respectively. Given the function, I invert the amenity supply in equation 12 and obtain fundamental amenities a_n^{θ}.

4.2.2 Labor and housing markets

Labor demand elasticities. Equations 15 and 16 determine wages of each type as a function of the number of high- and low-skilled workers in the workplace and the labor demand elasticities γ^{hh}, γ^{hl}, γ^{lh}, and γ^{ll}. Per skill, estimation requires an instrument that shifts skill-specific labor supply but is unrelated to changes in labor demand. I propose a shift-share design that leverages the historic prevalence of migrant ethnicities in Germany and skill- and ethnicity-specific national changes in immigration between 2000 and 2017. Appendix C details the estimation equation, measurement, and data sources. I show that the skill-specific shocks to immigration indeed predict changes in employment of the respective group. A one percent

increase in high-skilled labor increases high-skilled wages by 0.053 percent and decreases low-skilled wages by 0.010 percent, while a one percent increase in low-skilled labor decreases high-skilled and low-skilled wages by 0.007 and 0.061 percent, respectively. The results suggest labor demand is downward sloping for low-skilled and upward sloping for high-skilled workers, consistent with the observation that high-skilled workers generate productivity spillovers (Moretti 2004). The elasticities have the same sign as in Diamond (2016) but are somewhat smaller, possibly because stronger worker protection makes labor demand in Germany less wage-responsive than in the United States (Lichter et al. 2015). Given the labor demand elasticities, I invert equations 15 and 16 and obtain the productivity fundamentals z_n^h and z_n^l.

Housing supply elasticities. Equation 19 determines endogenous housing supply as a function of house prices and location-specific housing supply elasticities η_n. Following Saiz (2010), I model the elasticities as a function of geographic variation in land constraints. I consider the share of land in the district that is unavailable due to water bodies and steep terrain as well as the share of land that is already developed. Estimating the contribution of each variable requires an instrument that shifts housing demand, but that is unrelated to other changes in housing supply. Beze (2023) proposes a shift-share design that exploits the prevalence of industries in Germany and industry-specific national changes in employment. I use the estimates and data on land constraints at the district level to calculate the location-specific housing supply elasticity, see appendix C for details. I find an average housing supply elasticity of 0.26, with an interquartile range of 0.25 to 0.28. The estimates are somewhat smaller than in Saiz (2010) and Baum-Snow and Han (2024), consistent with cross-country evidence in Caldera and Johansson (2013) that housing supply is less price-responsive in Germany than in the United States. Given the housing supply elasticities, I invert the housing market clearing in equation 19 and obtain housing fundamentals $\bar{H}_n$.

5 Policy

5.1 Wind energy development until 2024

Using counterfactuals, I document four facts that characterize past wind energy development, before turning to discuss policy implications for the future.

Wind energy imposes large costs, but overall benefits prevail. I compare the model solutions assuming i) no turbines and ii) full turbine development in 2024.[9] I interpret differences in residential choices and welfare as the general equilibrium consequences of wind energy development, noting that the model-implied welfare costs measure exclusively the impact on residents and do not include any potential benefits of wind energy, which I calculate separately. Table 4 summarizes the results.

Wind energy entails substantial costs. While turbines generate about a quarter of electricity, they decrease quality of life for nearby residents, reducing average welfare by 0.60 percent. Given residents' income, the annual equivalent variation amounts to \$8.89 billion. This corresponds to \$0.08/kWh, which is approximately one-fifth of the average electricity price for residential consumers in Germany (Eurostat 2025).

To understand which assumptions drive magnitudes, I invert and solve the model under alternative parameter choices. The results remain stable across different choices of the share of income spent on housing as well as the labor supply, labor demand, and commuting elasticities. Varying each parameter by 20 percent changes welfare by at most 0.5 percent, as I report in table D.13 in the appendix. Welfare costs are more sensitive to the characterization of the amenity impact function. Relative changes in the scale impact welfare about one-for-one. Quantitative policy implications, such as the calculation of transfers, therefore rely most on careful estimation of the amenity impact. The previous sections show that the instrument is plausibly exogenous, rule out alternative explanations, and report robustness under a variety of assumptions.

[9] National statistics indicate that Germany operates 28,766 wind turbines in 2024 (BWE 2025). The data, on the other hand, overcounts turbines since it does not systematically identify when turbines are decommissioned. I use the 28,766 most recently installed turbines, ensuring that the estimated welfare cost can be compared to national statistics on electricity production from wind energy.

Table 4: Welfare

	Model-implied welfare effects for residents		
	Total	High-skilled	Low-skilled
Relative (%)	-0.60	-1.11	-0.47
Equivalent variation ($1B)	-8.89	-4.83	-4.06
	Cost-benefit analysis		
	Residents	Electricity	Emissions
Total ($1B)	-8.89	1.18	27.54
Total/generation ($/kWh)	-0.08	0.01	0.25

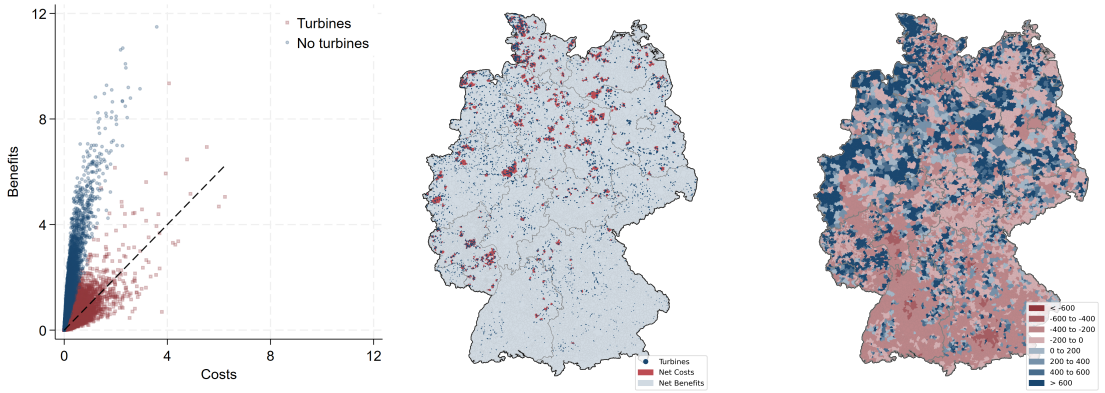
The top panel reports the change in model-implied welfare due to wind turbine development. I solve for the equilibrium with and without turbines and compare welfare calculated in equation 20. Total welfare weights skill-specific welfare changes by population. The equivalent variation multiplies relative welfare changes with average income in the data and is measured in year-2024 USD. The bottom panel compares the model-implied welfare effects to the benefits from electricity generation, which I quantify by comparing the levelized cost of electricity of wind energy and the traditional sources that it replaces, and the benefits from emissions abatement, which I calculate based on a wind energy production of 111.9 TWh, emissions reduction of 758 gCO_2/kWh and a social cost of carbon of \$325/tCO_2 (UBA 2024, 2025). Appendix D details the calculations.

Despite the costs of wind energy, I find that its aggregate welfare benefits prevail. First, as technology improves, wind energy becomes cheaper than traditional sources. Second, it reduces costly CO_2 emissions. To quantify the first, I compare the average lifetime cost of electricity generated by wind energy to the cost of non-renewable energy sources. To quantify the second, I rely on estimates by the German Environment Agency, which evaluates global climate damages using a social cost of carbon of \$325/tCO_2 (2024) and estimates that each kilowatt-hour of wind energy saves 758 gCO_2 in emissions (2025), see appendix D. As table 4 shows, the overall benefits of wind energy are about three times larger than its cost to residents. Since wind energy has been historically expensive, and its generation cost has only recently undercut non-renewable sources (see figure 1a), most of the benefits today accrue from abatement. Nevertheless, the choice of wind energy is optimal if the planner internalizes at least 28 percent of the global benefits of emissions reductions.

Local costs often exceed benefits, discouraging development. While aggregate benefits are larger than costs, incidence varies across neighborhoods. Wind energy is strongly concentrated, which I document in figure 5a. As a salient example, five percent of municipalities host three quarters of wind turbines. While the model only measures welfare of individuals, not of places, I approximate the local cost of wind energy by focusing on inframarginal residents. In the model, such residents have

Figure 4: Welfare across space and transfers

(a) Costs and benefits (1M$) (b) Net costs (1M$) (c) Transfers per resident ($)



The left and middle figures compare cost and benefits of wind energy across space. Local costs are calculated based on real-wage-adjusted amenity changes and neighborhood income, as detailed in appendix D. Local benefits scale down national benefits reported in table 4 based on population. The right figure shows net transfers computed in equation 28 divided by the number of residents. Maps aggregate outcomes at the municipality level to protect sensitive social security information.

a strong idiosyncratic preference for their neighborhood and their welfare change is equal to the real-wage-adjusted change in amenities that arises from turbine construction. Anecdotally, inframarginal residents have strong ties to their neighborhood, and they are therefore most likely to organize resistance against turbine development. I weight changes in real-wage-adjusted amenities by commuting shares at baseline and evaluate costs given average neighborhood income. For the comparison of costs and benefits, I assume that neighborhoods share aggregate benefits in proportion to their share in national population. Appendix D provides additional details.

I find that local costs exceed benefits for about a third of neighborhoods affected by turbines within 3 km, see figure 4a. If residents do not internalize the benefits from preventing global climate damages, costs outweigh benefits in all affected neighborhoods. Costs are especially prevalent in locations that concentrate many turbines in proximity to residents, which I document in figure 4b. The model-implied incentives are consistent with the anecdotal evidence of local opposition to renewable energy infrastructure and the slowdown in turbine development described in figure 1b.

Adequate compensation is possible, but likely politically infeasible. I derive proportional transfers τ_n^θ that compensate residents for amenity losses due to wind turbines. Since amenities and wages enter utility multiplicatively, increasing

wages by the inverse of the relative amenity loss restores utility. To finance transfers, I calculate a uniform proportional tax τ^θ that all residents pay. Summing compensation and tax payments of all residents yields the neighborhood's net transfer π_n. Appendix D derives the transfers formally.

$$\pi_n = \sum_{\theta \in \{h,l\}} R_n^\theta v_n^\theta (\tau_n^\theta - \tau^\theta) \tag{28}$$

$$\tau_n^\theta = 1/\exp\left(f^\theta(T_n)\right) \tag{29}$$

$$\tau^\theta = \sum_{n=1}^{N} R_n^\theta v_n^\theta \tau_n^\theta / \sum_{n=1}^{N} R_n^\theta v_n^\theta \tag{30}$$

I divide the net transfers in 28 by population and plot the result in figure 4c. Adequate compensation depends on the number of turbines as well as the residential composition and the average income in the neighborhood, and therefore varies considerably across space. It is especially high in the Northwest of Germany, where turbine development is historically concentrated, but would also benefit many locations in East Germany. The median municipality with turbines would receive \$89,829 per turbine. Such transfers are about an order of magnitude higher than existing compensation schemes. Business taxes, the main form of compensation paid over the sample period, yield between \$3,250 and \$9,700 per turbine, but only part of the income remains in the host municipality (Meier et al. 2025). In addition, the Renewable Energy Sources Act (2023) recommends developers to pay a voluntary compensation of \$0.002/kWh. The compensation is mandatory in some states. For the average wind turbine active in 2024 it would amount to an additional \$7,780 per turbine. Financing compensation for all turbines in Germany would require \$0.069/kWh, which is substantially higher than the recommended compensation and likely politically infeasible.

Alternative turbine allocations reduce costs and yield transfers that are more likely to be politically feasible. Adequate transfers are costly because past wind turbines have been sited inefficiently close to residents. I explore alternative allocations of turbines that reduce costs. Solving for the optimal distribution is a

high-dimensional, computationally intractable problem.[10] Instead, I provide a lower bound for the welfare benefits by solving a simplified turbine allocation problem, for which I then calculate the implied general equilibrium welfare costs. To identify the low-cost allocation, I treat costs as linear in the number of turbines and residents and focus on the first-order impact, which allows me to rank marginal costs across all locations independently of the full turbine distribution.[11] Drawing on the estimates from table 3, I solve

$$\underset{\{T_n\}_n}{\text{maximize}} \quad \sum_{n=1}^{N} \left(-0.013 R_n^h - 0.005 R_n^l\right) T_n \tag{31}$$

assuming that developers face three constraints. First, the allocation must achieve the same electricity capacity, taking into account the spatial distribution of wind power density. Second, land availability constrains turbine locations, which I measure using detailed maps provided by the climate policy think tank Agora (2021). Third, turbine locations are limited by the power grid. To respect long-distance transmission constraints, I require that each state produces at most the capacity observed in the data or its share of national population times national capacity. To respect local transmission constraints, turbines must be within 7 km of a high-voltage power line, matching distances observed in the data. Appendix D provides additional details.

I find that the alternative allocation reduces welfare cost to -0.10 percent, which is one-sixth of the cost in the baseline distribution. Cost reductions are large because the alternative shifts development further away from residents. At the same time, it concentrates turbines in fewer locations. Relative to the baseline, the alternative

[10] Evaluating the welfare cost of all turbine allocations is prohibitively expensive since there are 28,766 turbines and 360,479 grid cells, some of which can host multiple turbines. Further, turbines can be both complements and substitutes, for example due to spatial linkages in electricity transmission constraints and in the economy and due to the nonlinear amenity cost, so that the dimensionality cannot be reduced as in Jia (2008) and Arkolakis et al. (2025). Finally, the high dimensionality prohibits iterating through possible solutions as in Kreindler et al. (2025).

[11] I argue that the resulting allocation of turbines is likely to be close to the optimum. First, I assume that amenity cost is linear in the number of turbines, which biases the allocation towards lower spatial concentration. However, as a consequence of ranking marginal costs, almost all neighborhoods receive the maximum number of turbines possible, conditional on receiving any turbine. Second, I assume that the planner ignores general equilibrium effects. However, welfare results are stable under a variety of parameter choices, see table D.13, which suggests that general equilibrium forces are relatively unimportant for total welfare, and thus for the optimal distribution of turbines.

increases the share of turbines hosted by the top five percent of municipalities from 58 to 68 percent. Meanwhile, the average number of residents exposed per turbine declines from 897 to 167, and the share of high-skilled residents affected by turbines falls from 11 to 9.8 percent.

In its turbine allocation decision, the planner faces an equity-efficiency trade-off. High-skilled residents have a stronger preference against local renewable energy infrastructure and policymakers may seek to reduce average costs by avoiding high-skilled neighborhoods. Indeed, the baseline distribution shows that low-skilled residents are more exposed to wind turbines, even before sorting.[12] Similarly, rural regions have lower population density, which makes them well suited for wind turbines but can also deepen existing inequalities across space. Policymakers may care about such inequalities, especially when existing compensation schemes are insufficient. In the context of Germany, this is evidenced by the Onshore Wind Energy Act (2022), which requires states to designate an almost uniform share of their land for wind energy until 2032, despite large differences in wind resources and population density. In appendix D, I argue that such equity considerations may have shaped the current distribution of turbines. Relative to the baseline, wind turbines in the alternative allocation are significantly more likely to be in more rural, less educated, and poorer regions, while there is no significant difference in average wind resources, distance to the transmission network, or possible environmental damage, see table D.14.

While the alternative allocates turbines more unequally, they affect fewer residents, which reduces the total transfers required to compensate residents. The average tax required to finance compensation decreases from \$0.069/kWh in the baseline scenario to \$0.010/kWh in the alternative allocation. Transfers are still somewhat higher than the compensation under the Renewable Energy Sources Act, but they are similar in magnitude and more likely to be politically feasible as a result.

[12] Differences in exposure may arise from initial siting or ex-post sorting, see Banzhaf et al. (2019) for an overview. I disentangle both by computing average exposure to wind turbines before and after sorting. I find that the average low-skilled resident is 1.68 times as exposed to wind turbines as the average high-skilled resident, and that 31 percent of the gap arises due to initial placements and 69 percent arises due to sorting.

5.2 Wind energy development until 2045

Despite its aggregate benefits, past wind energy development in Germany is characterized by high costs for residents. Local incentives to support turbines remain therefore weak and net construction has reached its lowest point in two decades (see figure 1b).

In light of this challenge, I quantify the welfare consequences of future wind energy development under realistic and desired scenarios. Motivated by the benefits of wind energy, the Renewable Energy Sources Act (2023) aims to increase its capacity from 63 GW in 2024 to 160 GW by 2045, though along that path construction has repeatedly fallen short of the legislation's annual targets (FA Wind 2025). To assess the scale of the required expansion, I translate capacity targets into turbine targets accounting for the expected growth in capacity per turbine over time.[13] I contrast targets with development under business-as-usual, assuming annual construction equal to the average observed over the past decade.

Table 5 reports the projected and desired evolution of turbines over time. While technological progress permits achieving capacity targets without increasing the number of turbines, the gradual phase-out of old turbines implies that Germany needs to construct 1,314 new turbines each year. By contrast, current development is much slower, adding turbines at only one-third of the required rate. As a result, development is set to miss the legislation's targets for every five-year milestone along the path, eventually falling short of the 2045 capacity target by 26 percent.

I compare the welfare consequences under projected and desired development. Within each path, I estimate welfare in two scenarios. In the first, the planner does not prioritize residential concerns any more than in the past, and I assume that the average welfare cost per turbine stays constant, as calculated for 2024 in table 4. I call this scenario business-as-usual. In the second scenario, the planner prioritizes residential concerns within the limits of the technical constraints imposed by the spa-

[13] I assume that the capacity of newly installed turbines increases linearly as it has in the past, which I document in appendix D. Technological progress affects the composition of turbines with delay, as new turbines gradually replace old ones. The construction speed of new turbines varies by scenario. For old turbines, I assume a lifespan of 25 years, which I set slightly higher than the average decommissioning age observed in the data to be conservative (22.6 years, FA Wind 2025).

Table 5: Wind energy targets and projections

	2024	2030	2035	2040	2045
	Capacity (in GW)				
Target	63	115	157	160	160
Projection	63	76	91	103	118
	Turbines (in 1000s)				
Target	29	31	35	33	30
Projection	29	23	23	21	21

Wind energy capacity targets are reported from the Renewable Energy Sources Act (2023). Turbine targets match capacity targets, assuming constant technological progress in the capacity per turbine, see figure D.7a. Turbine projections assume that new wind turbines are added at the speed observed in the last ten years and that old turbines are decommissioned after 25 years. Turbine projections and technological progress yield capacity projections.

tial distributions of wind resources, available land, and transmission infrastructure. I assume that the planner allocates turbines in each reference year specified in the legislation to minimize the impact on residents under simplified assumptions, analogous to equation 31. I call this scenario low-cost alternative and proceed as follows.

Algorithm: For each year $t \in \{2030, 2035, 2040, 2045\}$:

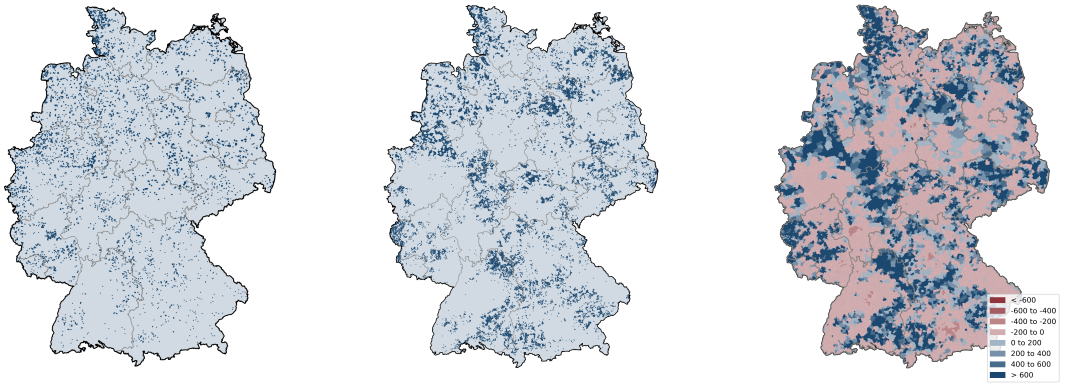
1. Identify the stock of old turbines that are still active in year t.
2. Update land use and transmission constraints given stock of turbines.
3. Calculate new turbines required to achieve projection or target.
4. Allocate new turbines based on the simplified welfare maximization problem.
5. Insert total turbines into model and calculate welfare costs.

Step 1 assumes that old turbines are retired after 25 years. Step 2 takes into account that land use and transmission constraints evolve with technology. As the capacity per turbine increases, turbines also become larger and thus require more space. On the transmission side, I assume that the network gradually expands as laid out in the power network development plan for the years 2037 and 2045 (BNetzA 2024), see appendix D for details. Step 3 assumes that the capacity per turbine evolves as projected in figure D.7a. Step 4 solves the maximization problem in equation 31. Finally, step 5 inserts the implied turbines distribution into the quantified model and solves for the welfare costs, thereby assuming that the estimated preferences reasonably approximate residents concerns in the future.

Figure 5 plots the distribution of wind turbines required to achieve the targets

Figure 5: Achieving targets in the alternative allocation scenario

(a) Turbines in 2024 (b) Turbines in 2045 (c) Transfers in 2045 ($)



The left figure shows wind turbines observed in the data in 2024. The middle figure shows turbines required to achieve targets under the alternative allocation in 2045. The scenario corresponds to the last column in table 6. The right figure shows net transfers for the scenario computed in equation 28 divided by the number of residents. Transfers compensate residents relative to no turbine development.

until 2045, as identified by the algorithm. Technological progress implies that targets are achieved with only a modest expansion in the number of turbines. At the same time, turbines become bigger over time, require larger spacing so that they do not cannibalize wind from each other, and thus take up more land, as shown in figure 5b. The presence of turbines in the southern low-wind regions increases as the electricity network expansion lags behind wind energy development and transmission constraints become more binding. Within regions, the scenario concentrates turbines further from residential population, similar to the alternative allocation for 2024. Future development under the scenario affects residents in multiple ways. On the one hand, the impact on residents increases as the turbine expansion gradually saturates low-cost locations and moves to areas with higher population density. On the other hand, the impact decreases relative to today since the alternative scenario takes residents' preferences into account when allocating turbines.

In table 6, I report the welfare consequences by scenario. Relative to 2024, the net welfare benefits per unit of electricity increase across all scenarios for 2045. On the benefit side, wind energy benefits from declining generation costs, which are projected to decrease by 43 percent (DNV 2024), and a rise in the social cost of carbon that the German Environment Agency uses to quantify climate change damages, which is estimated to increase by 36 percent (UBA 2025). On the cost side, the per-kwh

Table 6: Welfare in 2045

	2024	2045			
		Business-as-usual		Alternative	
	Data	Projection	Target	Projection	Target
	Welfare/generation ($/kWh)				
Residents	-0.079	-0.030	-0.033	-0.010	-0.015
Electricity	0.011	0.076	0.074	0.076	0.074
Emissions	0.246	0.332	0.332	0.332	0.332
Residents + Electricity	-0.069	0.045	0.042	0.065	0.059
Residents + Electricity + Emissions	0.177	0.378	0.374	0.400	0.391
	Welfare ($1B)				
Residents	-8.9	-6.4	-9.3	-2.2	-4.4
Residents + Electricity	-7.7	9.5	11.9	13.7	16.8
Residents + Electricity + Emissions	19.8	79.1	106.3	83.3	111.2

Each column reports a separate scenario. The top panel presents welfare effects per kilowatt-hour of electricity. Costs for residents vary by scenario. The first column reproduces the 2024 estimate from table 4. Business-as-usual multiplies turbines with the welfare cost per turbine in 2024. The alternative allocates turbines based on equation 31 and solves the model for welfare costs. Electricity benefits compare the generation cost of wind energy to that of non-renewable sources. Emissions benefits assume emissions reductions of 758 g CO_2/kWh and a social cost of carbon of \$443/tCO_2 in 2045 (UBA 2024, 2025). The bottom panel scales per kilowatt-hour estimates by generation, which I calculate based on each scenario's capacity in table 5 and a capacity factor of 1,776 hours, as observed in 2024.

impact on residents decreases as turines become more efficient. All in all, net benefits per unit of electricity more than double.

Two observations thus characterize the incentives for future wind energy. First, as shown in the top panel of table 6, wind energy becomes welfare-improving even if the social planner does not internalize the benefits of mitigating global climate change. Reductions in generation cost alone are sufficient to motivate the expansion as mandated by the Renewable Energy Sources Act. Second, as shown in the bottom panel, because wind energy creates net benefits for each unit of generated electricity, aggregate welfare benefits primarily scale with total capacity. Achieving targets is therefore essential to capture the largest part of the welfare benefits of wind energy. Going from projected to desired capacity under the business-as-usual scenario increases welfare benefits by \$27.2 billion or about 34 percent, while allocating wind turbines under the low-cost alternative yields an additional \$4.9 billion or about 6 percent in welfare benefits. Overcoming sluggish and costly development thus brings welfare benefits of \$32.1 billion per year, which is equivalent to about 0.7 percent of Germany's GDP in 2024.

Given equation 28, I calculate the transfers that are required to make desired development under the alternative scenario incentive-compatible. Figure 5c plots the transfers per capita. Transfers closely follow the distribution of turbines and benefit primarily rural regions, which often receive annual transfers of more than \$600 per resident. Financing the transfers requires an average tax of \$0.013/kWh, which is about five times lower than the benefits that arise from lower generation costs.

6 Conclusion

Wind energy is cheap and sustainable. Large benefits motivate ambitious targets, yet turbines impose local costs and development remains slow. I show that prioritizing residential concerns in siting decisions can substantially reduce costs and I design transfers that compensate communities for the remaining nuisance. Both policies incentivize development. Relative to business-as-usual, they may help Germany to save annual emissions of $0.06\,\mathrm{GtCO_2}$ and welfare of \$32.1 billion by 2045.

Against concerns raised globally, the case of Germany shows that the benefits of wind energy outweigh the nuisance costs for local residents. As renewable electricity becomes cheaper, these benefits grow and adoption becomes optimal even when the policymaker does not internalize global climate damages. While global coordination becomes less important, adoption of renewable energy faces its own obstacles, notably the concerns of local communities who bear a disproportionate share of the cost. As the energy transition unfolds, such distributional conflicts may only intensify. Future research will guide the design of policies that limit inequality, align incentives, and encourage adoption, including for solar, transmission, and battery storage infrastructure where similar tensions arise.

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Appendices

A Background and data

Table A.1: Global resistance against renewable energy infrastructure

Project	Country	Quote
Wind turbines	United States	America needs to undertake one of the biggest building booms in its history. Permitting energy infrastructure pits hyperlocal concerns against the public good. There is no perfect place to build a wind farm or transmission line. (Economist 2023)[a]
		"Projects have been getting more contentious," said Sarah Banas Mills [...] "The low hanging fruit places have been taken." (New York Times 2022)[b]
		One county scheduled 19 nights of meetings to debate one wind farm. [...] "I moved here for nature, for trees, for crops," said Sandy Coyle. "I'm not interested in living near an industrial wind farm." (New York Times 2022)[b]
	France	"[When] voters and politicians [are] openly anti-wind, it's very, very complicated" to obtain construction permits for wind farms from the authorities, said William Arkwright [...]. The pipeline of new projects is eroding "and commissioning is collapsing." (Review Energy 2025)[c]
	Germany	A group of about 6,660 people are behind a slew of over 440,000 letters objecting to plans for wind farm developments in 40 areas in the Neckar-Alb region of Baden-Württemberg [...] The regional association said it cost 104,000 euros to digitise the printed letters. [...] A revised version of the sub-regional wind power plan will be presented in the first half of the year, after which residents can submit comments once again. (Clean Energy Wire 2025)[d]
	Italy	"There's been a visceral rejection of renewables. The situation is really heated, the vandalism an attempt to intimidate policymakers," said Marta Battaglia, head of environmental group Legambiente in Sardinia. "People say renewables scare us... and they ruin the landscape, and therefore we will lose our identity," she said. (Sustainable Carbon 2024)[e]
	Spain	"Building plants massively here means we're taking the brunt of the production of energy that will actually supply Madrid and Barcelona," said Nestares [...] "That's unfair." (Bloomberg 2025)[f]
	United Kingdom	Several campaign groups have been set up to object to the plans, and a parliamentary petition calling on the government to ban wind farms on protected peat land such as the Haworth moors has drawn almost 15,000 signatures. [...] Stewart said the plans needed to be completely abandoned, not scaled down. He added: "Even one turbine would compromise the very idea of Brontë country. The plan needs to be completely abandoned and reconstructed elsewhere, in a more suitable and viable place." (Times 2025)[g]
Solar parks	United Kingdom	Berry and others have discovered three further large solar farms earmarked for the area. "Three months ago, we were living in a peaceful, unspoilt, rural community. Now it feels like we're under attack. Everything you thought was normal in life has been turned on its head," she says. (Guardian 2024)[h]

Continued on next page

Table A.1: Global resistance against renewable energy infrastructure (continued)

Project	Country	Quote
	United States	As solar developers propose new, often sprawling projects in places like Kansas, Maine, Texas, Virginia and elsewhere, local governments and activist groups are seeking to block them and often succeeding. They cite reasons ranging from aesthetics that would harm property values to fears about health and safety, and loss of arable land, farm culture, or wildlife habitat. (Reuters 2022)[i]
		"This is increasingly one of the top barriers that we're going to face," said Steve Kalland, executive director of the North Carolina Clean Energy Technology Center, a research center that supports clean energy development nationwide. "If we can't get projects sited and deployed, then we're going to have real problems on our hands." (Reuters 2022)[i]
Power lines	United States	Many of the best locations for wind and solar farms are, by their very nature, remote. And moving that energy elsewhere requires navigating a byzantine permitting process for transmission lines [...] "The scale of the undertaking and the speed at which it needs to occur are incredibly daunting." (New Yorker 2024)[j]
Batteries	United States	"This is a recipe for disaster," Correia said. "We will end up being the poster child for what not to do with battery storage facilities." (Coast News Group 2024)[k]
		Residents who've protested the planned facility said it's too close to their homes and businesses in the largely residential neighborhood, especially in light of the many fires caused by lithium-ion batteries. (Spectrum News 2025)[l]

[a] *Economist*, 29 Jan 2023: "America needs a new environmentalism"
[b] *New York Times*, 30 Dec 2022: "The US will need thousands of wind farms"
[c] *Review Energy*, 23 Jun 2025: "French National Assembly halts expansion of wind and solar energy"
[d] *Clean Energy Wire*, 31 Jan 2025: "Most of 440,000 objections to wind power in German state stem from core protest group"
[e] *Sustainable Carbon*, 23 Oct 2024: "Renewables revolt in Sardinia"
[f] *Bloomberg*, 7 Feb 2025: "Spain's Rural Areas Are Backing Wine Over Wind Farms"
[g] *Times*, 22 Jun 2025: "'Mass wuther' protest as giant wind farm threatens Brontë moors"
[h] *Guardian*, 28 Dec 2024: "Solar farms v people power: the locals fighting for their county"
[i] *Reuters*, 7 Apr 2022: "U.S. solar expansion stalled by rural land-use protests"
[j] *New Yorker*, 26 Jan 2024: "The Holdouts in the Quest for a Better Power Grid"
[k] *Coast News Group*, 8 May 2024: "Residents protest Seguro battery project at final workshop"
[l] *Spectrum News*, 19 Aug 2025: "Queens residents protest proposed battery storage facility over safety concerns"

Table A.2: Data sources

Source	Spatial resolution	Period	Description
Eichhorn et al. (2019)	Coordinates	1980-2015	Turbines, turbine diameter
The Wind Power (2025)	Coordinates	1980-2024	Turbines, turbine heights
BWE (2025)	National	2000-2024	Turbines, capacity
Global Wind Atlas (2023)	Raster	-	Wind power density
ImmobilienScout24 (2022a,b,c,d)	1-by-1 km	2007-2018	House prices
IAB (2023)	1-by-1 km	2000-2017	Population, employment, wages, income
Ganzer et al. (2018)	Municipalities	1975-2017	Population
BKG (2024b)	Raster	-	Altitude, ruggedness, slope, direction
BfN (2022)	Borders	-	Environmentally protected zones
EEA (2023)	Borders	-	Coast line
Copernicus (2024)	Borders	1990	Land use
BKG (2024a), BKG (2024c)	Borders	2017	Grid cells, municipality, district, and states
BBSR (2025)	Borders	2017	Labor markets
OSM (2018)	Municipality pairs	2017	Commuting times
Antoni et al. (2019)	District pairs	2017	Commuting flows
Antoni et al. (2019)	National	2000-2017	Origin-skill specific migration shocks
Destatis (2018)	National	2018	Share of income spent on housing
BRD (2023)	National	2030-2045	Wind energy capacity goals
Reiner Lemoine Institute (2022)	Borders	2022	Land available for wind energy
Infrageometics (2024)	Lines	2024	Transmission network
Pape and Geiger (2023)	States	2037, 2045	Transmission network extension
IRENA (2024, 2025), Lazard (2025)	Global	2000-2024	Levelized cost of electricity
DNV (2024)	Global	2024-2045	Levelized cost of electricity, wind
UBA (2024)	Global	2024-2045	Social cost of carbon

Variable definitions

Wind power density. Given the rasters from the Global Wind Atlas (2023), I calculate the average wind power density in the grid cell as well as within all surrounding distance bands. Since rasters are available at the heights 50, 100, 150, and 200 m, I calculate density at intermediate heights h by linear interpolation

$$w_{n,h} = \left(\left(\overline{h} - h\right) w_{n,\underline{h}} + \left(h - \underline{h}\right) w_{n,\overline{h}}\right) / \left(\overline{h} - \underline{h}\right) \tag{32}$$

where $\overline{h}$ and $\underline{h}$ are the closest upper and lower heights for which data is available.

Then, I calculate the technology-implied change in wind power density

$$\Delta w_n = w_{n,h(\overline{y})} - w_{n,h(\underline{y})} \tag{33}$$

where $h(\overline{y})$ and $h(\underline{y})$ are the average turbine height at the end and start of the sample period, respectively. I obtain heights from The Wind Power (2025) data, ensuring that heights are available over the entire sample period and stem from one consistent source.

Wind turbines. I measure the number of wind turbines located within the grid cell as well as within all surrounding distance bands. For each year, I compute the number of turbines constructed up to that year. Turbines built before and in 2015 stem from Eichhorn et al. (2019) while I obtain turbines built after from The Wind Power (2025). Together, both data sets align closely with national turbine construction statistics from BWE (2025), as I confirm in figure A.1.

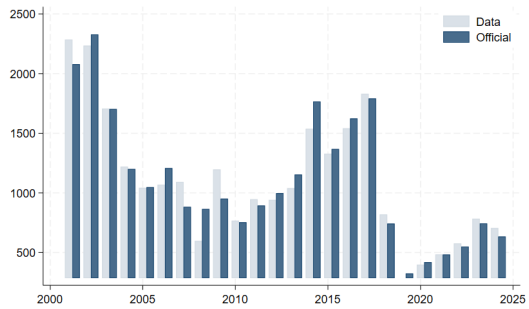
House prices. To calculate the house price index, I use data on houses and flats offered for rent or sale from ImmobilienScout24 (2022a,b,c,d). I translate sales prices into rental prices assuming a discount rate of 7.85 percent (Diamond 2016). Given the implied equivalent rental price per square meter $p_{o,t}$ of object o in year t, I estimate the hedonic regression

$$ln(p_{o,t}) = \gamma X_{o,t} + Q_{n,t} + \varepsilon_{o,t} \tag{34}$$

separately for 2007 and 2017. For each year, I also include objects listed in the preceding and following year to increase the sample size. For 2007, I only add data from the following year as previous data is not available. Object characteristics $X_{o,t}$ include an indicator of the object type (flat for rent, flat for sale, house for rent, house for sale), and deciles of total plot area, the number of rooms, and the construction year, all of which I include separately for objects for sale and for rent. The estimates of $Q_{n,t}$ thus yields a quality-adjusted house price index for each grid cell and year.

Neighborhood characteristics. I measure population, employment, income, and workplace wages using data from the GridAB (IAB 2023). The calculations in-

Figure A.1: Turbine construction by data source



Bars show annual turbine construction in the data in light blue and in national statistics in dark blue.

clude regular employees who are registered in the German social security system. I split variables by high- and low-skilled based on the attainment of a university degree. Population (employment) measures the number of individuals whose residential (workplace) address falls in the grid cell. In a minority of sectors, workplace locations are not accurately identified (eg. the store locations of a small bakery chain may be all grouped at one location) and the employment data therefore omits affected sectors. For the quantitative model, I rescale local employment, so that national employment matches population. Analogously, income (wages) measures average annual salaries of individuals whose residential (workplace) address lies in the grid cell. Consistent with the model, I calculate wages based on all full-time employees. Income, which I use to calculate the equivalent variation of welfare costs and transfers, is measured for all regular employees, including both full- and part-time workers.

Available share of land. I exclude only land where wind turbines are legally or technically prohibited, so that neighborhoods with zero available land around them can be interpreted as placebo locations. I exclude urban areas and 400 m minimum distance around them, industrial sites, road infrastructure, green urban areas, and sport and leisure facilities, and water bodies based on the corine land classification (Copernicus 2024) as well as nature reserves, national parks, the core areas of biosphere reserves, flora and fauna protection areas, and RAMSAR wetlands, where turbine construction is forbidden (UBA 2013).

Table A.3: Summary statistics

Variable	Spatial resolution	Observations	Mean	P25	P75
Quasi-experimental evidence					
Wind turbines, 2000	0-3 km	133,332	0.38	0	0
Wind turbines, Δ2000-17	0-3 km	133,332	1.38	0	0
Wind power density, 2000	0-3 km	133,332	297.8	204.8	346.4
Wind power density, Δ2000-17	0-3 km	133,332	155.6	114.1	194.0
Share area available	0-3 km	133,332	0.62	0.48	0.81
House prices, 2007	1-by-1 km	79,815	77.6	59.6	91.9
House prices, Δ2007-17	1-by-1 km	79,815	25.2	8.5	39.3
Share of high-skilled, 2000	1-by-1 km	128,448	0.07	0.03	0.10
Share of high-skilled, Δ2000-17	1-by-1 km	128,448	0.07	0.03	0.10
Altitude	1-by-1 km	133,332	246.3	57.8	402.0
Ruggedness	1-by-1 km	133,332	25.5	5.6	37.0
Slope	1-by-1 km	133,332	4.2	0.9	6.1
Land use, buildings	1-by-1 km	133,332	0.19	0	0.27
Land use, agriculture	1-by-1 km	133,332	0.66	0.45	0.94
Land use, forests	1-by-1 km	133,332	0.14	0	0.22
Land use, water	1-by-1 km	133,332	0.01	0	0
Quantified model					
House prices	1-by-1 km	133,332	97.0	70.0	116.8
Population, high-skilled	1-by-1 km	133,332	57.0	3.4	37.0
Population, low-skilled	1-by-1 km	133,332	230.9	27.8	219.4
Employment, high-skilled	1-by-1 km	133,332	57.0	0	14.7
Employment, low-skilled	1-by-1 km	133,332	230.9	0	134.3
Wages, high-skilled	1-by-1 km	133,332	131.3	105.3	150.6
Wages, low-skilled	1-by-1 km	133,332	84.5	72.4	93.7
Housing supply elasticity	Districts	401	0.27	0.23	0.29

The table provides summary statistics of the main variables. The spatial resolution 0-3 km measures variables within three kilometers of the centroid of the grid cell, while the resolution 1-by-1 km measures variables in the grid cell. The rows for the share of high-skilled in 2000 and the change in the share of high-skilled between 2000 and 2017 have identical summary statistics by coincidence, and not due to a duplication error. Reported summary statistics for the quantified model are based on the year 2017, the last year for which data is available.

B Quasi-experimental evidence

Benchmark

By height. In section 3, I compare the magnitude of the house price results to estimates in the literature. Figure B.2a shows that the estimates are consistent, once differences in turbine height across studies are taken into account. In the comparison, I include all studies that i) use a quasi-experimental design and ii) report estimates for any wind turbine development, irrespective of the size of the wind park. I contrast effect sizes with the median turbine height in the sample. For studies that do not report effects by height, I report the main coefficient as well as the median turbine height in the full sample. For studies that report coefficients by heights, I report the best approximation to the median turbine height in the subsample used by the study. Where median heights by subsample are not reported, I resort to the midpoint of the interval, eg. 125 m for 100-150 m, or the only known bound, eg. 150 m for 150 m and above. Where coefficients for multiple distance bands are reported, I take the estimates that come closest to the 0-3 km distance band used in this paper. Papers in the literature typically report the effect of having any turbine. To facilitate the comparison, I thus scale the per-turbine estimate obtained by this paper by a factor of three, the median number of turbines constructed during the sample period. Finally, I fit a linear regression line through the estimates in the literature, giving each paper equal weight. Across studies, small wind turbines have no or very small impacts while very large turbines may decrease house prices by up to 10 percent. With a median impact of -6.1 percent, the estimated effect in section 3 is 0.7 percentage points or 13 percent larger than the regression-implied average effect, which is -5.4 percent at the sample height of 111 m.

By number of turbines. Section 4 assumes that the functional form

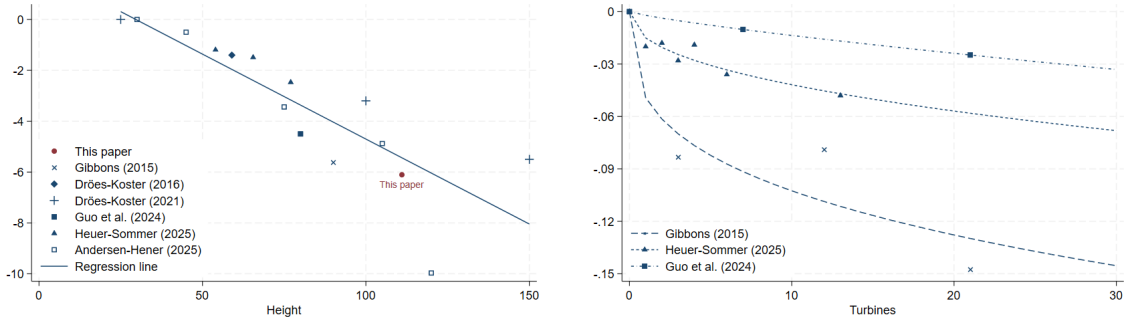
$$f^{\theta}(T_n) = \sigma_1^{\theta} (T_n)^{\sigma_2^{\theta}} \tag{35}$$

flexibly captures the nonlinear impact of wind turbines on amenities. To support the assumption, figure B.2b compares the functional form to the non-parametric

Figure B.2: Benchmark

(a) By height

(b) By number of turbines



The left figure reports house price effects by turbine heights. Each dot represents a separate estimate, with the marker indicating the source study (Gibbons 2015, Dröes and Koster 2016, Dröes and Koster 2021, Guo et al. 2024, Heuer and Sommer 2025, Andersen and Hener 2025). The y-axis measures house price effects in percent changes, the x-axis median turbine heights in meters. The regression line weights all studies equally. The estimate for this paper is based on the effect in table 2 and the median number of developed turbines between 2007 and 2017, which is three, and the average height in the sample, which is 111 m. The right figure reports house price effects by the number of turbines. Each dot represents a separate estimate, with the marker indicating the source study. The y-axis measures house price effects in log points, the x-axis the number of turbines. Where studies report effects for an interval, eg. 11-20 turbines, I plot the effect at the median number of turbines in the interval. When this is not reported in the paper, I resort to the median in the German data. For each study, I separately estimate equation 35 using nonlinear least squares, and I plot the implied function with a separate line per study.

estimates of house price effects in the literature (Gibbons 2015, Guo et al. 2024, Heuer and Sommer 2025). I include all studies that report effects separately by the number of turbines. For each study, I plot the reported effects along with the implied function, which I obtain by estimating equation 35 via nonlinear least squares. Across studies, the functional form approximates the individual coefficients well, and in particular so in the context of Germany (Heuer and Sommer 2025).

Compensation

I discuss four channels through which wind turbine development may partially compensate local residents: labor demand, electricity prices, compensation for farmers who rent out their land, and compensation for the local municipality.

Labor demand. In principle, wind energy infrastructure may benefit residents if it creates local job opportunities, for example, in wind energy related manufacturing or services, or in energy-intensive industries. Anecdotally, both are unlikely. While onshore wind energy creates about 94,000 jobs nationwide (BMWE 2024), turbine

production processes are complex and scale-intensive, and typically occur in regional capitals such as Bremen (operations and management, research and development), Hamburg (several headquarters), or Magdeburg (turbine components manufacturing), and not in the locations where turbines are eventually constructed. Installation of turbines requires specialized equipment and skills that are unlikely to be provided by residents who live within three kilometers of the turbine. In line with this, Fabra et al. (2024) find that wind turbine development has no sustained local employment effects in Spain. Secondly, firms located near renewable energy infrastructure in Germany do not benefit from lower electricity prices. Direct power purchasing agreements between wind turbine operators and firms are rare in Germany. The first one was signed in 2018, after the end of the sample period (WindEurope 2018). More importantly, even under such agreements firms in Germany typically do not source from local wind parks.

Beyond anecdotal evidence, I test whether wind turbine development had any positive employment effects by estimating equation 6 with employment changes as the dependent variable. Table B.4 reports the results. Consistent with the anecdotal evidence, I find no evidence that wind turbine development generated positive employment effects. The coefficients are negative, and only significant for high-skilled workers. In principle, such negative employment effects can partly be explained by the emigration of high-skilled residents and reduced productivity spillovers on other high-skilled workers. Overall, the results suggest that wind turbine development does not compensate residents through increased local labor demand.

Consumer electricity prices. Electricity is traded within a single bidding zone, and residents that live close to renewable energy infrastructure do not pay lower electricity prices. Regional surcharges (*Netzentgelte*) vary depending on local utility costs, but are, if anything, higher in the wind-rich regions of Northern Germany (Agora 2016). As a consequence, renewable energy infrastructure does not compensate residents through lower electricity prices.

Compensation for farmers. Wind turbines are typically developed on agricultural land, which operators lease from farmers. Lease payments vary across contracts, but amount to approximately $49,000 per year for a 3 MW turbine (average capacity of a turbine installed in 2017, DWG 2023). Lease payments for wind turbine sites

Table B.4: Wind turbine, population, employment, and income

	Δ Log population		Δ Log employment		Δ Log income	
	High-skilled	Low-skilled	High-skilled	Low-skilled	High-skilled	Low-skilled
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Wind turbines	-0.015	0.018*	-0.072**	-0.016	0.005	0.003
	(0.011)	(0.009)	(0.030)	(0.021)	(0.008)	(0.002)
Effective F-statistic	53	53	49	49	50	50
Observations	102,668	102,668	43,744	43,744	81,444	81,444

Each column reports a separate regression based on equation 6. The dependent variable measures log changes in population, employment, and income by skill. In each column pair I fix the sample size so that the dependent variable is non-missing for both skills. Across column pairs, sample sizes vary because not all grid cells have positive population, employment or non-missing wages in both years. I instrument wind turbine development with changes in wind power density. All changes are measured between 2000 and 2017. Controls include altitude, ruggedness, slope, land use, and district fixed effects. Standard errors clustered at the district level are reported in parentheses.

are considerably larger than those for standard agricultural land, and as a consequence high wind speeds are capitalized into land prices (Haan and Simmler 2018). While farmers benefit, I find no evidence that income spills over to other residents, see table B.4, and I therefore conclude that the average resident is not compensated through lease payments.

Compensation for municipalities. Wind turbine operators pay business taxes. Transfers vary between $3,250 and $9,700 per turbine per year and are split between the municipality that hosts the turbine and the municipality where the operator's headquarters is located (Meier et al. 2025). Although small, the host municipality may use the payments to finance public goods that increase local amenities. Residents may take the compensation into account, so that the estimated house price and sorting effects could be larger if no compensation existed. Similarly, the preferences and transfers that I estimate in sections 3 and 5 apply in addition to existing compensation. Nevertheless, the per-turbine per-year payments issued during the sample period are about 14 times smaller than the per-turbine per-year compensation for the median municipality, so that any attenuation bias would be very small.

Table B.5: Wind turbines, house prices, and residential sorting - robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ Log house prices						
Δ Wind turbines	-0.021*	-0.021	-0.022*	-0.021*	-0.021	-0.021	-0.015
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.012)
Observations	79,815	79,815	79,815	79,815	79,815	79,815	79,815
	Δ Share high-skilled residents						
Δ Wind turbines	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***	-0.005***	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	128,448	128,448	128,448	128,448	128,448	128,448	128,448
Additional control(s)	None	Direction	Distance to river	Distance to city	Distance to coast	Industries	Treatment intensity

Each column within a panel reports a separate regression based on equation 6. The first column reproduces estimates in columns 3 and 5 in table 2, subsequent columns add additional control variables. Direction includes four binary variables measuring the orientation of the neighborhood's slope (north-, east-, south-, or west-facing). Distance to river, city, and coast measure the neighborhood's distance to the next river, city, and coast. Industries adds the shares of residents employed in each two-digit industry. Treatment intensity adds a population- and distance-weighted measure of treatment intensity in the surrounding neighborhoods as proposed by Borusyak et al. (2023) and calculated in equation 8. The dependent variables are log changes in house prices in the top panel and changes in the share of high-skilled residents in the bottom panel. I instrument wind turbine development with changes in wind power density. All changes are measured between 2007 and 2017. Controls include altitude, ruggedness, slope, land use, and district fixed effects. Standard errors clustered at the district level are reported in parentheses.

Robustness

Table B.5 reports the robustness checks discussed in section 3.3. All main controls are measured at the grid cell level. To the extent possible, the controls considered in the robustness section are measured at the grid level, too. In some cases, however, I rely on municipality-level information because merging the social security data with grid-level information is restricted to the variables proposed in the original data application. Direction classifies neighborhoods as north-, east-, south-, or west-facing based on the orientation of the neighborhood's slope. Distance to river measures the distance between the centroid of the neighborhood's municipality and the nearest water body in the land use classification from Copernicus (2024). Distance to city measures the distance to the centroid of the nearest city, as classified in the administrative border maps provided by BKG (2024a). Distance to coast measures the distance to the coastline, as observed from EEA (2023). Industries includes the shares of residents in the neighborhood that work in each NACE Rev. 2 sector, which I obtain from the social security data (IAB 2023). Treatment intensity measures turbine construction outside of the neighborhood, following Borusyak et al. (2023). For all neighborhoods k, I predict changes in turbine construction $\Delta\hat{T}_k$ based on local changes in wind power density

Table B.6: Wind power density and turbine heights

	Δ Turbines	Δ Height
	(1)	(2)
Δ Wind power density	1.97***	-6.39
	(0.28)	(50.52)
Observations	133,332	522

Each column reports a separate regression based on equation 5. The dependent variable in the first column is changes in the number of wind turbines and the column reproduces the first column of table 2. The dependent variable in the second column is changes in the height of the installed wind turbines. All changes are measured between 2000 and 2017. The sample size is smaller because few neighborhoods experience turbine development in both years. Controls include altitude, ruggedness, slope, land use, and district fixed effects. Standard errors clustered at the district level are reported in parentheses.

$$\Delta T_k = \beta \Delta w_k + \varepsilon_k. \tag{36}$$

Treatment intensity weights predicted construction by population and distance as

$$\Delta \hat{T}^{dist}_{\neg n} \equiv \frac{\sum_{k \neq n} R_k dist_{nk}^{\zeta} \Delta \hat{T}_k}{\sum_{k \neq n} R_k dist_{nk}^{\zeta}} \tag{37}$$

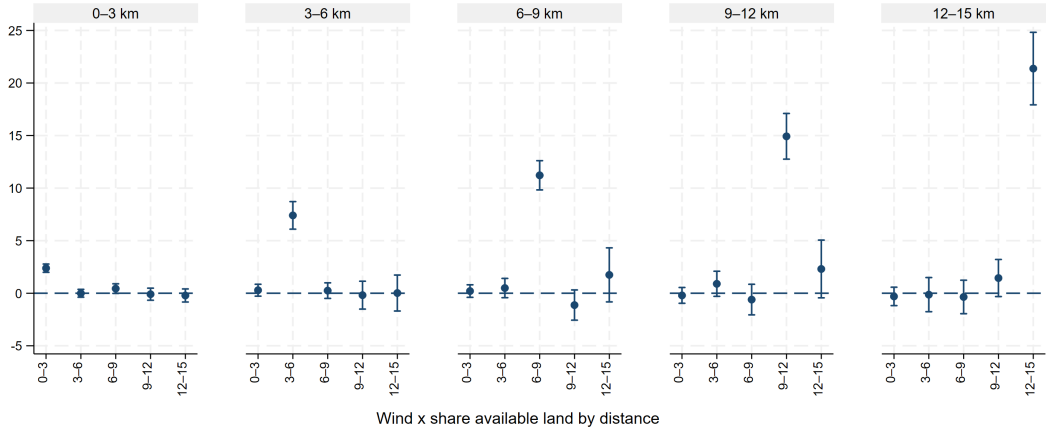
where R_k is the population of neighborhood k, $dist_{nk}$ measures the distance between the municipality centroids of neighborhoods n and k, and I set $\zeta = -1.25$ following Borusyak et al. (2023). Finally, in table B.6 I test if the instrument affects the size of turbines, a potential violation of the exclusion restriction. Changes in wind turbine height measure the difference in heights for turbines installed in 2000 and 2017, as observed in the TWP (2025) data.

Heterogeneity

Effects by distance. In section 3.4, I estimate the effect of wind turbine development separately by distance band. The IV specification is

$$\Delta y_n = \sum_{d=1}^{D} \beta^d \Delta T_n^d + \gamma X_n + \delta_{d(n)} + \varepsilon_n \tag{38}$$

Figure B.3: Effects by distance - first-stage



Each panel reports a separate regression based on equation 39. The dependent variable differs across panels and measures turbine development within 0-3, 3-6, 6-9, 9-12, 12-15 km, respectively. The reported coefficients β^d estimate the effect of changes in wind power density interacted with the share of land available in the respective distance band on wind turbine development. Standard errors are clustered at the district level and bars indicate 95 percent confidence intervals.

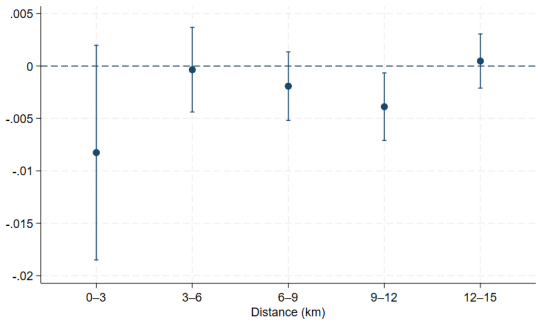
where I instrument $\{\Delta T_n^d\}_d$ with $\{\Delta w_n^d, \Delta w_n^d s_n^d\}_d$. I include both changes in wind power density and its interaction with the share of available land because changes in wind power density are correlated across distance bands. The interaction term breaks the spatial correlation. To show that, I estimate the first-stage separately for turbines in each distance band

$$\Delta T_n^k = \sum_{d=1}^{D} \left(\alpha^{d,k} \Delta w_n^d + \beta^{d,k} \Delta w_n^d s_n^d \right) + \gamma X_n + \delta_{d(n)} + \varepsilon_n \tag{39}$$

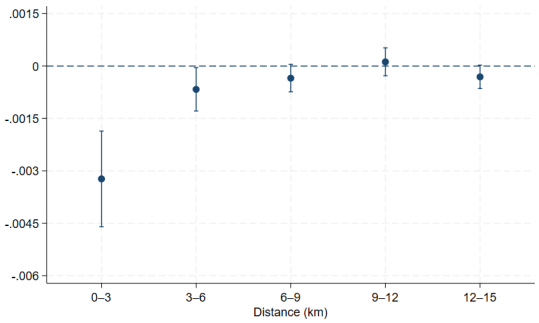
and plot $\beta^{d,k}$ for all k and d in figure B.3. The interaction of changes in wind power density with the share of available land predicts wind turbine development in the respective distance band, but not in any other distance bands.

Figure B.4: Effect by distance

(a) House prices



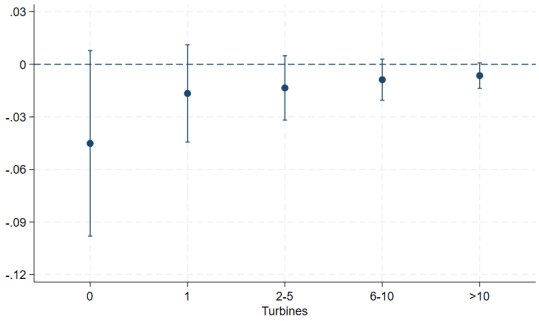
(b) Residential sorting



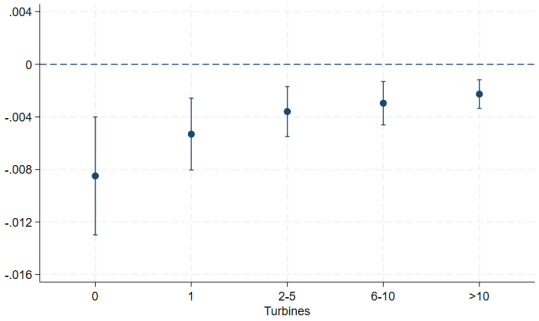
Each figure reports a separate regression. I estimate equation 9 and plot the effect of wind turbine development by distance. The dependent variables are changes in log house prices and the share of high-skilled residents. Wind turbines are measured within 0-3, 3-6, 6-9, 9-12, and 12-15 km. Wind turbine development by distance band is instrumented with changes in wind power density by distance band and their interaction with share of available land by distance band. Controls include altitude, ruggedness, slope, land use, and district fixed effects. Standard errors are clustered at the district level and bars indicate 95 percent confidence intervals.

Figure B.5: Effect by turbines at baseline

(a) House prices



(b) Residential sorting



Each figure reports a separate regression. I estimate equation 10 and plot the effect of wind turbine development by turbines at baseline. The dependent variables are changes in log house prices and the share of high-skilled residents. The independent variables interact turbine development with five indicators equal to one if the neighborhood had 0, 1, 2-5, 6-10, or more turbines at baseline. Wind turbine development by group is instrumented with changes in wind power density and its interactions with the five group indicators. Controls include altitude, ruggedness, slope, land use, and district fixed effects. Standard errors are clustered at the district level and bars indicate 95 percent confidence intervals.

C Estimation

Amenities

Estimation proceeds in two steps. First, I describe the estimation of the amenity impact function, including all required auxiliary parameters. Then, I turn to the estimation of the labor demand and housing supply elasticities. Table C.12 summarizes all parameters estimated in the process.

To estimate the impact of turbine development on amenities, I first calculate amenity changes given in equation 22. Computation requires data on residents, house prices, adjusted wages, and travel times $\{R_n^\theta, Q_n, \tilde{w}_i^\theta, d_{ni}\}$ as well as the share of income spent on housing and the labor supply elasticity $\{\alpha^\theta, \kappa^\theta\}$. I measure changes between 2007 and 2017. For residents and house prices, I use the data prepared for the main analysis. Where house prices are missing, I impute prices with municipality, or, if not available, district averages. I calculate the share of income that residents spend on housing from all individuals aged 25-65 in the Microcensus 2018, and I obtain the labor supply elasticity from Krebs and Pflüger (2023).

Commuting costs. Like Ahlfeldt et al. (2015), I model commuting costs as

$$d_{ni}^\theta = exp(\mu^\theta \tau_{ni}) \tag{40}$$

where τ_{ni} is the travel time between residence n and workplace i in minutes and μ^θ is the semi-elasticity of commuting costs with respect to travel times. I measure travel times using data from OpenStreetMap and the routing algorithm developed by Huber and Rust (2016). Computing travel times between 128,300 residential and 67,231 workplace neighborhoods is computationally prohibitive, and I approximate times as follows. For neighborhoods in different municipalities, I use the routing algorithm to calculate the travel time between the centroids of both municipalities. For neighborhoods in the same municipality, I calculate the distance as the crow flies and translate distances to travel times by assuming a commuting speed of 30 km/h. Then, I estimate the semi-elasticity by substituting costs into residents' commuting

Table C.7: Commuting semi-elasticity

	Log commuter share	
	High-skilled	Low-skilled
	(1)	(2)
Travel time	-0.038***	-0.062***
	(0.001)	(0.002)
Observations	160,801	160,801

Each column reports a separate regression. I use PPML to estimate equation 41 at the district-pair level.

choices in equation 13, which yields the commuting gravity estimation equation

$$ln(\lambda_{ni}^{\theta}) = \nu^{\theta}\tau_{ni} + \delta_n + \delta_i + \varepsilon_{ni} \tag{41}$$

where I denote the commuting elasticity with respect to travel time $\nu^{\theta} \equiv -\mu^{\theta}\kappa^{\theta}$. Residence fixed effects δ_n absorb amenities and house prices, workplace fixed effects δ_i absorb adjusted wages, and I add the error term ε_{ni} to account for the fact that bilateral travel times do not perfectly predict commuting shares in the data. Since commuting data at the neighborhood pair level is not available, I estimate equation 41 at the district pair level, which is the most granular level at which I observe skill-specific commuting shares. I compute commuting shares from the SIAB data, which is a two-percent random sample of workers in Germany. I restrict the sample to all individuals between 25 and 65 years and, following Monte et al. (2018), exclude commutes longer than 120 km one-way. I aggregate travel times at the district pair level by taking the population-weighted average of the travel times across all municipality pairs within each district pair. Since the commuting shares are zero for the majority of pairs, I estimate equation 41 using Poisson Pseudo Maximum Likelihood (PPML, Silva and Tenreyro 2006, Ahlfeldt et al. 2015). Table C.7 reports the results. Given the estimated semi-elasticities and travel times, I calculate commuting costs.

Adjusted wages. Given data on employment, population, and commuting costs, I invert the commuter market clearing

Table C.8: Wind turbines and amenities - robustness to controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ Log amenities, high-skilled						
Δ Wind turbines	-0.013**	-0.013**	-0.013**	-0.013**	-0.014**	-0.013**	-0.011**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
	Δ Log amenities, low-skilled						
Δ Wind turbines	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Additional control(s)	None	Direction	Distance to river	Distance to city	Distance to coast	Industries	Treatment intensity
Observations	111,148	111,148	111,148	111,148	111,148	111,148	111,148

Each column within a panel reports a separate regression based on equation 23. The first column reproduces estimates in columns 1 and 3 in table 3, subsequent columns add additional control variables. Direction includes four binary variables measuring the orientation of the neighborhood's slope (north-, east-, south-, or west-facing). Distance to river, city, and coast measure the neighborhood's distance to the nearest river, city, and coast. Industries adds the shares of residents employed in each two-digit industry. Treatment intensity adds a population- and distance-weighted measure of treatment intensity in the surrounding neighborhoods as proposed by Borusyak et al. (2023) and calculated in equation 8. The dependent variables are log changes in high-skilled amenities in the top panel and in low-skilled amenities in the bottom panel. I instrument wind turbine development with changes in wind power density. All changes are measured between 2007 and 2017. Controls include altitude, ruggedness, slope, land use, and district fixed effects. Standard errors clustered at the district level are reported in parentheses.

Table C.9: Wind turbines and amenities - robustness to parameters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ Log amenities, high-skilled						
Δ Wind turbines	-0.013**	-0.012**	-0.015**	-0.013**	-0.013**	-0.014**	-0.012**
	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)
	Δ Log amenities, low-skilled						
Δ Wind turbines	-0.005	-0.005	-0.005	-0.005	-0.005	-0.006	-0.004
	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)
Version	Base	High κ	Low κ	High μ	Low μ	High α	Low α
Observations	111,148	111,148	111,148	111,148	111,148	111,148	111,148

Each column within a panel reports a separate regression based on equation 23. The first column reproduces estimates in table 3, subsequent columns change the calculation of amenity changes in equation 22 by altering parameters. Standard parameters are summarized in table C.12. Each column increases or decreases a parameter for both types by 20 percent, holding all other parameters constant. κ refers to the labor supply elasticity. μ refers to the semi-elasticity of commuting. α refers to the share of income residents spend on housing. The dependent variables are log changes in high-skilled amenities in the top panel and in low-skilled amenities in the bottom panel. I instrument wind turbine development with changes in wind power density. All changes are measured between 2007 and 2017. Controls include altitude, ruggedness, slope, land use, and district fixed effects. Standard errors clustered at the district level are reported in parentheses.

Table C.10: Cumulative amenity impact - moment conditions

Turbines			Marginal effects		
Baseline	Median, 07	Median, 17	High-skilled	Low-skilled	Moment condition
(1)	(2)	(3)	(4)	(5)	(6)
0	0	2	-0.026	-0.009	$\beta^{b,\theta} = (f^\theta(2) - f^\theta(0))/2$
1	1	3	-0.013	-0.006	$\beta^{b,\theta} = (f^\theta(3) - f^\theta(1))/2$
2–5	3	6	-0.010	-0.003	$\beta^{b,\theta} = (f^\theta(6) - f^\theta(3))/3$
6–10	8	11	-0.006	-0.003	$\beta^{b,\theta} = (f^\theta(11) - f^\theta(8))/3$
>10	15	20	-0.004	-0.001	$\beta^{b,\theta} = (f^\theta(20) - f^\theta(15))/5$

Each row reports a pair of moment conditions used to estimate the cumulative amenity impact function. Column 1 partitions the sample into neighborhoods with 0, 1, 2-5, 6-10, or more than 10 turbines in 2007. Columns 2 and 3 report the median number of turbines in 2007 and 2017 for neighborhoods that are in the group and experience positive turbine development over the sample period. Columns 4 and 5 report the marginal amenity effect of each additional turbine, as estimated in equation 25 and reported in figure 3b. Moment conditions match the estimated group-specific marginal turbine impact to the average impact in the nonlinear impact function.

$$L_i^\theta = \sum_{n=1}^{N} \lambda_{ni|n} R_n^\theta = \sum_{n=1}^{N} \frac{\left(\tilde{w}_i / d_{ni}^\theta\right)^{\kappa^\theta}}{\sum_{s=1}^{N} \left(\tilde{w}_s / d_{ns}^\theta\right)^{\kappa^\theta}} R_n^\theta \tag{42}$$

to obtain adjusted wages. Because the equation does not generally admit a closed-form solution, I solve it numerically. Since repeated multiplication operations using the commuting matrix with 128,300 residential and 67,231 workplace neighborhoods are computationally prohibitive, I assume that residents can only commute to workplaces within the labor market of their neighborhood. This restriction reduces bilateral location choices to a block-diagonal matrix and allows the commuter market clearing problem to be solved separately for each labor market.

Amenities. Given data on house prices, population, adjusted wages, and commuting costs, I invert equation 13 to obtain amenities. Section 4 estimates the impact of wind turbines on amenities. The appendix provides additional robustness results. Tables C.8 and C.9 show that the main results are robust to the alternative explanations discussed in section 3.3 as well as to different parameter choices. Table C.10 reports the moment conditions used to estimate the cumulative amenity impact.

Housing and labor markets

Labor demand elasticities. To estimate the labor demand elasticities, I rewrite inverse labor demand in 15 and 16 in changes between 2000 and 2017.

$$\Delta ln(w_i^h) = \gamma^{hh}\Delta ln(L_i^h) + \gamma^{lh}\Delta ln(L_i^l) + \Delta z_i^h \tag{43}$$
$$\Delta ln(w_i^l) = \gamma^{hl}\Delta ln(L_i^h) + \gamma^{ll}\Delta ln(L_i^l) + \Delta z_i^l \tag{44}$$

Consistent estimation of γ^{hh}, γ^{hl}, γ^{lh}, and γ^{ll} requires two instruments that shift skill-specific labor supply but are not related to unobserved changes in labor demand. I use a migration shift-share design that leverages changes in national migration by origin and skill and cross-sectional variation in the neighborhood's composition of the population at baseline. Specifically, I calculate

$$\Delta B_i^\theta = \sum_{g \in G} \left(R^\theta_{g,2017,-i} - R^\theta_{g,2000,-i}\right) \cdot \frac{R_{ig,2000}}{R_{g,2000}} \tag{45}$$

where $R^\theta_{g,2017,-i} - R^\theta_{g,2000,-i}$ is the national change in immigrants of skill θ from country group g, leaving out migrants to i to avoid a mechanical effect, and $R_{ig,2000}/R_{g,2000}$ is the share of immigrants of group g that live in i among all immigrants of the group in Germany. Data on origin shares at baseline stem from the GridAB data, which also determines origin groups. Groups partition origins into Western European and North American countries, Eastern European countries, Balkan countries outside of the European Union, ex-Soviet countries, and countries that are historic origins of the refugee population in Germany. Data on national trends are calculated from the SIAB data. I estimate the first-stage and IV specifications

$$\Delta ln(L_i^\theta) = \beta^h \Delta B_i^h / L^h_{i,2000} + \beta^l \Delta B_i^l / L^l_{i,2000} + \varepsilon_i^\theta \tag{46}$$
$$\Delta ln(w_i^\theta) = \gamma^{h\theta}\Delta ln(L_i^h) + \gamma^{l\theta}\Delta ln(L_i^l) + z_i^\theta \tag{47}$$

Table C.11: Labor demand elasticities

	First-stage				Instrumental variable	
	$\Delta ln(L_i^h)$		$\Delta ln(L_i^l)$		$\Delta ln(w_i^h)$	$\Delta ln(w_i^l)$
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta B_i^h / L_{i,2000}^h$	0.097***	0.094***	0.006	0.004		
	(0.009)	(0.009)	(0.003)	(0.003)		
$\Delta B_i^l / L_{i,2000}^l$	-0.062***	-0.087***	0.050***	0.052***		
	(0.013)	(0.026)	(0.014)	(0.023)		
$\Delta ln(L_i^h)$					0.053***	-0.010*
					(0.016)	(0.006)
$\Delta ln(L_i^l)$					-0.007	-0.061**
					(0.047)	(0.023)
Kleibergen-Paap F					9.6	4.4
Observations	35,918	32,539	35,918	32,539	35,918	32,539

Each column reports a separate regression. The shift-share instrument measures the expected relative increase in high- and low-skilled workers, given national changes in origin- and skill-specific population and neighborhood shares in the origin population in 45. The first four columns show the first-stage estimated in 46 separately by the independent variable and by sample size. Columns 1 and 3 correspond to the sample of high-skilled wages, 2 and 4 to the sample of low-skilled wages. The last two columns show the IV specification estimated in 47.

and report the results in table C.11.

Housing supply elasticities. I approximate the location-specific housing supply elasticities using variation in local land constraints (Saiz 2010). Intuitively, housing supply reacts less to prices when there is little land available for development. I compute the shares of land in the neighborhood's district that is unavailable due to water bodies and steep terrain with a slope greater than 15 percent $\lambda_{d(n)}^{unav}$ as well as the share of land that is already developed $\lambda_{d(n)}^{dev}$. Drawing on recent estimates for Germany from Beze (2023), I calculate the housing supply elasticity as

$$\eta_n = 0.310 - 1.01\lambda_{d(n)}^{unav} - 0.463\lambda_{d(n)}^{dev}. \tag{48}$$

Contributions of each land type to the housing supply elasticity are estimated using labor demand shocks that shift housing demand but are arguably unrelated to confounding changes in housing supply. Estimation draws on long-run changes between 2008 and 2019, consistent with the static nature of the model.

Table C.12: Parameters

Parameter	Symbol	h	l	Estimation strategy / source
	Parameters required to solve for amenities			
Share spent on housing	α^θ	0.25	0.29	Microcensus 2018
Frechet scale parameter	κ^θ	4.56	4.56	Krebs and Pflüger (2023)
Commuting semi-elasticity	ν^θ	-0.038	-0.062	Commuting gravity equation
Total labor	L^θ	5.5M	22.2M	GridAB data 2017
	Parameters required to solve for fundamentals			
Amenities, scale	σ_1^θ	-0.037	-0.012	Wind IV + nonlinear least squares
Amenities, curvature	σ_2^θ	0.490	0.532	Wind IV + nonlinear least squares
Labor demand elasticity, w^h	$\gamma^{h\theta}$	0.053	-0.007	Migration shift share IV
Labor demand elasticity, w^l	$\gamma^{l\theta}$	-0.010	-0.061	Migration shift share IV
Housing supply elasticity	η_n	IQR = $[0.25, 0.28]$		Land use (Saiz 2010, Beze 2023)

D Policy

Wind energy development until 2024

Wind energy imposes large costs, but overall benefits prevail. The model-implied welfare costs in table 4 report the relative welfare change, going from no to full turbine development. Welfare in both scenarios is calculated per equation 20. For robustness, I also calculate welfare changes separately considering ±20 percent changes in each parameter value. Table D.13 shows the results.

For the cost-benefit calculation, I consider welfare benefits from reduced electricity generation costs and from emissions abatement. For generation costs, I compare the average levelized cost of electricity, which measures the cost of generating electricity averaged over the lifetime of a plant. I compare wind energy with the non-renewable sources coal, gas, and nuclear, which I weight by their share in the electricity mix in 2024. For wind turbines, I use the levelized cost of electricity in the year of construction and average over the age distribution of all turbines active in 2024. For non-renewable sources, I use the levelized cost in 2024, as the measure has been relatively stable over time. Information on the cost of wind energy stems from IRENA (2025), information on non-renewable sources comes from Lazard (2025). For emissions, I use an annual wind energy production of 111.9 TWh (BWE 2025), emissions reduction of 758 gCO_2/kWh (UBA 2025), and a social cost of carbon of \$325/tCO_2 (UBA 2024).

Table D.13: Wind energy and welfare - robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
ΔW	-0.60	-0.60	-0.59	-0.60	-0.60	-0.59	-0.60	-0.60	-0.59	-0.72	-0.47	-0.72	-0.50
ΔW^h	-1.11	-1.15	-1.08	-1.12	-1.12	-1.12	-1.11	-1.12	-1.11	-1.37	-0.88	-1.35	-0.95
ΔW^l	-0.47	-0.46	-0.47	-0.47	-0.47	-0.46	-0.47	-0.47	-0.47	-0.56	-0.37	-0.56	-0.39
Version	Base	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
		κ	κ	μ	μ	α	α	γ	γ	σ_1	σ_1	σ_2	σ_2

Each column reports a separate model counterfactual. I solve the model in the absence of turbines as well as under full turbine development observed in the data in 2024. Welfare by skill is calculated in equation 20. Total welfare weights skill-specific welfare by population. I report relative welfare changes, going from no to full turbine development. Column 1 reports the base choice of parameters summarized in table C.12. Columns 2 to 13 separately vary the version parameter by +20 percent (high) or -20 percent (low). I vary the parameter for both skill types simultaneously. High κ, for example, increases the labor supply elasticity for high- and low-skilled workers. μ refers to the semi-elasticity of commuting. α refers to the share of income that residents spend on housing. γ refers to the labor demand elasticities. σ_1 and σ_2 refer to the scale and curvature of the amenity impact function.

Local costs often exceed benefits, discouraging development. I compare the local costs and benefits of wind energy. On the cost side, I compute the relative welfare change for inframarginal residents, who choose the same workplace and residence across counterfactuals and thereby allow for within-individual, within-place welfare comparisons. Given the indirect utility in equation 11, the relative welfare change for an inframarginal worker ω is

$$\begin{aligned}\Delta ln\left(u_{ni}^{\theta}(\omega)\right) &= \Delta ln\left(A_n^{\theta}\right) + \Delta ln\left(\tilde{w}_i^{\theta}\right) - \Delta ln\left(d_{ni}^{\theta}\right) - \alpha^{\theta}\Delta ln\left(Q_n\right) + \Delta ln\left(\varepsilon_{ni}^{\theta}(\omega)\right) \\ &= \Delta ln\left(A_n^{\theta}\right) + \Delta ln\left(\tilde{w}_i^{\theta}\right) - \alpha^{\theta}\Delta ln\left(Q_n\right)\end{aligned} \tag{49}$$

where ΔX denotes the change in a variable X across equilibria. The second line drops the commuting costs, which do not change for inframarginal individuals, and the idiosyncratic taste shock, which I necessarily assume to remain constant to make location-specific welfare comparisons across counterfactuals sensible. I aggregate the relative welfare change to the residence level by weighting individuals by their baseline commuting probability, which yields the relative real-wage adjusted amenity change for an inframarginal resident

$$\Delta ln(\tilde{A}_n^{\theta}) \equiv \sum_i \lambda_{ni|n}^{\theta}\left(\Delta ln(A_n^{\theta}) + \Delta ln(\tilde{w}_i^{\theta}) - \alpha^{\theta}\Delta ln(Q_n)\right) \tag{50}$$

where $\lambda_{ni|n}^{\theta}$ is the conditional commuting probability at baseline. I multiply real-

wage-adjusted amenity changes with average local income and aggregate over low- and high-skilled residents.

Adequate compensation is possible, but likely politically infeasible. I calculate transfers that equalize the cost of wind energy development across space. For the derivation, note that a skill-specific relative utility increase of

$$\tau_n^\theta = 1/\exp\left(f^\theta(T_n)\right) \tag{51}$$

compensates residents for the amenity loss from wind energy development. Denoting $A_n^\theta(T_n)$ and $A_n^\theta(0)$ amenities in the presence and absence of turbine development,

$$\tau_n^\theta A_n^\theta(T_n) = 1/exp(\sigma_1^\theta T_n^{\sigma_2^\theta}) a_n^\theta exp(\sigma_1^\theta T_n^{\sigma_2^\theta}) = a_n^\theta exp(0) = A_n^\theta(0). \tag{52}$$

To calculate the monetary value of the compensation, I multiply the relative utility increase with the wage paid at the individual's workplace. Total compensation required in the economy aggregates individual payments over individuals, workplaces, and residences. To balance the budget, I calculate a relative tax τ^θ such that total tax collection equals the required compensation.

$$\sum_{n=1}^{N}\sum_{i=1}^{N} \lambda_{ni}^\theta w_i^\theta \tau_n^\theta = \sum_{n=1}^{N}\sum_{i=1}^{N} \lambda_{ni}^\theta w_i^\theta \tau^\theta \tag{53}$$

The relative tax is uniform across neighborhoods and therefore does not distort residents' choices. Substituting in average income and solving for τ^θ yields

$$\tau^\theta = \sum_{n=1}^{N} R_n^\theta v_n^\theta \tau_n^\theta / \sum_{n=1}^{N} R_n^\theta v_n^\theta. \tag{54}$$

Finally, multiplying the skill-specific compensation and tax with income and aggregating over all residents in the neighborhood yields the net transfers

$$\pi_n = \sum_{\theta \in \{h,l\}} R_n^\theta v_n^\theta (\tau_n^\theta - \tau^\theta). \tag{55}$$

Alternative turbine allocations reduce costs, and yield transfers that are more likely to be politically feasible. To obtain the alternative distribution of wind turbines, I solve for the allocation that minimizes welfare costs under three simplifying assumptions. First, I assume that the planner cares equally about relative welfare changes for all residents. Second, I consider the first-order impact, assuming that the planner does not take into account re-optimization of location choices after development. Third, I assume that the impact of turbines on amenities is linear, such that each turbine reduces amenities by 1.3 and 0.5 percent for high- and low-skilled, respectively, as estimated in table 3. These assumptions linearize the maximization problem

$$\begin{aligned} \underset{\{T_n\}_n}{\text{maximize}} \quad \sum_\omega \ln\left(u_{ni}^\theta(\omega)\right) &= \sum_\omega \ln\left(A_n^\theta\right) \\ &= \sum_n \sum_\theta R_n^\theta \ln(A_n^\theta) \\ &= \sum_n \sum_\theta R_n^\theta f^\theta(\mathcal{T}_n^\theta) \\ &= \sum_n \left(-0.013 R_n^h - 0.005 R_n^l\right) T_n \end{aligned} \tag{56}$$

and thus allow me to rank the local welfare costs of a marginal turbine independent of all other turbine locations. With this simplification in mind, I solve the maximization problem under three constraints.

First, the national electricity capacity of the alternative allocation must be at least as large as in the baseline. I measure effective capacity in each location as the number of wind turbines weighted by wind power density and aggregate over locations. To ensure that the maximization takes spatial differences in wind resources into account, I rank locations by their welfare cost contribution per unit of wind power density.

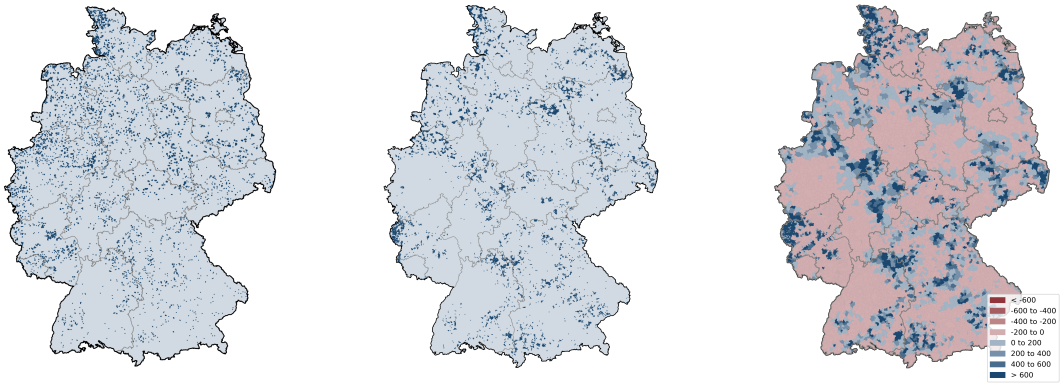
Second, each grid cell can host a maximum number of turbines, which depends on the area available and the area required per turbine. For available area, I draw on

detailed maps of scenarios for wind energy development in Germany by Agora (2021). The measure of available land differs in two important respects from the one used in the placebo exercise in section 3.2. First, while the measure in the placebo exercise is calculated using pre-treatment land use data, the scenario maps are drawn from recent data and provide an accurate account of land availability in 2024. Second, while the placebo measure excludes only land where development is strictly impossible, the scenario maps use rich information on the most common restrictions and thus provide a realistic account of land availability. Specifically, they exclude land used for residential and workplace areas, transport and electricity network infrastructure, military and radio navigation use, conservation zones as well as water bodies and steep terrain. The maps provide different scenarios for the minimum distance of turbines to residential areas and I choose a distance of 600 m for the main counterfactuals. In addition, the maps provide different scenarios that rule out forest and landscape protection areas, where turbine development is in principle possible but less common. To account for the restricted development in these areas, I first calculate the area available in the grid cell excluding forests and landscape protection areas, and then add in the forests and landscape protection areas that are indeed used for wind energy development in 2024, which I calculate for all of Germany and distribute across grid cells in proportion to the cell's forest and landscape protection area. Solving for the area required per turbine, on the other hand, is a complex optimal packing problem. Spacing wind turbines requires a minimum distance of four to six times the turbine diameter so that turbines do not cannibalize winds from each other (Bartl et al. 2012). In principle, the area required per turbine then depends on the shape of the polygon in each grid cell which is computationally prohibitive. To simplify the problem, for each turbine I calculate the circle area with radius equal to four times the turbine diameter, and divide the circle area by two as the areas of different turbines are likely to overlap. Given the area available and the area required per turbine, I calculate the number of potential turbines per grid cell. For grid cells where the number of turbines observed in the data exceeds the potential, for example due to measurement error, I replace the potential number of turbines by the turbines observed in the data.

Third, I require the allocation to fulfill constraints imposed by the existing electricity transmission network. To approximate interregional transmission constraints, I assign each state a maximum capacity, which I set to the capacity observed in the

Figure D.6: Alternative allocation, 2024

(a) Data (b) Alternative (c) Transfers per resident ($)



The left and middle figures show wind turbines in the data and in the alternative allocation in 2024, respectively. Turbines are aggregated at the grid cell level. The right figure shows net transfers for the alternative allocation computed in equation 28 divided by the number of residents. Transfers compensate residents in the alternative allocation relative to a scenario with no turbine development.

data or, if larger, the state's share in national population times total capacity. To approximate local constraints, I allow turbine development only within 7 km of a high- or ultra-high-voltage power line. I choose the distance threshold to match the average distance observed in the data.

Figure D.6b shows the implied alternative allocation of turbines. Finally, I calculate the budget-balanced transfers that residents would have to receive and pay to fairly distribute the cost of the alternative allocation using equation 28 and plot the transfers in figure D.6c.

Equity-efficiency trade-off. Relative to the baseline distribution, the alternative allocation achieves the required capacity at a welfare cost that is six times lower. Why does policy not encourage the lower-cost alternative? To shed light on this, I compare both allocations in terms of other variables that may shape policy preferences. I estimate

$$T_{ns} = \alpha X_n + \beta X_n \delta_s + \varepsilon_{ns} \tag{57}$$

where T_{ns} is the number of turbines in municipality n and scenario s and δ_s is an indicator equal to zero for the baseline and one for the alternative scenario. I estimate

the specification separately for different variables X_n, for which I consider indicators of spatial inequality, including population density, the share of high-skilled residents, and income per capita, average wind power density, distance to the power grid, and the share of the municipality's area covered by national parks (*Nationalparke*), nature reserves, biosphere reserves, and bird protection zones. For comparison, I standardize all variables.

Table D.14 reports the results. The first row shows the association between turbines and all variables in the baseline allocation, and therefore reveals current preferences for development. Wind turbines are somewhat less likely to be located in populous, educated, and rich regions, which is consistent with residents' preference to live away from turbines and the subsequent incentives for regulators. In line with developers' preferences, turbines are also more likely to be located in municipalities with high wind power density and shorter distance to the power grid. In addition, turbines are less likely to be developed in environmentally sensitive areas. The second row shows the additional association in the alternative allocation. Relative to the baseline, turbines are even less likely to be located in populous, educated, and rich regions. For population density and the share of high-skilled residents, the negative association approximately doubles. However, along the other dimensions there is no significant difference: the alternative allocation does not allocate turbines in locations that are less windy or further from the power network. The association with distance from the network is explicitly targeted by setting the distance threshold at 7 km, while the association with wind power density is not directly targeted. Similarly, wind turbines are not more likely to be located in national parks, nature monument zones, biosphere reserves, biosphere management zones, or in bird protection zones. The first three variables are indirectly targeted insofar as they are excluded from available land in current policy and in the alternative allocation. The last two variables are not targeted. Overall, the results suggest that the alternative does not come with obvious technical or ecological disadvantages. It does, however, increase spatial inequality, which suggests that policymakers primarily face an equity-efficiency trade-off.

Table D.14: Policy motives

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Wind Turbines									
Variable	-0.45***	-0.44***	-1.15***	1.81***	-0.47***	-0.62***	-0.15***	-0.34***	-0.24***	-0.37***
	(0.05)	(0.05)	(0.07)	(0.09)	(0.06)	(0.06)	(0.02)	(0.03)	(0.02)	(0.06)
Variable	-0.55***	-0.40***	-0.22**	-0.12	0.05	0.11	0.00	0.01	0.04	0.04
x Altern.	(0.06)	(0.06)	(0.10)	(0.09)	(0.08)	(0.07)	(0.01)	(0.04)	(0.04)	(0.06)
Variable	Population density	Share of high-skilled	Income per capita	Wind power density	Distance to power grid	National park	Nature monument	Biosphere reserve	Biosphere management	SPA bird protection
Observ.	22,406	22,406	22,406	22,406	22,406	22,406	22,406	22,406	22,406	22,406

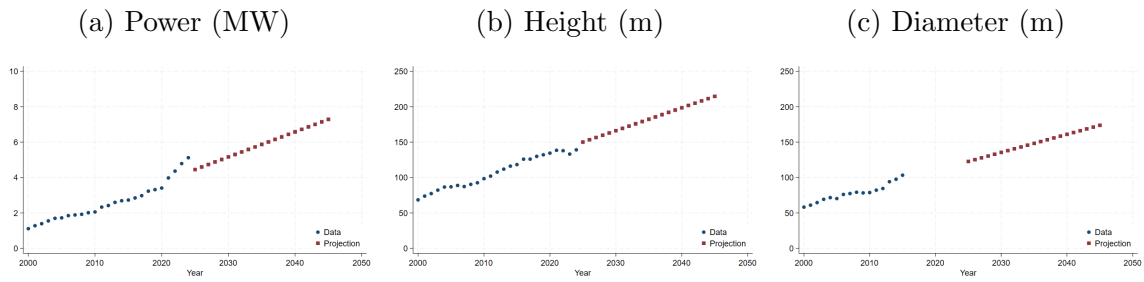
Each column reports a separate regression. I estimate equation 57 at the municipality-by-scenario level. The dependent variable is the number of turbines in the municipality in the base or alternative scenario. Each regression includes the independent variable indicated in the third row, once by itself and once interacted with an indicator that is zero in the baseline and one in the alternative scenario. The independent variables measure the population density, share of high-skilled residents, and income per capita in 2000, the average wind power density, the distance to the nearest high- or ultra-high-voltage transmission lines, and the share of area in the municipality covered by a national park, nature monument, biosphere reserve, biosphere management area, or bird protection zone. All independent variables are standardized. Standard errors clustered at the municipality level are reported in parentheses.

Wind energy development until 2045

Wind energy targets and projection. I collect the capacity targets for wind energy development from the Renewable Energy Sources Act (2023). Capacity targets are available for the milestone years 2030, 2035, 2040, and 2045. For each year, I calculate the capacity covered by wind turbines observed in the data. To account for the gradual phaseout of old turbines, I exclude turbines developed more than 25 years before the target year. For the years after 2030, existing capacity also includes capacity built to achieve the previous target. Subtracting existing capacity from the target yields missing capacity. I translate missing capacity to missing turbines, assuming that the capacity per turbine continues to increase linearly with each year, which I project in figure D.7a, and that development is uniform in the years leading up to the target year. For the projection of wind energy development under realistic conditions, I assume that new turbines are constructed at the average speed observed in the last ten years and that old turbines are phased out after 25 years. I translate turbine projections to capacity projections given the observed and projected capacity per turbine, and report the results in table 5.

Welfare costs under business-as-usual scenarios. I calculate the average welfare costs per turbine in 2024, dividing the model-implied costs reported in table 4 by a total of 28,766 turbines, and multiply it by the total number of turbines required in the target and projection scenarios, respectively.

Figure D.7: Wind energy scenario assumptions



Each graph shows a turbine characteristic between 2000 and 2024, and the linear prediction between 2025 and 2045. Average power per turbine is calculated from BWE (2025). Turbine height refers to average hub height and stems from TWP (2025). Diameter refers to the average diameter spanned by turbine blades from Eichhorn et al. (2019) and is only available until 2015.

Welfare costs under alternative scenarios. I allocate wind turbines based on the simplified welfare maximization problem in equation 31. For all future scenarios, I adapt the constraints to reflect how technology, land use, and power transmission constraints are projected to evolve in the future. I solve the allocation problem iteratively for the years 2030, 2035, 2040, and 2045, effectively assuming that the policymaker aims to achieve the targets for each year specified in the Renewable Energy Sources Act. First, I determine the turbines that will remain active in the target year given past development. As before, I assume that old turbines are phased out after 25 years. Thus, in 2030, for example, only turbines built after 2005 remain active. For all subsequent years, I use the turbines allocated in the scenario for the previous milestone, again excluding turbines that would be older than 25 years. Given active turbines and the evolution of capacity per turbine over time, see figure D.7a, I determine the capacity additions required to meet each target. I translate missing capacity to turbines, taking into account that technological change increases the capacity per turbine over time. I assume capacity per turbine to increase linearly, as it has in the past, see figure D.7a. Then, I allocate the missing turbines in each target year given the simplified welfare maximization problem in equation 31. As before, the maps from Agora (2021) determine the available land. I subtract the area taken up by turbines developed in the past, taking into account that turbines become larger over time, see figure D.7c, and thus require more space. For transmission, I assume that development of power lines that connect wind parks to the existing high-voltage network is flexible in the long-run, and there are thus no local transmission constraints. Long-distance transmission, on the other hand, especially between the

wind-rich regions in the North and residential and industrial consumers in the West and South, is projected to remain a major bottleneck in the future (Fraunhofer ISE 2024). I assume that the high-voltage network is progressively updated as determined in the Network Development Plan 2037/2045 (*Netzentwicklungsplan*, BNetzA 2024). Based on the plan, Pape and Geiger (2023) determine realistic scenarios for the development of wind energy in each state, which I use as the maximum capacity that long-distance transmission can absorb. Finally, I insert the implied allocation of wind turbines into the quantitative spatial model, update amenities given equation 12, and solve for the equilibrium in 2045, allowing residents and markets to adjust to turbine development. Skill-specific welfare costs are computed given equation 20, comparing the equilibrium to a counterfactual with no turbine development. Total welfare costs weight skill-specific welfare costs by population.

Welfare benefits. I project the future benefits of wind energy as follows. For the generation cost of wind energy, I use data on the levelized cost of electricity generation until 2024 from IRENA (2025), and the relative generation cost decrease predicted by DNV (2024) between 2024 and 2045. As before, I compare the LCOE of wind with that of traditional energy sources weighted by the traditional electricity mix in Germany in 2024. Future changes in the LCOE of traditional energy, especially for coal and gas, depend mostly on carbon pricing and how quickly the energy sources are phased out (DNV 2024). To be conservative, I fix generation costs at the level of 2024, which I obtain from Lazard (2025).

For the benefits of emissions abatement, I assume that wind energy continues to save 758 gCO_2/kWh as in 2024 (UBA 2025), and that the social cost of carbon rises from \$325/tCO_2 in 2024 to \$443/tCO_2 in 2045. I obtain the latter from the German Environment Agency's recommendations for 2024 and 2050 (UBA 2024), using linear interpolation. I assume that electricity production scales with capacity as observed in 2024 and calculate total abated emissions by multiplying production in each scenario with abatement per unit of generated electricity.