Gone with the Wind: Renewable Energy Infrastructure, Welfare, and Redistribution*

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Abstract

Electricity production from wind and solar energy is projected to grow twelvefold until 2050. This paper studies the impact of renewable energy infrastructure on surrounding neighborhoods, its potential welfare costs for residents, and the implications for inequality. I focus on the wind energy expansion in Germany, 2000-2017. Using neighborhood data at 1-by-1 kilometer resolution and a novel IV strategy that exploits technology-induced changes in effective wind potential, I document that wind turbines decrease house prices and lead to residential sorting driven by the emigration of college-educated residents. Combined with a theory-consistent revealed preference argument, the reduced form results suggest that residents would be willing to pay between 0.9 and 1.4 percent of their income to avoid an additional wind turbine. I develop and estimate a quantitative spatial model in which wind turbines decrease amenities, residents can adapt, for example through sorting, and housing and labor markets respond in general equilibrium. The quantified model suggests that the disamenities from the total wind turbine expansion cost residents 0.83 percent of welfare or 31 billion USD. Allocating wind turbines to neighborhoods with low willingness-to-pay substantially reduces welfare costs but also places the burden on rural, poorer, and less educated regions. Finally, I discuss Germany's wind development plans for 2030, and the implications for welfare and inequality.

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1 Introduction

Renewable energies are becoming increasingly cheap. By 2050 wind and solar energy are estimated to account for a staggering 70 percent of global electricity production (Arkolakis and Walsh, 2023, DNV, 2023). The transition requires a large expansion of decentralized infrastructure. Local residents, however, often object to the installation of wind turbines and solar parks (Economist, 2021, New York Times, 2022), and their resistance remains a key obstacle to a rapid energy transition (Jarvis, 2022). Against this backdrop, it is important to understand the local costs of renewable energy infrastructure, and to learn how future allocations of renewable energy infrastructure can achieve climate targets while keeping adverse impacts on welfare and inequality low.

Quantifying the impact of renewable energy infrastructure on residents' welfare is challenging. Anecdotally, residents are concerned about visual impacts, noise pollution, and potential adverse health effects, but how much these concerns affect their utility is unobserved. To overcome the challenge, I build a theory-consistent revealed preference argument to infer residents' welfare costs from changes in their observed behavior.

First, I develop a novel instrumental variable (IV) strategy that exploits technology-induced changes in wind potential to predict which locations become more suitable for wind energy over time. I use the IV and granular data from the wind energy expansion in Germany, 2000-2017, to show that wind turbine development leads to long-run decreases in house prices, population and the share of college-educated residents in surrounding neighborhoods. Second, I leverage that state-of-the-art location choice models (Rosen, 1974, Roback, 1982, Ahlfeldt et al., 2015) allow to infer changes in local quality of life, for example due to wind turbines, from changes in population, house prices, and income. I combine the IV results and the model-implied mapping to estimate residents' willingness-to-pay to avoid wind turbines in their neighborhood. Third, I embed residents' preference against wind turbines in a quantitative spatial general equilibrium model. In the model, wind turbines decrease the local quality of life, residents can adapt by moving to other locations, and housing markets and labor markets adjust in general equilibrium. I use the quantified model to study how different allocations of wind turbines affect residents' welfare and inequality, and the implications for wind turbine development in the future.

Wind energy in Germany is an ideal empirical setting. First, the country is an early adopter of wind energy which allows to study its long-run consequences. Since the early 2000s Germany has heavily subsidized wind energy, and today wind energy is Germany's largest source of electricity, producing 32.2 percent of the national mix (German Federal Statistical Office, 2023).[1] Second, the context highlights the challenges that residents and policy-makers face as wind energy becomes a prominent energy source. The country operates a staggering 28,000 wind turbines, of which 97 percent are located within two kilometers of residential population. Residents' objections and local policy-makers' attempts to restrict turbine development close to residences are ubiquitous themes in the German energy transition, and they are likely to have contributed to the recent slowdown in turbine development. Third, Germany has ambitious wind development goals that are threatened by residents' concerns. The federal government plans to double wind energy capacity until 2030, which may require the installation of an additional 25,000 wind turbines. Understanding the costs for residents and how to mitigate them is decisive for a successful energy transition.

Throughout the empirical analysis, I draw on a unique data set that links turbine construction, house prices, population, income, employment, and wage data for the universe of German neighborhoods at 1-by-1 kilometer resolution. The information on population, income, employment, and wages stems from restricted-access social security data hosted by the Institute for Employment Research in Nuremberg, Germany. It is constructed from the universe of employees covered by German social security, approximately 40 million workers annually. To construct the local house price index, I leverage geo-located information on 35 million houses and flats offered on Germany's largest online real estate platform. I collect the data for the years 2000 to 2017 (except house prices which are available from 2007), covering the key period of the German expansion in wind energy.

In the first part of the paper, I provide systematic evidence that wind turbine development decreases house prices and the share of high-skilled residents in surrounding neighborhoods. I develop a novel IV strategy that exploits how changes in technology interact with local wind conditions, making some neighborhoods more attractive for wind energy over time than others. Specifically, wind turbines have become taller over time, from 71 meters in 2000 to 127 meters in 2017. Wind conditions are better high above the ground, though how much a neighborhood benefits depends on the topography around it. High terrain ruggedness upwind of the neighborhood, for example due to hills, blocks wind speeds closer to the ground, leading to a larger vertical dispersion of wind speeds, see Figure 4 for an illustration. In these neighborhoods, turbine development becomes disproportionally more attractive as wind turbine heights increase. I show that the implied changes in wind energy suitability

[1] In the first quarter of 2023, wind energy contributed 32.2 percent of electricity, ahead of coal (30 percent), natural gas (14.6 percent), biogas (5.5 percent), solar (4.9 percent), and nuclear energy (4.3 percent). In 2021 and 2022, two years with weaker wind conditions, coal was the largest source, in 2020 wind was ahead.

strongly predict turbine development. Comparing neighborhoods that are relatively close and have similar geography, I use the IV strategy to estimate the long-run effect of turbine development on surrounding neighborhoods.

Wind turbine development has important local costs. I find that the construction of an additional wind turbine within three kilometers of a neighborhood reduces house prices by 2.1 percent. As neighborhoods become less attractive, high-skilled residents with college-education move away. For each additional wind turbine, the share of high-skilled residents decreases by 0.6 percentage points.

In the second part of the paper, I use a revealed preference argument to quantify the first-order impact of wind turbines on residents' welfare. I build on the formulation of residents' location choice in the Rosen-Roback framework (Rosen, 1974, Roback, 1982) and more generally in the standard quantitative urban model (Ahlfeldt et al., 2015). I show that the models imply a mapping between changes in local quality of life, for example due to wind turbines, and changes in population, house prices, and income. Intuitively, if real income increases, for example due to lower house prices, and yet residents move away, by revealed preference the neighborhood must have become less attractive. Combining the mapping and my IV strategy, I show that high-skilled and low-skilled residents would be willing to pay 1.4 and 0.9 percent of their income, respectively, if they could avoid an additional wind turbine within three kilometers of their residence.

In the third part of the paper, I develop a quantitative spatial general equilibrium model to study how the large-scale expansion of wind turbines affects aggregate welfare and the distribution of economic activity across space. In the model, wind turbines decrease local quality of life, henceforth referred to as amenities. Residents choose where to live and where to work given amenities, house prices, wages, and commuting costs (as in Ahlfeldt et al., 2015). To capture residential sorting, I model residents as either high- or low-skilled (similar to Tsivanidis, 2023). Labor demand flexibly allows for substitution and productivity spillovers across skill types (following Diamond, 2016), and housing supply is inelastic with a supply elasticity that depends on local land constraints (following Saiz, 2010).

I estimate the model for 133,339 neighborhoods at 1-by-1 kilometer resolution. To make the estimation computationally feasible, I allow individuals to choose any neighborhood as their residence, but restrict that they can only commute to workplaces in the neighborhood's labor market, which allows me to invert and solve the model as a series of smaller block matrices. I calibrate the key parameter, residents' preference against wind turbines, from the willingness-to-pay estimated using the model-consistent amenity mapping and the IV strategy.

In my main exercise, I counterfactually remove all wind turbines and compare the resulting equilibrium to the data observed in 2017. Wind turbine neighborhoods, especially concentrated in the North and North-West, see decreases in house prices, population, and the share of high-skilled residents, as residents move to rural locations nearby, big cities, and the South that is less affected by wind turbine construction. I find that the disamenities from wind turbines result in welfare costs of 0.83 percent, or about 31 billion USD. A cost-benefit analysis suggests that the benefits outside of the model, for example from abated emissions, are likely larger than the costs. Nevertheless, the costs are substantial and in line with the resistance against renewable energy infrastructure observed worldwide.

I show that placing wind turbines in neighborhoods with low willingness-to-pay reduces the model-implied welfare costs from 0.83 percent to 0.13 percent, or by about 26 billion USD. At the same time, this and other alternative allocations of wind turbines place a larger share of wind turbines in rural, poor, and low-education municipalities. Thus, the model suggests that there is a trade-off between reducing the average welfare costs from wind turbines and keeping inequality across regions low. For policy-makers that are interested in both goals, the result highlights the importance of sharing the profits of wind energy more strongly with the communities that are affected by wind turbines, and I use the estimated willingness-to-pay to calculate budget-balanced transfers that distribute the costs equally turbine and non-turbine regions.

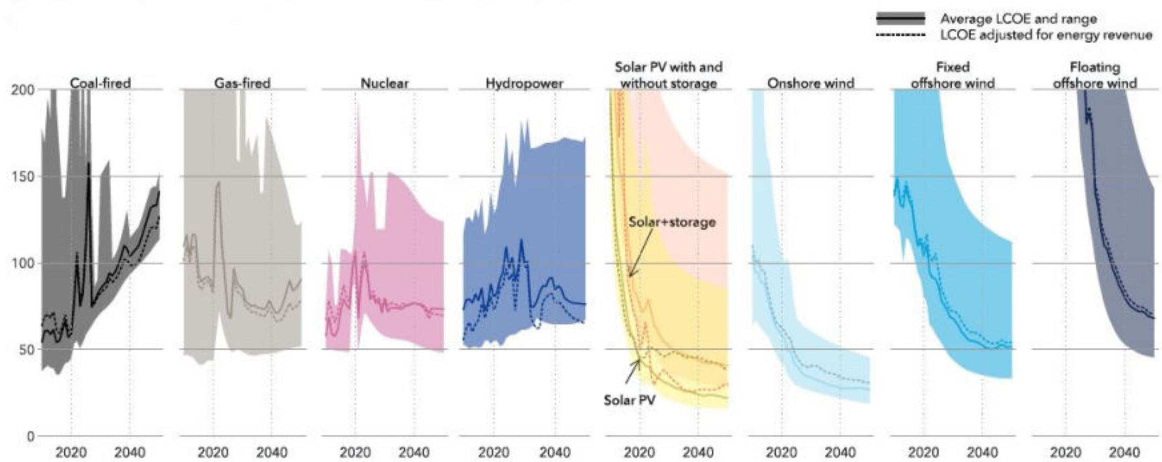
Finally, I use the model to evaluate Germany's wind development plans until 2030. I describe three wind turbine scenarios that achieve the national wind energy capacity goal under different assumptions on regional planning and land use policy. Allocating wind turbines to neighborhoods with low willingness-to-pay can limit the additional welfare costs to 0.18 to 0.31 percent, and reduces total costs per Gigawatt of capacity by between 29.5 and 43.5 percent. As before, I show that the distribution of wind turbines would increase inequality and calculate transfers for each scenario that distribute the costs equally.

The paper relates to several strands in the literature. Most directly, it connects to a large literature that estimates the welfare costs of environmental disamenities, primarily focusing on house prices as a revealed preference measure of decreased quality of life. Previous papers have studied the impact of renewable energy infrastructure (Gibbons, 2015, Dröes and Koster, 2016, Sunak and Madlener, 2016, Frondel et al., 2019, Dröes and Koster, 2021), as well as other environmental disamenities (Chay and Greenstone, 2005, Greenstone and Gallagher, 2008, Currie et al., 2015). I make four contributions. First, studies on wind turbines commonly use difference-in-difference and event-study methods, and find a wide range of house price effects between -1.6 and -14.0 percent. I develop a novel IV strategy that exploits geographic and time variation in local suitability for wind energy, and find a per turbine effect of -2.1 and a total effect of -6.3 percent for the median neighborhood. The results confirm the previous results qualitatively and point to effect sizes in the lower half of the distribution. Second, I use a location choice model to infer the implied welfare costs.[2] I show that ignoring population and income responses would lead to an underestimation of the amenity cost of wind turbines by 41.7 percent for low-skilled and by 65.5 percent for high-skilled residents. Third, I embed the the amenity costs in a quantitative spatial model to understand the welfare costs in general equilibrium, and to show that alternative allocations of wind turbines may achieve the same electricity production while reducing welfare costs by almost an order of magnitude.

Secondly, the paper connects to a growing literature that uses quantitative spatial general equilibrium models to study the geographic implications of climate change. A large share of the literature focuses on *adaptation* to climate change. Previous papers study where individuals move in response to higher temperatures and rising sea levels (Conte, 2022; Cruz and Rossi-Hansberg, 2022; Bilal and Rossi-Hansberg, 2023), how firms diversify their production network in response to increasing risk of natural disasters (Castro-Vincenzi, 2022; Balboni et al., 2023), and how countries adapt to a warming world by specializing in the sector of their comparative advantage (Conte et al., 2021; Nath, 2022). I contribute to a small but growing literature that focuses on climate change *mitigation* (Conte et al., 2022; Arkolakis and Walsh, 2023). The implications of climate change mitigation are particularly policy-relevant because they can inform current efforts to reduce emissions and reduce the welfare costs that will eventually arise as individuals, firms, and countries have to adapt to a warming world. Most closely related to me are Arkolakis and Walsh (2023) who integrate renewable energy production into a spatial growth model to measure the welfare effects of increasingly cheap electricity. Their paper abstracts from the negative externalities that renewable energy infrastructure creates for residents. My paper shows that local costs are quantitatively important for aggregate welfare and the optimal allocation of renewable energy production. I also complement Balboni (2021) and Hsiao (2023) who study the optimal allocation of infrastructure, roads and seawalls respectively, in response to rising sea levels.

[2]Here, I also relate to Bartik et al. (2019) and Brinkman and Lin (2022) use the same class of location choice models to infer the amenity costs of fracking and freeway construction, respectively. Compared to them, I contribute by estimating the amenity costs separately for high- and low-skilled residents.

Figure 1: Projection Cost of Electricity by Energy Source (in USD/MWh)



Notes: Figure 1 shows projections of the levelized cost of electricity (in USD/MWh) for coal, gas, nuclear, hydro, solar, onshore wind, fixed offshore, and floating offshore wind energy. Source: Energy Transition Outlook 2023 (DNV, 2023).

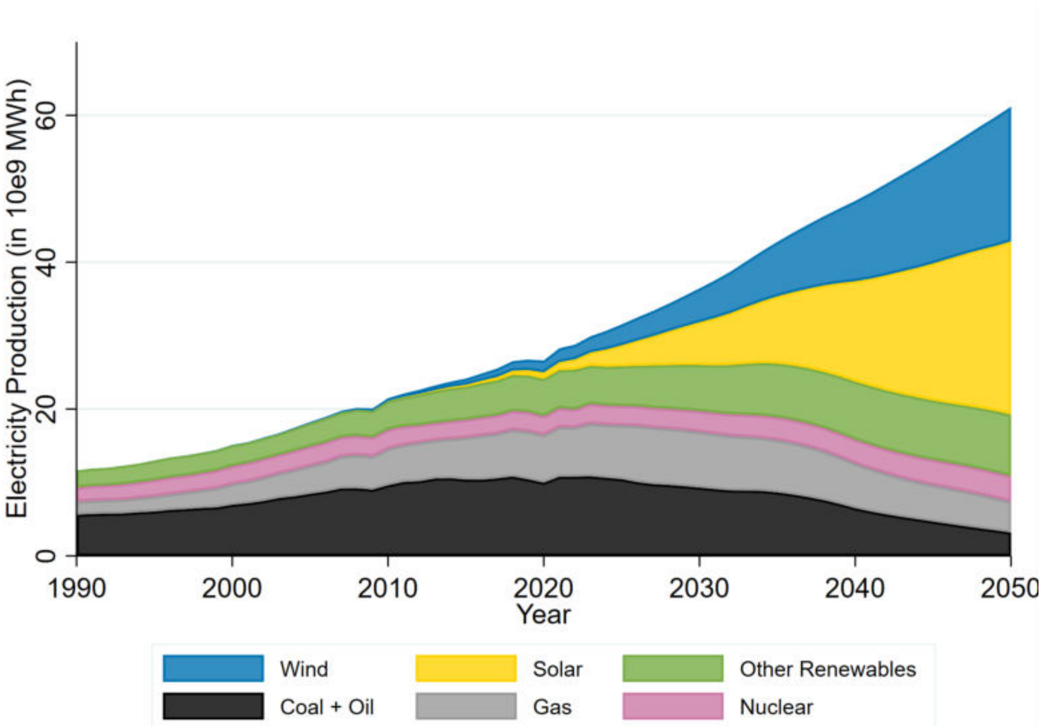
I study optimal infrastructure allocation of renewable energy production, a policy to reduce emissions and limit damages before they arise.

2 Background

Climate change and the rise of renewable energy. Climate change is caused by the emission of greenhouse gases (GHGs) into the atmosphere. In the Paris Agreement in 2015 the international community declared its goal to reduce net GHG emissions to zero by 2050 in order to limit global warming relative to pre-industrial temperature levels to a maximum of $2°C$ and ideally to $1.5°C$. One of the largest contributors to emissions is heat and electricity production from fossil fuels. Renewable sources of energy, such as wind, solar, hydro, and geothermal energy are sustainable alternatives. Especially, wind and solar energy are becoming increasingly prevalent as technological advances cut down their costs. Figure 1 shows the evolution of electricity costs by source. Costs are shown for the period 2010 to 2050 as estimated in the Energy Transition Outlook (DNV, 2023). The estimates report the levelized cost of electricity (LCOE), a standard measure that calculates the net present cost of electricity of a plant installed in a given year, taking into account the plant's fixed and variable cost as well as the total electricity produced over its lifetime.

The costs of wind and solar energy have fallen sharply between 2010 and 2020. Today,

Figure 2: Projection Electricity Production by Energy Source (in billion MWh)



Notes: Figure 2 shows projections of global electricity production (in billion MWh) for wind, solar, other renewables, coal and oil, gas, and nuclear energy. Source: Own calculation based on the Energy Transition Outlook 2023 (DNV, 2023).

both sources are cheaper than traditional sources such as coal, gas or nuclear energy. In 2022, a newly installed wind turbine produces electricity at 49 USD/MWh, while newly installed fossil and nuclear plants produce electricity at around 75 USD/MWh (DNV, 2023). Moreover, the price of wind energy is projected to fall to 27 USD/MWh by 2050, while the cost of gas and nuclear stays constant, and the price of coal is projected to sharply increase.

As a result, wind and solar energy are becoming increasingly present. Figure 2 reports the evolution of the global electricity mix between 1990 and 2050. Electricity production from 2023 onward is based on projections in the Energy Transition Outlook (DNV, 2023). Between 2000 and 2010, electricity production from wind energy grew by 454 percent, and its contribution to the global mix grew from 1.6 to 6.0 percent. By 2050, the report expects the share of wind energy in global electricity to grow to 30 percent, and for solar and wind energy together to account for 69 percent. Arkolakis and Walsh (2023) find that by 2040, solar and wind energy will account for 50 to 70 percent of global electricity production.

Wind energy in Germany. Systematic wind development in Germany began in the mid 1990s. From the early 2000s the government heavily subsidized turbine development through feed-in-tariffs. Today, wind energy, alongside with coal, is Germany's largest source of electricity. In the first quarter of 2023, wind energy contributed 32.2 percent (German Federal Statistical Office, 2023).

Wind energy can be produced by wind turbines at land ("onshore") and at sea ("offshore"). In Germany, approximately 87 percent of wind energy are produced at land. In 2022, Germany operated 28,443 wind turbines at land. Due to the high population density of the country, 97 percent of turbines are located within two kilometers of residential population.

Impact of wind turbines on residential amenities. The two primary channels through which wind turbines may affect residential amenities are visual and sound pollution. Modern wind turbines are up to 200 meters high with rotor blades up to 75 meters long. Exploiting that wind turbines are visible for some residents but not for others due to the terrain, for example hills between residents and the turbine, Gibbons (2015) shows that a wind turbine reduces house prices by 6.5 percent within one kilometer and between 5.5 and 6 percent within two kilometers. The results suggest that the visual impact of turbines is important for residential amenities.

A second concern is that the rotation of wind turbines' blades produces noise and infrasound that are negatively perceived by residents. The noise effects of turbines are very localized. At a distance of 500 meters, turbines can be heard at about 45 decibel, comparable to the noise that light car traffic generates for residents at a street. After 500 meters, the noise level declines rapidly. This suggests that the disamenity effect of noise is relatively low. Residents have also complained about infrasound, low frequency sound that cannot be perceived by the human ear, claiming that it disrupts their sleep and causes stress. The medical literature is mostly doubtful of the health effects of infrasound. However, even the belief in adverse health effects may harm sleep quality and induce stress. Zou (2020) shows that wind turbines decrease self-reported sleep quality and may even increase suicide rates.

Development plans until 2030. Germany has ambitious goals for the further development of wind energy. With the 2021 Climate Act Germany is bound to reduce its GHG emissions by 65 percent until 2030 (relative to 1990 emission levels) and to achieve climate neutrality by 2045. As part of the legislation, the government plans to provide 80 percent of gross electricity consumption in 2030 from renewable sources. Figure A.1 in the Appendix shows the explicit capacity development goal that the government has given out for wind and solar energy as well as the evolution of the electricity mix in the past.

For wind energy at land, the law requires that capacity grows approximately 98 percent from 58 GW in 2022 to 115 GW in 2030. Despite the expected growth in turbine efficiency, the capacity goal requires an enormous speed-up in the number of wind turbines constructed per year. Figure A.2 in the Appendix shows the net number of wind turbines installed each year as well as the turbines required to reach the 2030 goal.[3] On average, Germany would have to add about 2200 wind turbines per year, more than were installed in any year in the past two decades.

The ambitious goals are in stark contrast to the recent slowdown in turbine development. Between 2017 and 2022 the number of active wind turbines decreased from 28,675 to 28,443 turbines. Because today's turbines are more efficient than the older models that are deinstalled, total capacity is still growing but more slowly than ever before.

The central reason for the slowdown in turbine construction is that there is not enough area for new constructions (Wind, 2023). Since 2017 various states have enacted minimum distance rules that forbid turbine construction close to residential population. Minimum distance rules vary across states, ranging from 500 to 1500 meters. Conservation, for example to protect birds, and construction regulation at the local level further amplify the problem.

3 Data

This section describes the main data used in the analysis. Details on the construction of variables and further information on auxiliary data can be found in Appendix B.

In brief, I divide Germany into 133,339 populated 1-by-1 kilometer cells and collect information on wind turbines, house prices, residential and workplace population and wages at this level. With the exception of house prices (which are available from 2007), I collect all data between 2000 and 2017. I add cross-sectional information on wind conditions and other geographic variables.

Geographic unit of analysis. As the unit of analysis, I choose the 1-by-1 kilometer grid cell level. The cells are delineated using the European cartography standard INSPIRE.

[3] The Climate Act specifies only the wind energy capacity in 2030, not the number of wind turbines. To translate capacity into the number of turbines needed, I assume that capacity per turbine grows linear (as it did between 2000 and 2022) and that Germany adds an equal number of wind turbines each year.

Compared to administrative units such as municipalities, the grid cells are considerably finer and have consistent shape and size. For the analysis this is important because wind turbines are likely to have local effects and may lead to substantial within-municipality residential sorting across neighborhoods that an analysis at a coarser level would mask.

Sample. The base sample consists of 133,339 grid cells in contiguous Germany that have positive residential or workplace population.[4] 92 percent of cells have positive population, 49 percent have positive employment, and 45 percent have both positive population and employment. I refer to all cells as neighborhoods.

Wind Turbines. The data on onshore wind turbines stems from Eichhorn et al. (2019) who collect and systematize the information from the authorities of the federal states in Germany. Most importantly, the data comes with the coordinates and the construction year of each turbine. Since the data only includes wind turbines built until 2015, for the years 2016 and 2017 I complement the data with information from the wind energy intelligence company The Wind Power. Figure 3 shows the distribution of wind turbines in Germany in 2000, the start of my sample period, and in 2017, the end of the sample period.

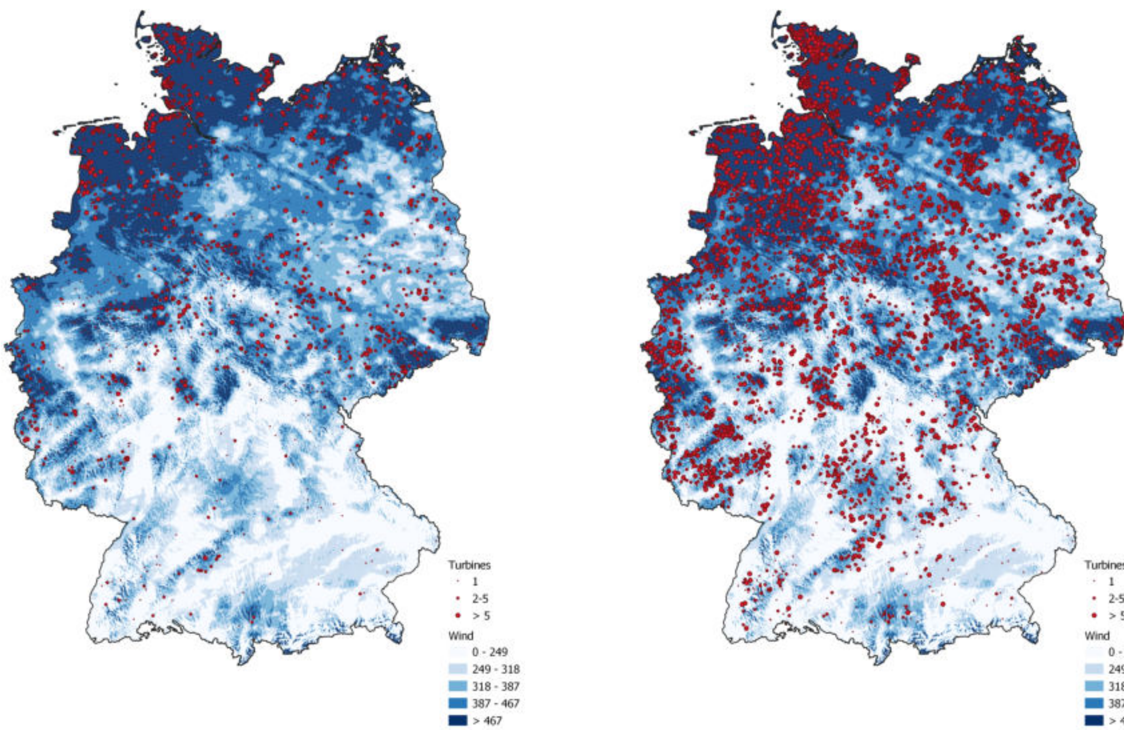
House prices. I construct a quality-adjusted house price index using object level data from Germany's largest online real estate platform ImmobilienScout24. The data has been previously used in Economics research; a detailed description can be found in Schaffner (2020). Due to the website's start year, the data is only available from 2007. Over the sample period, the website listed more than 35 million houses and flats. 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. To obtain the quality-adjusted house price index, I residualize the rental price per square meter on a flexible function of these characteristics, and calculate the average residual house price in the neighborhood. Since the number of listings each year varies especially for smaller neighborhoods, I take a three year rolling window average.

Residents, workers, and wages. The data on the residential and workplace population as well as workers' wages in each neighborhood stems from the GridAB data provided by the Institute for Employment Research (IAB). The GridAB draws on the Integrated Employment Biographies (IEB), individual level social security data that cover close to the universe of

[4] Residential and workplace population are measured from the Integrated Employment Biographies. The data includes the universe of all employees in Germany, excluding civil servants and self-employed. To preserve anonymity of the population in smaller cells, the base sample only includes cells with at least ten residents or ten employees in all years between 2000 and 2017. Nevertheless, in 2017 the base sample captures 98.4 percent of total residential population and 97.8 percent of total workplace population.

Figure 3: *Wind Turbines*

(a) 2000 (b) 2017



Notes: Figure 3 shows the distribution of wind turbines installed in 2000 and 2017, respectively. For reference, the wind power density (in kg/s^3) at 100 meters above ground is shown in blue. Wind power density is grouped into quintiles. Dark blue indicates strong winds, light blue indicates weak winds. Source: Own calculation using data on wind turbines from The Wind Power and data on wind power density from the Global Wind Atlas.

the German workforce, including approximately 40 million individuals every year.[5]

A neighborhood's residential population is measured as the number of individuals in the IEB that have their residential address in the neighborhood. Conversely, the workplace population is measured as the number of individuals whose job address is located in the neighborhood. Finally, I calculate wages as the average wage among all full-time workers (not residents) in a neighborhood. To measure residential sorting, I obtain all variables separately for college-educated residents and workers and those without college education. Following the literature on residential sorting (for example Diamond, 2016), I refer to college-

[5]The data includes regular (full- or parttime) employees whose jobs are subject to social security contributions, marginal employees whose jobs are not subject to social security contributions, individuals who report seeking employment or who receive unemployment benefits. It excludes civil servants, self-employed, and individuals outside of the labor force.

educated as high-skilled and to individuals without college education as low-skilled.

Instrument data. To construct the instrument, I collect information on wind power density at 50, 100, and 150 meters above ground from the Global Wind Atlas. I also obtain information on the average turbine height for a wind turbine installed in a given year from the company The Wind Power. Moreover, I collect geographic information on land use from the German Environment Agency and on natural reserves from the German Federal Agency for Nature Conservation.

4 Estimating the Impact of Turbines on Neighborhoods

4.1 Empirical Strategy

The goal of this section is to estimate the impact of wind turbine development on housing prices and the residential composition of the surrounding neighborhood. Since households may face short-term migration frictions that prevent them from reacting immediately to the change in residential amenities, I focus on the long-term effects of turbine development. Due to data availability, I use changes between 2007 and 2017 for house prices, and changes between 2000 and 2017 for residential sorting and all other outcomes. Specifically, I am interested in a causal estimate of β in the following specification.

$$\Delta y_n = \beta \cdot \Delta T_n + \varepsilon_n \tag{1}$$

Where Δy_n are long-run changes in the outcome variable, for example in house prices, in neighborhood n and ΔT_n is the number of wind turbines constructed over the same period. Following previous studies that suggest that the cost of wind turbines, as measured by house price changes, drops sharply at two to three kilometers (Gibbons, 2015, Dröes and Koster, 2016, Sunak and Madlener, 2016), throughout the paper ΔT_n measures turbine construction within three kilometers of neighborhood n.

The identification challenge in Equation (1) is that wind turbine development may be correlated with unobserved trends in the outcome variable ε_n. On the demand side, politicians may preferentially allow wind turbine development in regions where they expect electricity demand to grow. On the supply side, wind turbine developers may avoid regions in which they expect strong resistance from residents. To overcome the identification challenge, I develop an instrumental variable (IV) strategy that exploits technology-induced changes in wind turbine development that are arguably unrelated to confounding demand and supply factors.

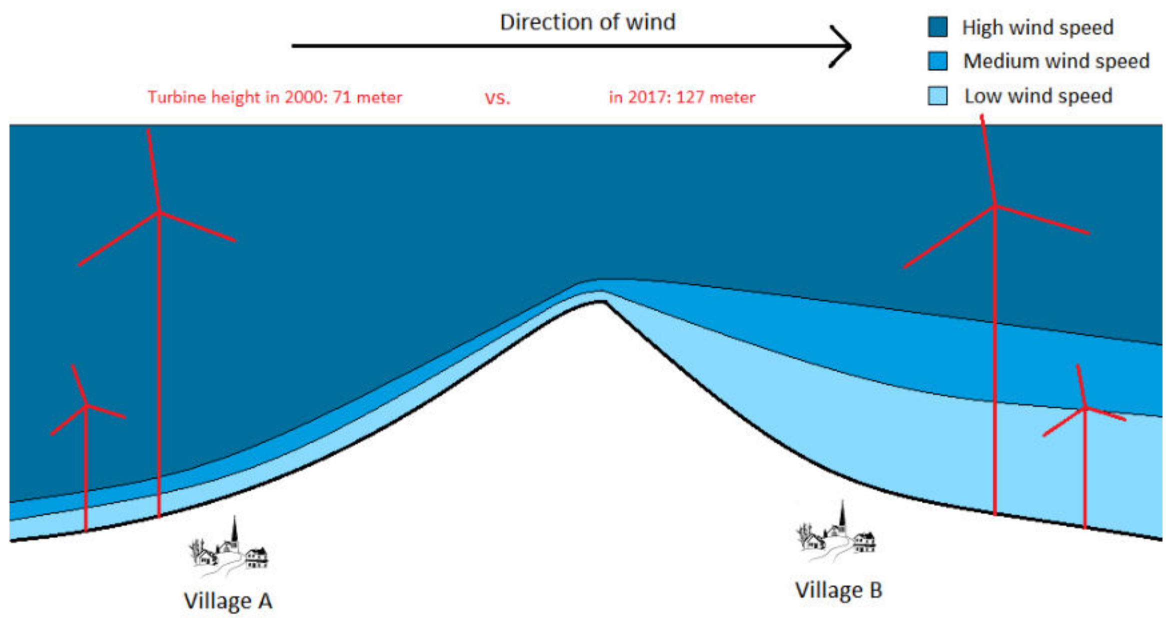
Instrumental variable strategy. The electricity production of a wind turbine depends on local wind conditions, specifically the local wind power density. Local wind conditions do not vary decisively over the years, and in my data they are cross-sectionally fixed. However, the effective wind power density that turbines reap has changed considerably due to technology-induced increases in wind turbine height. Between 2000 and 2017, the average height of wind turbines has increased from 71 to 127 meters. Wind conditions are better high above the ground, and for the average neighborhood in Germany, a typical[6] turbine installed in 2017 would reap a wind power density that is 59 percent higher than a wind turbine installed in 2000, simply due to the height increase.

I exploit that the common technology change has made some neighborhoods more attractive for wind energy than others because their vertical wind shear - how much cross-sectional wind power density increases with turbine height above ground - is larger. The variation in wind shear that I use arises from the direction of the wind and its interaction with elements of rugged terrain, for example hills, that block the wind at lower heights and lead to larger vertical wind shear up to ten kilometers downwind of the rugged terrain (Global Wind Atlas, 2023). Figure 4 illustrates the idea for two hypothetical neighborhoods A and B that are separated by a hill. In the example, wind flows from West to East. The hill blocks the wind at lower heights, leading to a higher vertical wind shear in neighborhood B on the east side of the hill. As a consequence, wind turbine development becomes more attractive in village B over time, relative to village A.

Construction of the instrument. I obtain cross-sectional data on wind power density from the Global Wind Atlas. The data is available at three heights, at 50, 100, and 150 metersabove ground. For heights in between, I calculate wind power density by linear interpolation. Since I want to predict wind turbine development within three kilometers of a neighborhood, I also calculate the average wind power density within three kilometers. Then, I calculate the effective change in wind power density between 2000 and 2017 as the change in wind power density between height 71 meter, the average height of a turbine installed in 2000, and height 127 meter, the average height of a turbine installed in 2017.

[6] I define a "typical" turbine in a year as one that is as tall as the average turbine installed in the year. Figure A.3 in the Appendix plots the distribution of turbine heights in 2000 and 2017 and confirms that a

Figure 4: *Schematic Illustration of IV Strategy*



Notes: Figure 4 illustrates the idea of the IV strategy. It depicts two villages A and B, separated by a hill. In the hypothetical example, wind flows from West to East. The wind is disrupted by the hill which leads to higher vertical wind shear on the right side of the hill. Since wind turbines become taller over time - from 71 meters in 2000 to 127 meters in 2017 - effective wind power density accessible for a turbine installed in a given year increases over time. As a consequence, wind turbine development becomes more attractive in village B over time, relative to village A.

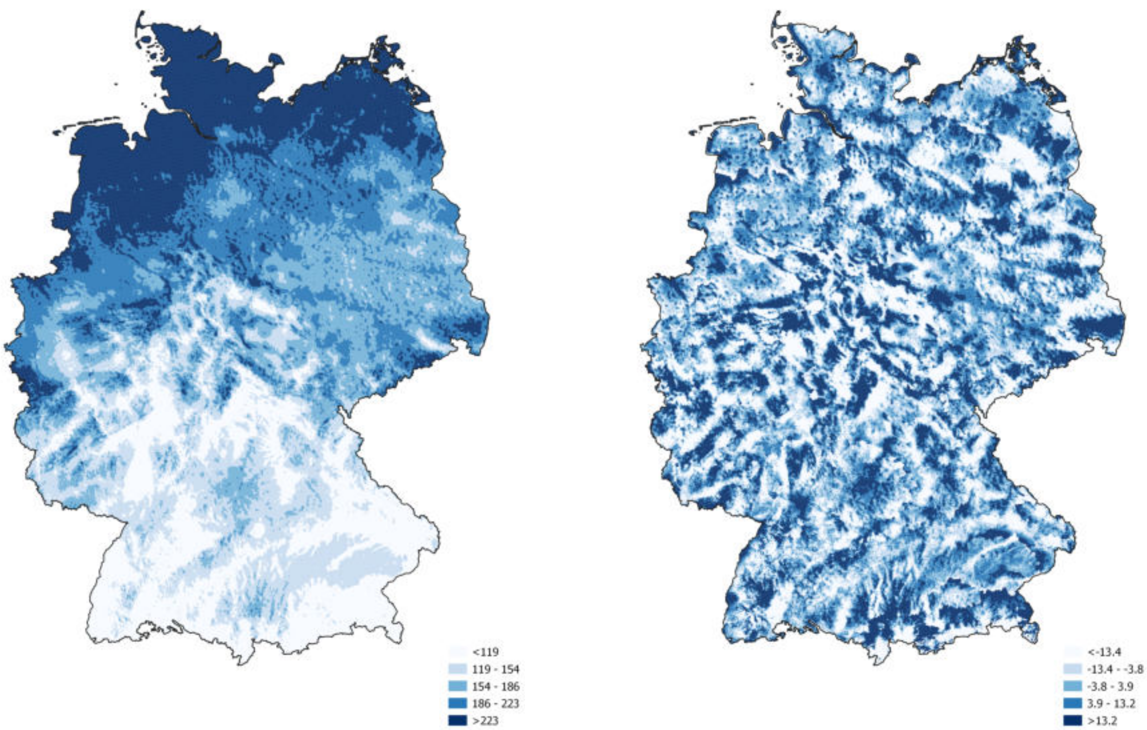
Figure 5 shows the resulting change in effective wind power density across all 1-by-1 kilometer grid cells in Germany. Panel 5a reports the raw variation, Panel 5b reports the residual variation that remains after controlling for district fixed effects as well as the neighborhood's altitude, ruggedness, slope, and the share of land used for buildings, agriculture, forests, and water bodies. My empirical specification uses the residual variation. Importantly, the district fixed effects ensure that I compare only neighborhoods relatively close to each other, and the geographic controls ensure that I remove any variation in vertical wind shear that arises from the neighborhood's geography. The identifying variation, thus, comes from larger scale wind patterns and their interaction with topography upwind of the neighborhood.

Secondly, I construct the share of land within three kilometers of each neighborhood that is available for wind turbine development. I use this variation as a placebo check as changes in wind power density should not affect wind turbine development in places where no turbines can be constructed, for example a densely built city like Berlin. Moreover, I

turbine of average height indeed represents a typical turbine.

Figure 5: *Change in Wind Power Density, 2000-2017*

(a) Raw Variation (b) Residual Variation



Notes: Figure 5 shows the effective change in wind power density (in kg/s^3) between 2000 and 2017 that occurs due to increases in turbine heights. Wind power density in 2000 is measured as cross-sectional wind power density at 71 meters, the average height of turbines installed in 2000. Analogously, wind power density in 2017 is measured at 127 meters, the average height of turbines installed in 2017. Panel 5a shows the raw variation. Panel 5b shows the residual variation in wind power density changes that remains after controlling for district fixed effects as well as geographic characteristics including altitude, terrain ruggedness, slope and the share of land that is covered by buildings, agriculture, forests, and water. The variation is grouped into quintiles. Dark blue indicates large changes, light blue indicates small changes. Source: Own calculation based on wind power density data from the Global Wind Atlas.

interact changes in wind power density with the share of land available for wind energy as it increases the precision of the IV estimates.

To construct the share of land available, I obtain high-resolution data on built areas and water bodies, where turbine construction is physically impossible, and on conservation zones that forbid wind turbine development. I also exclude 400 metersbands around urban areas accounting for the legally mandated minimum distance between residential areas and wind turbine development. Section B.1 in the Appendix provides additional details.

IV specification. I estimate the following specification,

$$\Delta y_n = \beta \cdot \Delta\hat{T}_n + \gamma X_n + \delta_{d(n)} + \varepsilon_n \tag{2}$$

where Δy_n is a change in the outcome variable between 2000 and 2017, $\Delta\hat{T}_n$ is the number of wind turbines constructed between 2000 and 2017 as predicted from the corresponding first-stage regression, X_n is a vector of geographic controls including altitude, ruggedness, slope, and the share of land used for built areas, agriculture, forests, and water bodies, and $\delta_{d(n)}$ denotes district fixed effects. I instrument $\Delta\hat{T}_n$ with changes in wind power density ΔW_n between 2000 and 2017, and depending on the specification, also with the interaction of changes in wind power density with the share of land that is available for wind turbine development $\Delta W_n S_n$.[7]

The parameter of interest is β, the long-run effect of wind turbine development on the outcome. The identifying assumption is $E[\varepsilon_n|\Delta W_n, \Delta W_n S_n, X_n, \delta_{d(n)}] = 0$ which holds if changes in wind power density are quasi-randomnly assigned, conditional on all control variables. Since the estimation equation is in long differences, any (unobserved) time-invariant variation is already differenced-out, so that any correlation of changes in wind power density with variation in geography, invariant wind conditions, or cross-sectional socio-economic characteristics does not affect the consistency of the estimate. Moreover, I include district fixed effects, which take out any changes in the outcome variable that are common in the district and ensure that, effectively, I compare neighborhoods that are close[8] to each other. Furthermore, I control for all the local geographic characteristics that, according to the data provider (Global Wind Atlas, 2023), may affect vertical wind shear. I argue that the remaining variation comes exclusively from the interaction of wind patterns and terrain ruggedness outside of the neighborhood as depicted in Figure 4, and is as-good-as-random as supported by the evidence in Figure 5. Finally, in Section 4.2, I show that changes in wind power density affect all outcome variables only in areas where wind turbine development is possible, lending further support to the identifying assumption.

To account for spatial correlation in the error term, I cluster the standard errors at the district level in all specifications.

[7] Due to data availability, in regressions that include changes in house prices as the dependent variable, all changes - in the outcome, in turbine construction, and in the instrument - are measured between 2007 and 2017.

[8] The average district in Germany has 892 square kilometers, a bit under a third of the size of a US county.

4.2 Main Results

First-stage. Table 1 reports the first-stage results. Column (1) regresses wind turbine construction between 2000 and 2017 on the change in wind power density over the same period. The coefficient indicates that changes in wind power density are a strong and significant predictor of turbine development. Moving a neighborhood from the 25th to the 75th percentile in the distribution of wind power density changes at baseline, i.e. from 205 to 347 kg/s^3 increases the expected number of turbines constructed within three kilometers of the neighborhood by 2.5 wind turbines.

Column (2) regresses wind turbine construction on the change in wind power density and the interaction of wind power density with the share of land that is available for wind turbine construction. The results indicate that changes in wind power density affect turbine construction only in neighborhoods that have land available. For neighborhoods that are in the urban core or surrounded by natural parks, on the other hand, changes in wind power density do not significantly affect turbine construction. Moving a neighborhood from the 25th to the 75th percentile in the distribution of wind power density changes increases wind turbine development by 0.13 turbines if there is no land available and by 3.3 turbines if all land around the neighborhood is available.

House prices. Table 2 reports the effect of wind turbine development on house prices. Panel A shows the intention-to-treat effects, regressing changes in log house prices on changes in wind power density and its interaction with the share of land available for turbine construction. Panel B shows the IV effects, regressing changes in log house prices on wind turbine development. Since house prices are only available from 2007, I measure changes in house prices, wind power density and wind turbine development between 2007 and 2017. Columns (1) and (2) report the effects using only wind power density as the instrument, Columns (3) and (4) include wind power density and the interaction with land available as instruments.

The intention-to-treat effects in Panel A indicate that changes in wind potential are associated with a decrease in house prices. When including wind power density and its interaction with land available, the entire negative effect is picked up by the interaction coefficient. This result is consistent with the first-stage results in Table 1 which indicates that changes in wind power density strongly predict turbine development only in neighborhoods with potential areas for turbine development. In neighborhoods that have no area around them that can be used for turbine development, changes in wind power density do not

Table 1: *First-Stage*

	(1)	(2)
	Δ *Wind Turbines*	
Δ Wind power density	1.76***	0.09
	(0.24)	(0.21)
Δ Wind power density		2.21***
x Share land available		(0.17)
District FE	y	y
Geographic controls	y	y
Observations	133,339	133,339

Notes: Table 1 shows the first-stage results. The dependent variable is changes in wind turbines between 2000 and 2017. The independent variable is changes in wind power density (in 100 kg/s^3) induced by changes in wind turbine heights between 2000 and 2017 (in both columns) and the interaction of changes in wind power density with the share of land within three kilometers that is available for wind turbine construction (only in the second column). All regressions are at the neighborhood level and control for district fixed effects as well as altitude, terrain ruggedness, slope and the share of land that is covered by buildings, agriculture, forests, and water. The standard errors are clustered at the level of 401 districts.

predict turbine development or decreases in house prices. These results lend support to the identifying assumption that changes in wind power density are unrelated to unobserved trends in house prices.

The IV estimates in Panel B show that the effect is robust across specifications. My preferred specification, reported in Column (3), indicates that each additional wind turbine within three kilometers decreases house prices by 2.1 percent. The result are broadly in line with the previous literature. Gibbons (2015) finds that visible wind turbines reduce house prices by 5-6 percent within two kilometers, and by 2 percent between two and four kilometers. Dröes and Koster (2016) find that wind turbines within two kilometers reduce house prices by 1.4 percent. However, their analysis focuses on an earlier period in which the average wind turbine was only 60 metershigh while wind turbines in my sample are on average 100 meters high. For wind turbines larger than 100 meter, they find that house prices decrease by 3.7 percent.

Residential sorting. Table 3 reports the effect of wind turbine development on residential sorting. The outcome variable is the change in the share of high-skilled residents between 2000 and 2017. High-skilled residents are defined as individuals with college education. The intention-to-treat estimates indicate that changes in wind power density decrease the share

Table 2: *Effects of Turbines on House Prices*

	(1)	(2)	(3)	(4)
	Δ Log House Prices, 2007-2017			
Panel A: Intention-To-Treat				
Δ Wind power density	-0.031*	-0.028	-0.006	-0.006
	(0.018)	(0.018)	(0.019)	(0.019)
Δ Wind power density			-0.032***	-0.029***
x Share land available			(0.008)	(0.008)
Panel B: IV Estimates				
Δ Wind turbines	-0.024*	-0.022	-0.021***	-0.020***
	(0.014)	(0.014)	(0.005)	(0.005)
Effective F-Statistic	34	33	66	64
District fixed effects	y	y	y	y
Geographic controls	y	y	y	y
Socioeconomic controls		y		y
Observations	79,573	79,573	79,573	79,573

Notes: Table 2 shows the estimates for the intention-to-treat and IV specification corresponding to Equation (2). Panel A shows the intention-to-treat effect, Panel B the IV effect. The dependent variable are log changes in house prices between 2007 and 2017. The independent variables are changes in wind power density and its interaction with the share of land within three kilometers that is available for wind turbine construction in Panel A, and the instrumented change in wind turbines in Panel B, all between 2007 and 2017. The Effective F-Statistic is calculated following Montiel and Pflueger (2013). Geographic controls include altitude, terrain ruggedness, slope and the share of land that is covered by buildings, agriculture, forests, and water. Socioeconomic controls include population density, income per capita and the share of high-skilled residents in 2000. The standard errors are clustered at the level of 401 districts.

of residents that is high-skilled. As for house prices, the effect appears only in neighborhoods with sufficient area for turbine development.

The IV estimates in my preferred specification in Column (3) suggest that each additional wind turbine within three kilometers decreases the share of residents by 0.6 percentage points. Among neighborhoods that see wind turbine development between 2000 and 2017, the median neighborhood receives three wind turbines, implying a cumulative effect of 1.8 percentage points.

Table 3: *Effects of Turbines on Residential Sorting*

	(1)	(2)	(3)	(4)
	Δ Share High-Skilled Residents, 2000-2017			
Panel A: Intention-To-Treat				
Δ Wind power density	-0.011***	-0.013***	-0.002	-0.0003
	(0.002)	(0.003)	(0.002)	(0.003)
Δ Wind power density			-0.012***	-0.017***
x Share land available			(0.001)	(0.001)
Panel B: IV Estimates				
Δ Wind turbines	-0.007***	-0.007***	-0.006***	-0.008***
	(0.002)	(0.002)	(0.001)	(0.001)
Effective F-Statistic	52	51	134	131
District fixed effects	y	y	y	y
Geographic controls	y	y	y	y
Socioeconomic controls		y		y
Observations	128,209	128,209	128,209	128,209

Notes: Table 3 shows the estimates for the intention-to-treat and IV specification corresponding to Equation (2). Panel A shows the intention-to-treat effect, Panel B the IV effect. The dependent variable are changes in the share of high-skilled residents between 2000 and 2017. The independent variables are changes in wind power density and its interaction with the share of land within three kilometers that is available for wind turbine construction in Panel A, and the instrumented change in wind turbines in Panel B, all between 2000 and 2017. The Effective F-Statistic is calculated following Montiel and Pflueger (2013). Geographic controls include altitude, terrain ruggedness, slope and the share of land that is covered by buildings, agriculture, forests, and water. Socioeconomic controls include population density, income per capita and the share of high-skilled residents in 2000. The standard errors are clustered at the level of 401 districts.

4.3 Further Outcomes and Robustness

High-skilled emigration drives sorting. The main results show that wind turbine development decreases house prices and leads to a reduction in the share of high-skilled residents. Columns (3) and (4) in Table 4 suggest that (net) emigration of high-skilled residents drives changes in the residential composition. Specifically, each wind turbine decreases the number of high-skilled residents by 1.9 percent while there is no effect on low-skilled residents. For the median neighborhood that sees construction of three wind turbines, this implies a total effect of 5.7 percent.

Downstream effects on the labor market. The emigration of high-skilled residents affects employment. Columns (5) and (6) in Table 4 show that each additional wind turbine decreases high-skilled and low-skilled employment in the neighborhood by 4.7 and 2.2 percent, respectively. Since the sample of residential and workplace neighborhoods differ considerably, the comparison of residential and workplace sorting is not straightforward. Taken at face value, however, the results suggest that the emigration of high-skilled residents causes more than a one-for-one decrease in high-skilled workers. This is consistent with the literature on agglomeration economics that shows that high-skilled workers increase the productivity of other high-skilled workers around them (Moretti, 2004, Diamond, 2016) as well as the estimation of the labor demand function in Section 6, Table 8. Secondly, the results suggest that low-skilled employment falls even though low-skilled residential population stays constant which is consistent with positive spillovers of high-skilled workers on low-skilled workers as well as with complementarity between the two.

Finally, I find that wages increase in respond to lower employment. As Columns (7) and (8) show that each additional wind turbine increases high-skilled and low-skilled wages by 1.4 and 0.6 percent, respectively. Wage increases are larger for high-skilled, consistent with the fact that high-skilled employment falls more than low-skilled employment. Overall, the results support the interpretation that wind turbines make neighborhoods less attractive for residents which results in a negative labor supply shock while ruling out alternative interpretations. For example, if wind turbines made neighborhoods more productive we should observe rising wages and rising employment. The results are also consistent with Fabra et al. (2023) who find limited employment effects of wind energy infrastructure.

Robustness. Finally, Table A.1 in the Appendix reports additional robustness checks for the two main results on house prices and residential sorting. Column (1) repeats the base specification, Column (2) repeats the augmented base specification that additionally controls for population density, income per capita, and the share of high-skilled residents in 2000. Since the specification is in (long) differences, including these variables controls for trends in the outcome variable in less dense, poorer, or less educated neighborhoods. Thus, the wind turbine effect is not driven by initial differences in the three socioeconomic indicators. Column (3) controls for the demography of the residential population in 2000, including the share of female residents, the share of residents aged 15-25, 26-35, 36-45, 46-55, and above 55, and the share of foreign residents. Initial differences in demography do not drive the wind turbine results. Column (4) controls for the industrial structure in and around the neighborhood. Specifically, I control for the share of residents that work in each of the 21 industries in the WZ 2008 classification. The results do not change significantly.

Table 4: *Effects on Population, Employment, and Wages*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Δ Log	Δ Log Residents		Δ Log Workers		Δ Log Wages	
	Δ Turbines	House Prices	High-Skilled	Low-Skilled	High-Skilled	Low-Skilled	High-Skilled	Low-Skilled
Panel A: Intention-To-Treat								
Δ Wind power density	0.09	-0.006	0.005	0.027*	-0.036	0.008	-0.029	0.007
	(0.21)	(0.019)	(0.020)	(0.015)	(0.041)	(0.031)	(0.018)	(0.007)
Δ Wind power density x Available Land	2.21***	-0.032***	-0.041***	0.004	-0.089***	-0.045**	0.029***	0.010**
	(0.17)	(0.008)	(0.011)	(0.007)	(0.021)	(0.018)	(0.009)	(0.004)
Panel B: IV								
Δ Wind turbines		-0.021***	-0.019***	0.004	-0.047***	-0.022***	0.014***	0.006***
		(0.005)	(0.005)	(0.003)	(0.011)	(0.008)	(0.004)	(0.002)
Effective F		64	162	162	141	141	122	122
District FE	y	y	y	y	y	y	y	y
Geographic controls	y	y	y	y	y	y	y	y
Observations	133,339	79,573	102,597	102,597	43,748	43,748	33,419	33,419
Neighborhoods	All	House Data	Residential	Residential	Workplace	Workplace	Wage Data	Wage Data

Notes: Table 4 shows the estimates for the intention-to-treat and IV specification corresponding to Equation (2). Panel A shows the intention-to-treat effect, Panel B the IV effect. Each column shows a regression with a different outcome. Changes in outcomes are measured between 2000 and 2017, except for housing prices which due to data availability are measured between 2007 and 2017. The independent variables are changes in wind power density and its interaction with the share of land within three kilometers that is available for wind turbine construction in Panel A, and the instrumented change in wind turbines in Panel B. The Effective F-Statistic is calculated following Montiel and Pflueger (2013). Geographic controls include altitude, terrain ruggedness, slope and the share of land that is covered by buildings, agriculture, forests, and water. The standard errors are clustered at the level of 401 districts.

Column (5) adds wind power density in 2000. With this column, I confirm that changes in wind power density due to technological advances drive the result, not differences in initial wind conditions. Column (6) adds the longitude and latitude of the neighborhood, clarifying that the changes in outcomes are not driven by the location of the neighborhood within the district, for example because neighborhoods closer to the coast in Northern Germany experience different changes in wind power density and different changes in the outcome variable.

Finally, Columns (7) and (8) interrogate the validity of the Stable Unit Treatment Value Assumption (SUTVA). There are two potential concerns. First, how many residents leave when turbines are built depends on their outside option. If there are many turbines built in the whole region fewer people emigrate, and from the observed migration and house price responses, we would underestimate residents' preferences against wind turbines, see Borusyak et al. (2023) for a detailed explanation of the concern. Second, the reduced form compares neighborhoods that experience turbine construction with neighborhoods that remain unspoiled. The latter serve as a control group but as residents leave wind turbine neighborhoods and settle in unspoiled neighborhoods, the control group, too, maybe affected, potentially biasing the results upwards.

To rule out both concerns, I include a measure of the aggregate shock that surrounding neighborhoods experience as a control variable. Following Borusyak et al. (2023), the aggregate shock weights shocks in surrounding neighborhoods by their population as well as the distance.[9] Column (7) includes changes in wind power density and its interaction with land available aggregated over surrounding neighborhoods. Column (8) includes predicted wind turbines based on both instruments aggregated over surrounding neighborhood. Compared to the base specification, the coefficient is virtually unchanged. This lends support to the assumption that potential violations of SUTVA do not bias the results. Intuitively, under both violations of SUTVA discussed above, being surrounded by neighborhoods that are also treated induces bias in the estimates. Under concern one, it leads to worse outside options and less emigration. Under concern two, it leads to a higher ratio of treated to control units, inducing larger spillovers on the control group and a larger bias. By controlling for the prevalence of shocks in surrounding neighborhoods, I account for these two alternative stories, confirming that the results are not driven by SUTVA violations.

[9]Specifically, the shock is $\hat{z}_{-n}^{\text{dist}} \equiv (\sum_{k \neq n} \frac{R_k}{(\text{ dist }_{nk})^{\varsigma}} \widehat{z}_k) / (\sum_{k \neq n} \frac{R_k}{(\text{ dist }_{nk})^{\varsigma}})$, $\widehat{z}_k$ is the shock, for example changes in wind power density, or predicted wind turbines, R_k is the number of residents in k, $dist_{nk}$ is the distance between n and k and ς is the elasticity of migration with respect to distance which I set as -1.25 as Borusyak et al. (2023).

5 Using Theory to Infer the Implied Amenity Cost

Section 4 shows that wind turbine development decreases house prices and leads to emigration of high-skilled residents. Implicitly these results suggest that wind turbine development makes neighborhoods less attractive, especially for high-skilled residents. In Section 5, I use a revealed preference argument to infer how much residents would be willing to pay to avoid wind turbine development and the associated amenity cost. Specifically, I show location choice models in the spirit of the Rosen-Roback framework (Rosen, 1974, Roback, 1982) and the standard urban quantitative spatial model (Ahlfeldt et al., 2015) admit a mapping between changes in house prices, population, and (model-implied) income and changes in amenities, and I combine the mapping and the reduced form strategy to estimate the impact of wind turbines on amenities. For ease of exposition, I develop the amenity mapping for the Rosen-Roback framework and discuss how it generalizes in the case of Ahlfeldt et al. (2015) at the end of the section.

5.1 Mapping Between Reduced Form Effects and Amenity Costs

Setup. The economy is populated by L workers. Each worker ω is high-skilled or low-skilled. Variables and parameters that differ by type are denoted with a superscript $\theta \in \{h, l\}$. The total measure of high- and low-skilled workers in the economy is L^h and L^l, respectively. There are N neighborhoods in the economy, denoted by subscript n.

Utility. Workers derive utility from non-tradable housing h^θ with Cobb-Douglas weight α^θ and from a freely tradable consumption good c^θ. I denote Q_n the price of housing and normalize the price of consumption to one. Workers also derive utility from the amenities in their neighborhood A_n^θ and an individual location-specific taste shock $\varepsilon_n^\theta(\omega)$. Workers inelastically supply one unit of labor and earn wage w_n^θ. They choose housing and consumption to maximize their utility.

$$\max_{h,c} u_n^\theta(\omega) = A_n^\theta \cdot \left(h^\theta\right)^{\alpha^\theta} \cdot \left(c^\theta\right)^{1-\alpha^\theta} \cdot \varepsilon_n(\omega) \qquad \text{s.t.} \qquad Q_n \cdot h^\theta + c^\theta = w_n^\theta \tag{3}$$

Location choice. The maximization yields the workers' indirect utility of living in neighborhood n which depends on the local amenities, wages, and housing costs, as well as the taste shock.

$$v_n^\theta(\omega) = \frac{A_n^\theta w_n^\theta}{Q_n^{\alpha^\theta}} \varepsilon_n^\theta(\omega) \tag{4}$$

Workers choose to live and work in the neighborhood that maximizes their utility. I follow the quantitative spatial literature and assume that the taste shock is drawn from a Frechet distribution with shape parameter κ^θ, that is $\varepsilon_n^\theta(\omega) \sim F^\theta(\varepsilon) = exp(-\varepsilon^{-\kappa^\theta})$. Under this assumption, one can show that the share of workers that choose to live in neighborhood n is

$$\lambda_n^\theta = \frac{\left(\frac{A_n^\theta w_n^\theta}{Q_n^{\alpha^\theta}}\right)^{\kappa^\theta}}{\sum_{r=1}^N \left(\frac{A_r^\theta w_r^\theta}{Q_r^{\alpha^\theta}}\right)^{\kappa^\theta}} \tag{5}$$

and the number of residents in a neighborhood is $R_n^\theta = L^\theta \cdot \lambda_n^\theta$. Solving for amenities and taking logs, one can derive the mapping between amenities, population, house prices, wages, and the two parameters κ^θ and α^θ. Specifically,

$$ln\left(A_n^\theta\right) = \frac{1}{\kappa^\theta} \cdot ln\left(R_n^\theta\right) + \alpha^\theta \cdot ln\left(Q_n\right) - ln\left(w_n^\theta\right) + c^\theta \tag{6}$$

where I denote the constant c^θ short for the denominator sum and total population.[10]

Interpretation. Models in the spirit of the Rosen-Roback framework and Ahlfeldt et al. (2015) use amenities, which are unobserved, as a fundamental characteristic of a neighborhood that rationalizes the distribution of population across space. Intuitively, if many residents live in a neighborhood despite high house prices and low wages, by revealed preference, there must be something in the neighborhood that makes it attractive, and the models use amenities a summary statistic for that attractiveness, without having to take a stance what exactly makes the neighborhood attractive.

To understand the welfare costs of wind turbines, the revealed preference summary statistic is particularly useful. First, wind turbines may affect the quality of a neighborhood through various channels, for example, through their visual impact on the landscape, their effect on noise pollution, or their (perceived) health costs for residents. Second, a change in

[10] Formally, $c^\theta \equiv 1/\kappa^\theta (ln(\sum_{r=1}^N \left(\frac{A_r^\theta w_r^\theta}{Q_r^{\alpha^\theta}}\right)^{\kappa^\theta}) - ln(L^\theta))$.

amenities has a clear economic interpretation. Amenities enter the utility multiplicatively. A one percent decrease in amenities is equivalent to a one percent decrease in income, which helps to interpret the magnitudes of an amenity change.

Generalization. In Appendix C, I show that the amenity mapping generalizes to the location choice problem in Ahlfeldt et al. (2015), in which residents are allowed to choose a different residence and workplace, and to commute between the two. In the general case, the amenity mapping is almost unchanged. Specifically,

$$ln\left(A_n^\theta\right) = \frac{1}{\kappa^\theta} \cdot ln\left(R_n^\theta\right) + \alpha^\theta \cdot ln\left(Q_n\right) - ln\left(W_n^\theta\right) + c^\theta \tag{7}$$

where the key change is that model-consistent income in the residential neighborhood W_n^θ now depends on the wages in surrounding workplaces i, weighted by the commuting cost d_{ni}^θ. Formally, $W_n^\theta \equiv \left(\sum_{i=1}^N \left(w_i^\theta / d_{ni}^\theta\right)^{\kappa^\theta}\right)^{1/\kappa^\theta}$. In the case of the Rosen-Roback framework, where commuting costs are one for $n = i$ and infinite for $n \neq i$, commuting cost-weighted access to wages W_n^θ collapses to income in the neighborhood w_n^θ. I show that using either approach does not change the estimated amenity costs of wind turbines (in Section 5.2), and develop and estimate the quantitative spatial model (in Section 6) allowing residents to commute between the different neighborhoods at 1-by-1 kilometer resolution.

5.2 Estimation of Amenity Costs

Next, I use the amenity mapping and my IV strategy to estimate how much wind turbine development decreases amenities, and thus welfare. Given Equation (6), estimating the effect of wind turbine development on amenities requires information on population, house prices, and wages (which are observed in the data) as well as the parameters α^θ, and κ^θ.

Parameters. I estimate α^θ, the income share that residents spend on housing, from the expenditure survey in the German Microcensus in 2018. I find α^θ to be 0.25 for low-skilled and 0.23 for high-skilled residents. Secondly, I calibrate the Frechet parameter κ^θ to be 4.56, drawing on a recent estimate for Germany by Krebs and Pflüger (2023). Choosing a uniform value for high- and low-skilled residents has the obvious disadvantage that it ignores (potential) differences in labor mobility across skill types. Nevertheless, I find that the different strategies to estimate κ^θ that are common in the literature (Ahlfeldt et al., 2015, Monte et al., 2018) yield very different results in my context. In light of this, I choose the value of 4.56, which conveniently lies between the value 3.3 estimated by Monte et al. (2018) for the US, and the value 6.83 estimated by Ahlfeldt et al. (2015) for Berlin, and, for transparency, report how the estimated wind turbine preference of each type changes as I vary the parameter.

Estimation. Since I am interested in the long-run impact of wind turbines on amenities, I take long-differences of Equation (6).

$$\Delta ln\left(A_n^\theta\right) = \frac{1}{\kappa^\theta} \cdot \Delta ln\left(R_n^\theta\right) + \alpha^\theta \cdot \Delta ln\left(Q_n\right) - \Delta ln\left(w_n^\theta\right) + \Delta c^\theta \tag{8}$$

Because the data on house prices is only available from 2007, I take long-differences between 2007 and 2017. Then, I calculate changes in amenities given changes in population, house prices, and wages, and the estimated parameters, and I regress the resulting log amenities on the predicted number of wind turbines using the IV strategy in Equation (2) discussed in Section 4.[11]

Main results. Table 5 shows the results. Panel A reports the results for high-skilled, Panel B for low-skilled residents. As Column (1) reports, I find that each additional wind turbine within three kilometers of a neighborhood decreases amenities by 1.4 percent for high-skilled and by 0.9 percent for low-skilled residents. For the median neighborhood affected by wind turbine development, the effects imply a total decrease of amenities by 4.2 percent for high-skilled and by 2.7 percent for low-skilled, respectively. Thus, the estimates indicate a strong average residential preference against local wind turbine development. The closest comparable paper in the literature, Brinkman and Lin (2022), shows that living directly next to a highway decreases amenities by 18 percent. The comparison suggests that wind turbines have a meaningful but reasonable negative effect on amenities.

To better understand the estimates, Columns (2), (3), and (4) report the separate effects of wind turbines on R_n^θ, Q_n, and w_n^θ, respectively. The columns highlight how much the individual effects on population, house prices, and wages contribute to the total amenity effect. First note, that the difference in the amenity effect for low- and high-skilled is mostly driven by skill-differences in population changes. Each turbine decreases high-skilled population by 3.2 percent and low-skilled population by an imprecisely estimated 0.7 percent. Weighted by $1/\kappa^\theta$ with κ^θ being 4.56 for both types, the contribution to the amenity effect

[11] Alternatively, one can use the IV strategy to estimate the reduced form impact of wind turbines on population, house prices, and wages, and weigh them by the parameters to get effect of wind turbines on amenities. Since (6) exactly decomposes amenities, both yield the same point estimates.

Table 5: *Effects of Turbines on Amenities*

	(1)	(2)	(3)	(4)
	Δ ln(A) Amenities	Δ ln(R) Population	Δ ln(Q) House Prices	Δ ln(W) Wages
Panel A: High-Skilled				
Δ Wind turbines	-0.014***	-0.032***	-0.021***	0.002**
	(0.003)	(0.008)	(0.005)	(0.001)
Panel B: Low-Skilled				
Δ Wind turbines	-0.009***	-0.007*	-0.021***	0.002
	(0.002)	(0.004)	(0.005)	(0.001)
Effective F-Statistic	77	77	77	77
District fixed effects	y	y	y	y
Geographic controls	y	y	y	y
Observations	76,497	76,497	76,497	76,497

Notes: Table 5 shows the estimates for the intention-to-treat and IV specification corresponding to Equation (2). The dependent variable are log changes in Amenities in Column (1), log changes in the number of residents in Column (2), log changes in house prices in Column (3), and log changes in wages in Column (4). Panel A reports all variables for high-skilled, Panel B reports all variables for low-skilled residents. Model-consistent amenities are calculated given Equation (6): $ln\left(A_n^\theta\right) = \frac{1}{\kappa^\theta} ln\left(R_n^\theta\right) + \alpha^\theta ln\left(Q_n\right) - ln\left(W_n^\theta\right) + c^\theta$ with κ^θ set to 4.56 for both types, and α^θ set to 0.23 for high-skilled and 0.25 for low-skilled. Weighting the estimates in Columns (2) to (4) as shown in the formula yields the estimate in Column (1), up to rounding errors. Changes in the dependent variable are measured between 2007 and 2017, due to data availability. The IV estimates use both instruments, changes in wind power density and its interaction with the share of land available for wind turbine development. The Effective F-Statistic is calculated following Montiel and Pflueger (2013). All regressions control for district fixed effects, altitude, terrain ruggedness, slope and the share of land that is covered by buildings, agriculture, forests, and water. Standard errors are clustered at the level of 401 districts.

is -0.70 percent for high-skilled and -0.15 percent for low-skilled. The estimate on house prices is not skill-specific but its weight, the share spent on housing is. Each wind turbine decreases house prices by 2.1 percent. High-skilled spend an income share of 0.23 on housing, low-skilled spend 0.25. As a consequence, the contribution of house prices is -0.48 percent for high-skilled and -0.53 percent for low-skilled. Finally, wages increase by 0.2 percent for both types. Summing these contributions, yields the (rounded) amenity cost of 1.4 percent for high-skilled and 0.9 for low-skilled.

6 Estimating Welfare Costs in General Equilibrium

Section 5 shows that wind turbine development has important first-order costs for residents. Since residents may adapt, for example through residential sorting as evidenced by the reduced form results, the first order costs are only indicative. In Section 6, I develop and estimate a quantitative spatial model that allows residents to adapt and labor and house markets to adjust in general equilibrium, as motivated by the reduced form results, and use it calculate the welfare costs of the turbine expansion in general equilibrium.

6.1 Model

Setup. The economy is populated by L workers. Each worker ω is high-skilled or low-skilled. Variables and parameters that differ by type are denoted with a superscript $\theta \in \{h, l\}$. The total measure of high- and low-skilled workers in the economy is L^h and L^l, respectively. There are N neighborhoods in the economy, denoted by subscript n and.

Residence and workplace choice. Individuals choose a residence neighborhood n and a workplace i given the amenities $A_n'^{\theta}$ in the residential neighborhood, the wages $w_i'^{\theta}$ paid at the workplace, the commuting cost d_{ni}^{θ} between n and i, house prices Q_n in the residence, and a residence-workplace pair specific individual taste shock $\varepsilon_{ni}^{\theta}(\omega)$.[12] Their corresponding indirect utility is

$$v_{ni}^{\theta}(\omega) = \frac{A_n'^{\theta} w_i'^{\theta}}{d_{ni}^{\theta} Q_n^{\alpha^{\theta}}} \varepsilon_{ni}^{\theta}(\omega) \tag{9}$$

Wind turbines affect amenities such that $A_n'^{\theta} = a_n'^{\theta} \cdot exp(\beta^{\theta} \cdot T_n)$ where $a_n'^{\theta}$ are fundamental amenities in the neighborhood, T_n is the number of wind turbines within three kilometersof the neighborhood and β^{θ} is the skill-specific preference against wind turbines estimated in Section 5. I model commuting cost as $d_{ni}^{\theta} = exp(-\mu^{\theta} \tau_{ni})$ where τ_{ni} is the commuting time in minutes and μ^{θ} is the semi-elasticity of costs with respect to travel times (Ahlfeldt et al., 2015).

For each residence-workplace pair individuals draw an idiosyncratic preference shock from a Frechet distribution such that $\varepsilon_{ni}^{\theta}(\omega) \sim F(\varepsilon) = exp(-D_n^{\theta} E_i^{\theta} \varepsilon^{-\kappa^{\theta}})$. The shape parameter

[12] Amenities and wages are indicated with a prime to simplify notation further down the line.

κ^θ controls the dispersion of the taste shock distribution and can be interpreted as the labor supply elasticity. The scale parameters D_n^θ and E_i^θ determine the average utility of living in n and working in i, respectively. Empirically, they are used to match the spatial distribution of residents and workers in the data.

Using the properties of the Frechet distribution, we can write the share of individuals that live in n and work in i as

$$\lambda_{ni}^\theta = \frac{D_n^\theta E_i^\theta \left(\frac{A_n'^\theta w_i'^\theta}{d_{ni}^\theta Q_n^{\alpha^\theta}}\right)^{\kappa^\theta}}{\sum_{r=1}^N \sum_{s=1}^N D_r^\theta E_s^\theta \left(\frac{A_r'^\theta w_s'^\theta}{d_{rs}^\theta Q_r^{\alpha^\theta}}\right)^{\kappa^\theta}} = \frac{\left(\frac{A_n^\theta w_i^\theta}{d_{ni}^\theta Q_n^{\alpha^\theta}}\right)^{\kappa^\theta}}{\sum_{r=1}^N \sum_{s=1}^N \left(\frac{A_r^\theta w_s^\theta}{d_{rs}^\theta Q_r^{\alpha^\theta}}\right)^{\kappa^\theta}} \tag{10}$$

The scale parameters for the average utility D_n^θ and the amenities $A_n'^\theta$ enter isomorphically and cannot be identified separately. To simplify notation I denote $A_n^\theta \equiv (D_n^\theta)^{1/\kappa^\theta} A_n'^\theta$ as adjusted amenities. Similarly, average utility at the workplace E_i^θ and wages $w_i'^\theta$ enter isomorphically. I denote $w_i^\theta \equiv (E_i^\theta)^{1/\kappa^\theta} w_i'^\theta$ as adjusted wages. Summing the bilateral commuting shares over workplaces yields the share of residents, summing over residences yields the share of workers, so that the number of residents and workers is

$$R_n^\theta = L^\theta \sum_{i \in N} \lambda_{ni}^\theta, \qquad L_i^\theta = L^\theta \sum_{n \in N} \lambda_{ni}^\theta \tag{11}$$

where L^θ is total number of individuals of type θ in the economy.

Labor market. Labor supply is given by L_i^θ above. For labor demand, I follow Diamond (2016) and model (inverse) labor demand as log-linear function of high-skilled and low-skilled workers, so that high-skilled wages in workplace i are determined as

$$ln(w_i^h) = \gamma^{hh} ln(L_i^h) + \gamma^{lh} ln(L_i^l) + z_i^h \tag{12}$$

and low-skilled wages are determined as

$$ln(w_i^l) = \gamma^{hl} ln(L_i^h) + \gamma^{ll} ln(L_i^l) + z_i^l \tag{13}$$

The labor demand parameters γ^{hh}, γ^{hl}, γ^{lh}, and γ^{ll} allow to capture substitution patterns across skill types and spillovers between workers without taking a stance on the functional form of the production function and the embedded agglomeration externalities. Finally, the labor market clearing implies that

$$L^{\theta} = \sum_{n \in N} R_n^{\theta} = \sum_{n \in N} L_n^{\theta} \tag{14}$$

Housing market. The demand for housing HD_n is the total income that both types spend on housing divided by the price of housing

$$HD_n = \frac{R_n^h \bar{v}_n^h \alpha^h + R_n^l \bar{v}_n^l \alpha^l}{Q_n} \tag{15}$$

where $\bar{v}_n^{\theta}$ is the average income of residents in the neighborhood. Average income is calculated over the wages in the surrounding neighborhoods i weighted by the probability that a resident from n commutes to i.

$$\bar{v}_n^{\theta} = \sum_{i \in N} \lambda_{ni|n}^{\theta} w_i^{\theta} = \sum_{i \in N} \frac{\left(w_i^{\theta}/d_{ni}^{\theta}\right)^{\kappa^{\theta}}}{\sum_{s \in N} \left(w_s^{\theta}/d_{ns}^{\theta}\right)^{\kappa^{\theta}}} w_i^{\theta} \tag{16}$$

For the supply of housing, I assume that each neighborhood draws on a fixed pre-existing housing stock H_n and that housing is supplied inelastically with elasticity η_n such that

$$HS_n = \bar{H}_n Q_n^{\eta_n} \tag{17}$$

Equating supply and demand, the market clearing is

$$\bar{H}_n Q_n^{1+\eta_n} = R_n^h \bar{v}_n^h \alpha^h + R_n^l \bar{v}_n^l \alpha^l \tag{18}$$

Welfare. From the indirect utility and using properties of the Frechet distribution, the expected utility of a resident is

Table 6: *Summary Parameters*

Parameter	Symbol	h	l	Estimation Strategy
Amenity cost of turbines	β^{θ}	-0.014	-0.009	Wind power density IV
Share spent on housing	α^{θ}	0.23	0.25	Microcensus 2018
Frechet scale parameter	κ^{θ}	4.56	4.56	Krebs and Pflüger (2023)
Commuting semi-elasticity	ν^{θ}	-0.085	-0.120	Commuting gravity equation
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
Total Labor	L^{θ}	7.6M	30.8M	GridAB Data 2017
Housing supply elasticity	η_n	IQR $= [0.25, 0.28]$		Saiz (2010), Beze (2023)

$$\bar{U}^{\theta} = E\left[v_{ni}^{\theta}(\omega)\right] = \Gamma\left(\frac{\kappa^{\theta}-1}{\kappa^{\theta}}\right)\left[\sum_{r\in N}\sum_{s\in N}\left(A_r^{\theta}w_s^{\theta}\right)^{\kappa^{\theta}}\left(d_{rs}^{\theta}Q_r^{\alpha^{\theta}}\right)^{-\kappa^{\theta}}\right]^{\frac{1}{\kappa^{\theta}}} \tag{19}$$

where Γ is the Gamma function. Because residents are free to move expected utility equalizes across locations.

Equilibrium. An equilibrium is a vector $\left\{R_n^{\theta}, L_n^{\theta}, \bar{v}_n^{\theta}, w_n^{\theta}, Q_n\right\}_{n,\theta}$ and two scalars $\bar{U}^{\theta}$ such that residents R_n^{θ} and workers L_n^{θ} are determined by Equations (29) and (30), wages w_n^{θ} are determined by firms' labor demand given by (12) and (13), average income $\bar{v}_n^{\theta}$ is given by (16), the housing market clearing (18) pins down the rental price Q_n, and the labor market clearing (14) pins down $\bar{U}^{\theta}$.

6.2 Parameters

Table 6 summarizes the model parameters as well as the estimation strategy or source. I detail the estimation of each parameter in the rest of the section.

Previously estimated parameters. For the estimation of the semi-elasticity of amenities with respect to wind turbines, the share of income that residents spend on housing, and the Frechet parameter, I refer to Section 5.2.

Commuting semi-elasticity ν^h, ν^l and travel times τ_{ni}. Given the commuting shares in Equation (29) and the commuting costs, the model implies the commuting gravity estimation equation

$$ln\left(\lambda_{ni}^{\theta}\right) = \nu^{\theta} \cdot \tau_{ni} + \delta_i + \delta_n + \varepsilon_{ni} \tag{20}$$

where $\nu^{\theta} = \mu^{\theta} \cdot \kappa^{\theta}$ is the commuting semi-elasticity with respect to travel times, τ_{ni} measures travel times in minutes, the workplace fixed effect δ_i absorbs wages, the residence fixed effects δ_n absorbs neighborhood amenities and house prices, and I add ε_{ni} to allow for measurement error and other deviations from the model-implied commuting equation in the data.

I construct bilateral travel times using data from OpenStreetMap and the routing software developed by Huber and Rust (2016), see Section B.3 in the Appendix for details. For commuting shares, I use data on the district-pair level that I construct from the SIAB data, a two percent random sample of the German workforce, see Section B.2 in the Appendix.

Since the commuting shares are zero for the majority of pairs, I estimate Equation (20) using Poisson Pseudo Maximum Likelihood (PPML, Silva and Tenreyro, 2006, Ahlfeldt et al., 2015). Table 7 shows the results. Columns (1) and (3) indicates that an increase in travel times by one minute decreases commuting by 8.5 percent for high-skilled and by 12 percent for low-skilled. As Columns (2) and (4) show, the results are robust to excluding district pairs with less than 10 commuters. Quantitatively, the results are higher than in Ahlfeldt et al. (2015) who find that each additional minute travel time decreases commuting in Berlin by 7 percent. A possible reconciliation of both estimates is that pecuniary commuting costs are higher in Germany (which includes rural commutes) due to higher mileage and fuel costs per minute travelled.

Labor demand elasticities γ^{hh}, γ^{hl}, γ^{lh}, γ^{ll}. To estimate the long-run labor demand elasticites, I take long differences of the model's labor demand in Equations (12) and (13). Specifically,

$$\Delta ln(w_i^h) = \gamma^{hh} \Delta ln(L_i^h) + \gamma^{lh} \Delta ln(L_i^l) + \Delta z_i^h \tag{21}$$

and

$$\Delta ln(w_i^l) = \gamma^{hl} \Delta ln(L_i^h) + \gamma^{ll} \Delta ln(L_i^l) + \Delta z_i^l \tag{22}$$

Table 7: *Commuting Semi-Elasticity*

	(1) High-Skilled	(2) High-Skilled	(3) Low-Skilled	(4) Low-Skilled
Travel time (ν^{θ})	-0.085***	-0.083***	-0.120***	-0.121***
	(0.001)	(0.001)	(0.001)	(0.001)
Sample	All	> 10 Commuters	All	> 10 Commuters
Observations	160,801	5,881	160,801	9,468

Notes: Table 7 shows Poisson Pseudo Maximum Likelihood estimates for the commuter gravity Equation (20). Each Column reports a separate regression. The regressions are at the district-pair level. Standard errors are clustered at the residence and at the workplace level. Columns 2 and 4 only include residence-workplace pairs with at least 10 commuters.

where $\Delta ln(w_i^{\theta})$ are log changes in the wage of type θ between 2000 and 2017, and $\Delta ln(L_i^{\theta})$ are log changes in the number of workers of type θ between 2000 and 2017. Estimating the labor demand equations using OLS would likely yield bias estimates due to reversed causality. Instead, I develop a migration shift share IV strategy that shifts labor supply and allows me to trace out the (inverse) labor demand curve. The strategy exploits the historical distribution of migrants from different origin countries and national skill-specific shifts in immigration between 2000 and 2017. Specifically, I construct the expected increase in workers over the period as

$$\Delta B_i^{\theta} = \sum_{g \in G} \left(R_{g,2017,-i}^{\theta} - R_{g,2000,-i}^{\theta} \right) \cdot \frac{R_{ig,2000}}{R_{g,2000}} \tag{23}$$

where $R_{g,2017,-i}^{\theta} - R_{g,2000,-i}^{\theta}$ is the national change in immigrants of skill θ from country group g between 2000 and 2017, leaving out migrants to i to avoid a mechanic effect, and $R_{ig,2000}/R_{g,2000}$ is the share of immigrants of group g that live in i among all immigrants of group g in Germany. For the national trend, I net out the number of migrants in i, indicated by the $-i$ subscript, to avoid any mechanic correlation with changes in L_i^{θ}. Data Appendix B.4 describes the data sources, the construction of groups and the variables in detail.

Since $\Delta ln(L_i^h)$ and $\Delta ln(L_i^l)$ capture relative changes, I use $\Delta B_i^h/L_{i,2000}^h$ and $\Delta B_i^l/L_{i,2000}^l$ as the instruments, respectively. Table A.3 in the Appendix reports the first-stage results. One caveat is that the first-stage is moderately strong, with a Kleibergen Paap F-Statistic of 9.6 and 4.4, respectively. More reassuringly, the first stage results show that the predictive power in the change in labor supply of each skill type comes from the migration-induced

Table 8: *Labor Demand Elasticities*

	(1)	(2)
	Log Wages	
	High-Skilled	Low-Skilled
Log workers, high-skilled	0.053***	-0.010*
	(0.016)	(0.006)
Log workers, low-skilled	-0.007	-0.061**
	(0.047)	(0.023)
Observations	35,918	32,539

Notes: Table 8 estimates the long-run labor demand elasticities in Equations (21) and (22). I instrument $\Delta ln(L_i^h)$ and $\Delta ln(L_i^l)$ using the migration shift-share instruments $\Delta B_i^h/L_{i,2000}^h$ and $\Delta B_i^l/L_{i,2000}^l$ constructed in Equation (23). The standard errors are clustered at the level of 401 districts.

labor supply shock for that skill type.

Table 8 shows the IV estimates for the four labor demand elasticities. For high-skilled workers, I find that a one percent increase in high-skilled workers increases wages by 5.3 percent while a one percent increase in low-skilled workers decreases wages by 0.7 percent. The positive own-wage elasticity suggests positive spillovers between high-skilled workers and is qualitatively consistent with previous estimates, for example in Diamond (2016). For low-skilled workers, a one percent increase in high-skilled and low-skilled workers decreases wages by 1.0 percent and 6.1 percent, respectively. The own-wage elasticity suggests that there are few (if any) spillovers between low-skilled workers, again consistent with previous evidence (Diamond, 2016).

Housing supply elasticity η_n. Following Saiz (2010) and Beze (2023), I approximate the location-specific housing supply elasticity as function of variation in land constraints. The intuition is that housing supply typically reacts less to house prices when there is little land for development available. Specifically, I construct the share of land that is unavailable due to water bodies and steep terrain with a slope larger than 15 percent as well as the share of land that is already developed, and calculate the housing supply elasticity as

$$\eta_n = 0.310 - 0.463 \cdot \text{share\_developed}_{d(n)} - 1.01 \cdot \text{share\_unavailable}_{d(n)} \tag{24}$$

using long-run estimates for the German housing market, 2008-2019 by Beze (2023).[13]

The average neighborhood in my sample has a housing supply elasticity of 0.26. The 25th percentile is 0.25, the 75th percentile 0.28. Although the estimates are small relative to the US context (Saiz, 2010), they are consistent with Beze (2023) who finds an average elasticity of 0.22 and Caldera and Åsa Johansson (2013) who report a Germany-wide housing supply elasticity of 0.43.

6.3 Estimation

I estimate the model for 133,339 neighborhoods in Germany. Since individuals choose among bilateral commutes, estimating and solving the model would require $133,339^2$, or approximately 10^{10} calculations per matrix multiplication. To make the estimation computationally feasible, I divide Germany into 257 regional labor markets and assume that individuals commute only within their labor market. Empirically, the simplification is reasonable. First, quantitative spatial models that study the allocation of economic activity within a city, for example Ahlfeldt et al. (2015), implicitly assume that there is no commuting beyond the city's labor market. Secondly, Dauth and Haller (2020) show that the vast majority of German workers commutes less than 20 kilometer, and approximately 94 percent of Germans commute less than 50 kilometer. Third, I show that the number of residents and workers in each labor market is fairly balanced, see Figure A.5 in the Appendix. o ensure that the commuter market clears everywhere, I re-scale the number of workers in all workplaces so that the total population matches total employment in each labor market.

Recovering location fundamentals. Given data on population, employment, house prices, and bilateral travel times as well as the parameters estimated in Section 6.2, one can invert the model and obtain adjusted amenities A_n^θ, adjusted wages w_n^θ, productivity z_n^θ, and the housing stock $\bar{H}_n^\theta$. Adding data on wind turbines, one can further obtain adjusted fundamental amenities a_n^θ. Section D in the Appendix formalizes the model inversion and shows that the obtained location fundamentals are unique, in the case of amenities and wages up to a normalization.

First, I use the commuter market clearing and data on population, employment, and commuting costs to recover adjusted wages w_n^θ. Intuitively, the model structure uses adjusted

[13]Five districts, Berlin, Munich, as well as Oberhausen, Gelsenkirchen, Herne in the Ruhr area are so densely built that the implied supply elasticity would be (slightly) negative. For these districts, I replace the elasticity with zero.

wages to match employment in the data. If a workplace has high employment even though observed wages are low and the workplace has bad access to commuters, the location must pay high adjusted wages. Second, I use the labor supply equation, the adjusted wages and data on population, house prices, and commuting costs to recover adjusted amenities A_n^θ. Intuitively, the model structure uses adjusted amenities to match population in the data. If a residence has high population despite high house prices and weak commuting-cost weighted access to jobs with high adjusted wages, the neighborhood must have high amenities. Given adjusted amenities and data on wind turbines, one can infer adjusted fundamental amenities a_n^θ. Third, I use the labor demand equations and data on adjusted wages and employment to recover productivity fundamentals z_n^θ. Fourth, I use the housing market clearing and data on house prices, population, adjusted wages, and commuting costs to recover the housing stock $\bar{H}_n^\theta$.

7 Welfare, Redistribution, and Policy

Section 7 uses the quantified model to evaluate the wind turbine expansion in Germany. Using model counterfactuals, I find that the specific allocation of wind turbines led to substantial welfare costs for residents, amounting to 0.83 percent of welfare or about 31 billion US Dollar. I then show that an alternative allocations of wind turbines that takes the varying willingness-to-pay across neighborhoods into account could have decreased welfare costs by almost an order of magnitude. While the alternative allocation substantially reduces welfare costs, it also allocates wind turbines to more rural, poorer, and less educated regions. I use the model to calculate budget-balanced transfers that compensate residents in disadvantaged neighborhoods, and to discuss Germany's wind development plans for 2030.

7.1 Wind Energy Development until 2017

In my main exercise, I analyze how the expansion of wind energy until 2017 has affected the geographic distribution of residents and economic activity and its implications for welfare. Specifically, I counterfactually remove all wind turbines active in 2017 and solve for the equilibrium distribution of residents, workers, house prices, and wages, and compare the resulting equilibrium with the equilibrium observed in the data in 2017.[14]

[14]Since I observe when wind turbines are connected to the grid but not if and when they are removed or replaced, taking all wind turbines constructed until 2017 may imply that some wind turbines are counted

Effect on residents' location choices. The quantified model suggests that the amenity costs associated with the expansion of wind energy substantially affected the distribution of residents and workers, and as a consequence of house prices, income, and wages. Figure 8 shows how the expansion of wind energy affects the two main outcomes, house prices and residential sorting. Figures A.8 and A.9 in the Appendix show the effect on population, employment, income, and wages, separately for high- and low-skilled.

By construction, wind turbine development decreases amenities. Neighborhoods close to wind turbines become less attractive, especially for high-skilled residents, who move to other locations. Low-skilled residents move predominately to neighborhoods that are far enough from the wind turbines but still in the larger area. High-skilled residents, on the other hand, move predominantly to larger cities as well as to Southern Germany. Both types relocate differently responding to different incentives in the labor market. Labor demand for low-skilled is downward-sloping. As low-skilled residents leave, workers in places within commuting-distance are compensated by higher wages, and this binds low-skilled workers to the larger area around the wind turbines. High-skilled workers, on the other hand, increase the productivity of other high-skilled workers. When they leave turbine neighborhoods, high-skilled wages in the larger area fall, incentivizing high-skilled residents to leave the entire region.

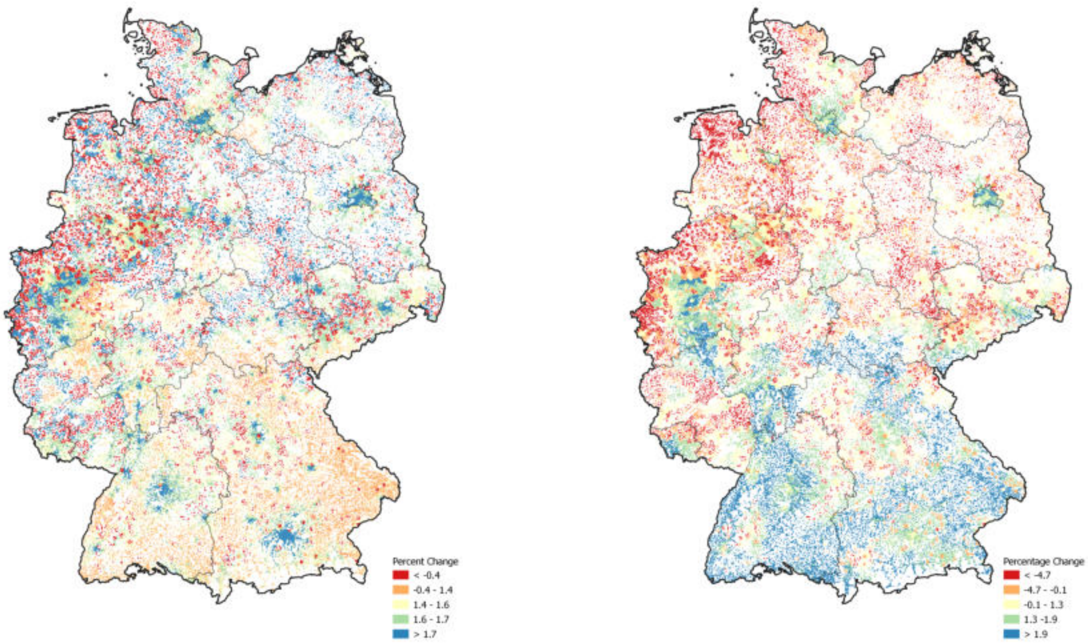
Effect on welfare. Using Equation (19) to calculate welfare in the counterfactual equilibrium without wind turbines and in the data, I find that the local costs of the full wind turbine expansion amount to 0.83 percent of welfare. Residential adaptation is important - not allowing residents and the economy to respond would have increased costs by an additional 0.07 percent - but even after that the costs are substantial. Relative to Germany's GDP in 2017, the welfare costs would suggest total losses of about 31 billion USD or about 371 USD per capita.[15]

double. In the reduced form, the instrumental variable strategy corrects for the implied measurement error. In the quantitative model, double-counting would lead to inflated welfare costs of the expansion. To correct for this, I follow the common assumption that wind turbines have a lifetime of 20 years (see also the discussion in FA Wind, 2018), after which increasing maintenance costs and halted government subsidies reduce the incentives for continued operation. Figure A.7 in the Appendix shows the geographic distribution of wind turbines active in 2017 for reference.

[15] In a cost-benefit analysis in Appendix E.1, I show that the welfare cost is likely smaller than the benefits of wind energy outside of the model, today due to the saved greenhouse gas emissions, and in particular in the future as renewable electricity becomes increasingly cheap.

Figure 6: Effects of Wind Turbines on House Prices and Sorting

(a) House Prices (b) Share of High-Skilled Residents



Notes: Figure 8 shows the general equilibrium effects of wind turbine development on house prices and the share of high-skilled residents. Changes are calculated as percent changes, comparing the variables observed in the data in 2017 with the model counterfactual assuming the absence of wind turbines. Panel (a) shows the changes in house prices, Panel (b) shows the changes in the share of residents that are high-skilled. The variation is grouped into quintiles, ranging from the most negative changes in red to the most positive changes in blue.

7.2 Alternative Turbine Placements, Welfare, and Redistribution

The quantified model suggests that wind turbine development has important costs for residents, around 0.83 percent of welfare. In the following, I use model counterfactuals to show that alternative placements of wind turbines can achieve the same electricity production while substantially lowering model-implied welfare costs.

Alternative turbine placement. Identifying the optimal allocation of wind turbines is a high-dimensional discrete choice problem that does not appear to have an analytical solution and that is computationally intractable.[16] Instead, I minimize the log-linearized

[16]Importantly, the welfare cost of placing an additional wind turbine depends on the distribution of all other wind turbines in the economy since locations are spatially linked through residence and employment choices. With approximately 25,000 wind turbines and more than 100,000 potential locations, each of which can potentially accommodate more than one wind turbine, brute force optimization is impossible. Secondly, simulating different turbine distributions to understand properties of the optimal allocation as in Kreindler

first-order welfare costs and use the quantified model to calculate the resulting welfare costs in general equilibrium, a procedure that allows me to find the lower bound of welfare gains that alternative distributions can achieve relative to the current distribution. In Appendix E.2, I show that minimizing the log-linearized first-order costs comes down to minimizing the willingness-to-pay weighted by the number of high- and low-skilled residents, formally,

$$\underset{\{T_n\}_n}{\text{minimize}} \quad \sum_{n=1}^{N} \left(-0.014 \cdot R_n^h - 0.009 \cdot R_n^l\right) \cdot T_n \tag{25}$$

To replicate the problem of the social planner as closely as possible, three constraints restrict the possible allocations of wind turbines

1. Given maps on land availability, wind turbines are only allocated to areas that can be physically and legally used for wind development.
2. Given maps on wind power density, wind turbines in each state achieve the same electricity capacity as in the data in 2017.
3. Every municipality receives at most 0.96 wind turbines per square kilometer, which is the highest municipal wind turbine density in 2017 after removing outliers.

Constraint 1: Areas available for wind development. I draw on a recent study published by the German think tank Agora Energiewende (2021) that assesses in which areas in Germany wind turbine development is allowed and physically possible. The list of excluded areas is detailed and exhaustive, and can be found in Appendix E.3. For areas with unclear status, in particular forests, protected landscapes (”Landschaftsschutzgebiete”), and areas within short distance of residential population, Agora Energiewende (2021) provides different maps. I choose the strictest scenario, excluding forests and protected landscapes, and assuming a minimum distance to residential population of 1000 meters, so that the minimization problem yields a lower bound for the welfare gains from alternative wind turbine allocations.

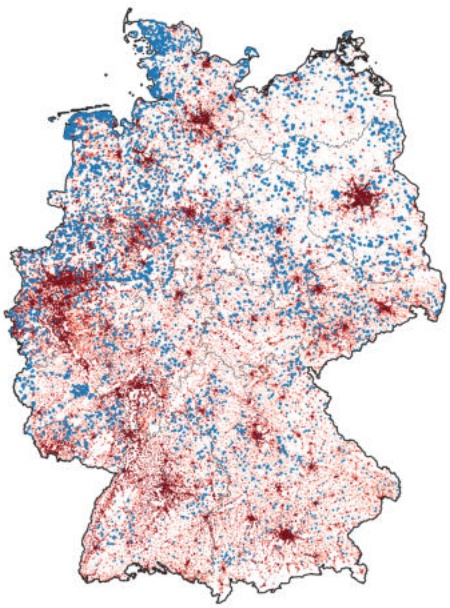
Constraint 2: Achieving the same electricity capacity as in the data. Second, the minimization problem allocates wind turbines conditional on achieving the same wind energy capacity as in the data. I match the electricity output for each state as German states

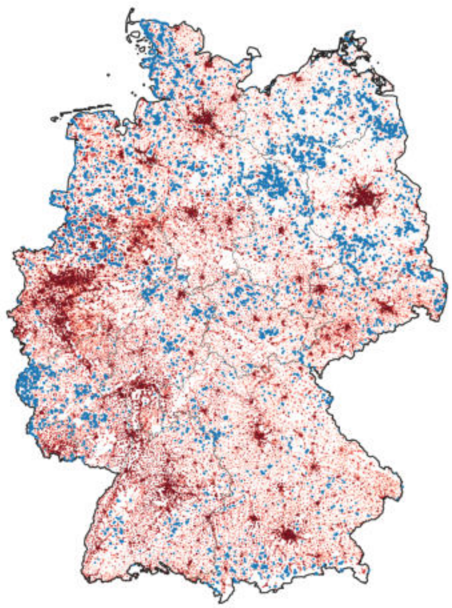
et al. (2023) is computationally infeasible due to the large number of repetitions required and the prohibitive time it takes to solve the model in my context.

Figure 7: Wind Turbine Scenarios, 2017

(a) Data, 2017

(b) Cost-Minimizing Alternative





Notes: Figure 7 shows the distribution of wind turbines (in blue) relative to the population density (in red, larger density in darker tones). Panel (a) plots the distribution of wind turbines in the data in 2017. Panel (b) plots the alternative distribution derived from the cost-minimization problem in Equation (25).

make their turbine development plans independently of each other. Finally, I calculate the capacity reached in each state, by aggregating the number of wind turbines multiplied with the wind power density in each neighborhood.

Constraint 3: Maximum wind turbine density. Third, I assume that there is a maximum density of wind turbines that no municipality is allowed to exceed. The constraint ensures that there are no unrealistically dense clusters of wind turbines that would be politically infeasible. As the maximum density, I choose 0.96 wind turbines per square meter, the highest density observed in the data, after dropping outliers in the top one percent of municipalities that have even higher turbine density.

Actual vs. cost-minimizing turbine distribution. Figure **??** shows the geographic distributions of wind turbines in the data, and in the cost-minimizing scenario. Overall, the two distributions of wind turbines are similar, which suggests that the minimization problem captures well the incentives for turbine construction. Both scenarios tend to allocate wind turbines to the high-wind Northern parts of Germany, as well as in areas with lower population density. The cost-minimizing scenario, however, is even stricter in avoiding populated areas, which can be seen most clearly in the Rhein-Ruhr area in West Germany, and around cities such as Hamburg and Berlin. Instead, the cost-minimizing scenario concentrates wind turbines more strongly in sparsely populated areas, such as the North-East, for example.

Welfare and inequality. I use the quantitative spatial general equilibrium model to understand how much welfare would have decreased under the cost-minimizing turbine allocation, and find that the losses would have been 84 percent lower, reducing from a loss of 0.83 percent of welfare to 0.13 percent.

Next, I try to understand why policy-makers chose the current distribution of wind turbines, when there were alternative distributions that could have alleviated welfare costs substantially. My hypothesis is that policy-makers choose the inefficient turbine distribution because it distributes the burden of wind turbines more equally, appears fairer and thus becomes politically feasible. An indication is the recent Land for Onshore Wind Turbines Act, in which the federal government mandates that all German states to contribute an (almost) uniform share of their land to wind development, largely ignoring differences in wind potential and population density (WindBG, 2022). And indeed, I find that the cost-minimizing distribution would substantially increase inequality across space. In the cost-minimizing scenario, 72.6 percent of wind turbines are concentrated in five percent of municipalities, relative to 61.3 percent under the current turbine distribution. Moreover, the scenario tends to place the burden on rural, low-income, and low-educated municipalities. Going from the turbine distribution in the data to the cost-minimizing scenario, the share of wind turbines in rural, low-income, and low-educated municipalities increases by 13, 6, and 5 percentage points, respectively.

Compensation. I derive budget-balanced transfers that allow the social planner to implement any allocation of wind turbines without changing the relative welfare across locations. Specifically, I denote τ_n^θ the proportional compensation that a resident of type θ in neighborhood n receives, and τ^θ the proportional tax that residents in all neighborhoods pay so that transfers are budget balanced. The indirect utility is thus

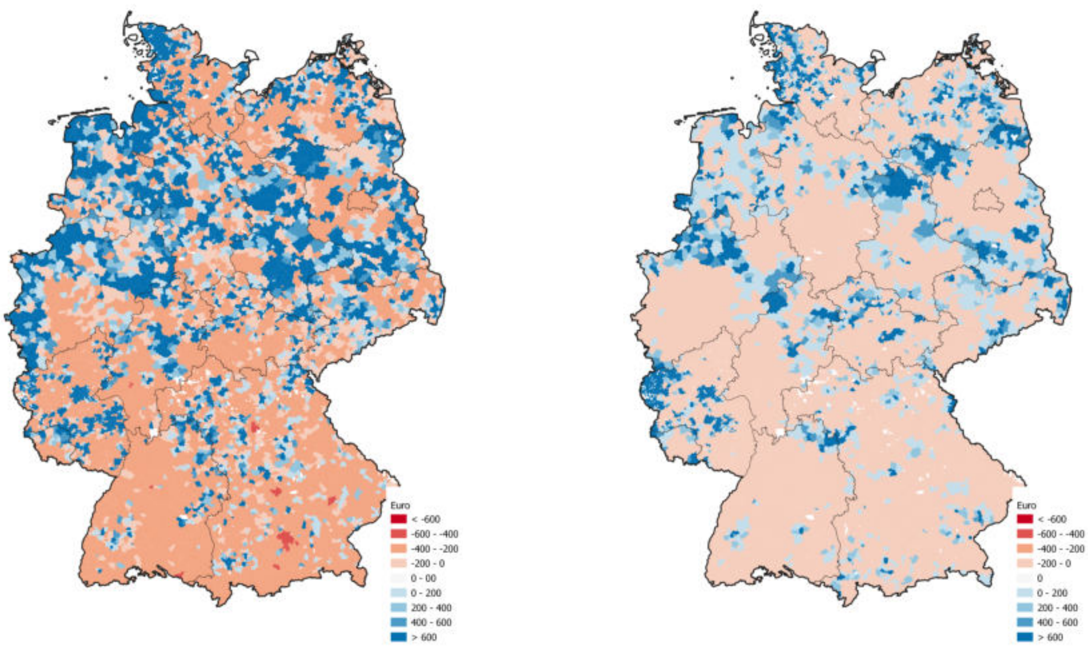
$$v_{ni}^\theta(\omega) = \frac{\tau_n^\theta}{\tau^\theta} \cdot \frac{A_n'^\theta w_i'^\theta}{d_{ni}^\theta Q_n^{\alpha^\theta}} \cdot \varepsilon_{ni}^\theta(\omega) \tag{26}$$

In Appendix E.4, I show that setting $\tau_n^\theta = 1/exp(-\beta^\theta T_n)$ fully compensates residents and I derive the proportional uniform tax τ^θ as well as the absolute net transfers that each

Figure 8: Compensatory Transfers, 2017

(a) Data, 2017

(b) Cost-Minimizing Alternative



Notes: Figure 8 shows budget-balanced transfers (in Euro per capita, aggregated at the municipality level) that compensate residents close to wind turbines for their welfare loss. On net, municipalities in blue receive transfers, municipalities in red pay transfers. Panel (a) plots the transfers for the distribution of wind turbines in the data in 2017. Panel (b) plots the the transfers for the alternative distribution derived from the cost-minimization problem in Equation (25). Transfers are calculated based on Equation (26) and as derived in Appendix E.4.

neighborhood receives. Figure 8 shows the implied net per capita transfers for the current allocation of wind turbines as well as for the alternative, cost-minimizing scenario. I aggregate the neighborhood-level transfers at the municipality level, which is the lowest consistent political unit in Germany. While both scenarios achieve the same electricity output, the current allocation creates larger costs for residents, and thus both the net transfers that municipalities with wind turbines receive as well as the net payments of all other municipalities are larger than in the cost-minimizing scenario.

7.3 Wind Energy Development Plans for 2030

In light of the trade-off between aggregate welfare and spatial inequality, I discuss Germany's wind development plans for 2030. I propose three scenarios that can achieve Germany's development goals, discuss the implications for welfare, and calculate budget-balanced transfers that mitigate the impact on inequality.

Wind turbine goal. With the Renewable Energy Act the German government declared to increase onshore wind energy capacity from 58 Gigawatt (GW) in 2022 to 115 GW in 2030. A back-of-the-envelope calculation suggests the expansion until 2030 may require an additional 24,970 wind turbines.[17] While the Renewable Energy Act does not specify where turbines should be build, in a separate act the federal government commits each state to provide a fraction of its land to wind energy development (WindBG, 2022). The city states Berlin, Hamburg, and Bremen are required to provide 0.5 percent of their area while the other states are required to provide between 1.8 and 2.2 percent of their area. I translate the national turbine goal to state-specific goals, by assuming that states are mandated to contribute to the national goal proportional to the area that they are required to provide.

Wind turbine development scenarios. Under the conservative land restrictions used in Section 7.2 - 1000 meters minimum distance to residential population, no wind turbines in forests, no wind turbines in protected landscapes -, some states are not able to achieve their wind turbine goals. I relax the restrictions in three scenarios. In the first scenario, I maintain the land restrictions but allow wind turbines to be built anywhere in Germany, ignoring any state-specific goals. In the second and third scenario, I maintain the state-specific goals but relax on which land wind turbines can be built. In the second scenario I reduce the minimum distance to residents from 1000 to 600 meters. In the third scenario, I allow that wind turbines can be built in forests but at most in ten percent of all forest area in each state, and that wind turbines can be built in protected landscapes but at most in five percent of all protected landscapes area in each state.

I solve the minimization problem in Equation (25), relaxing different assumptions as described above. Figure A.10 in the Appendix shows the wind turbine distribution in the three scenarios. Table 9 shows the impact on welfare and inequality. Depending on the scenario, I find that the cost-minimizing allocations require the installation of an additional 25,501 to 31,546 wind turbines to reach the wind energy capacity targets. The turbine allocations create welfare costs between 0.18 and 0.31 percent of GDP, which makes them between 2.7 and 4.6 times cheaper than the allocation of wind turbines in 2017. The cost reductions are even stronger when calculated per wind turbine or Gigawatt of capacity.

[17] I translate the capacity goal, 57 GW, to a wind turbine goal by assuming that added capacity per wind turbine increases at the same speed as between 2000 and 2022, and that Germany builds the same number of wind turbines each year.

Table 9: *Welfare and Inequality for Different Scenarios, 2022-2030*

	(1)	(2)	(3)	(4)
	Data, 2017	Scenarios, 2022-2030		
Welfare Loss (in Percent)	-0.83	-0.24	-0.31	-0.18
Share turbines in disadvantaged municipalities:				
Low-income	0.47	0.55	0.53	0.50
Low-education	0.54	0.58	0.62	0.57
Low-population density	0.61	0.75	0.73	0.74
Turbine goals		National	State	State
Relaxed restriction			Distance	Forests
Wind turbines	23,413	25,501	29,396	31,546

Notes: Table 9 reports the welfare and inequality implications of different wind turbine scenarios. Column (1) repeats the implications of the wind turbine allocation in the data in 2017. Columns (2) to (4) show the implications of three scenarios for wind turbine development for the years 2022-2030. All scenarios allocate wind turbines to minimize the costs for residents in Equation (25), subject to land availability and achieving Germany's capacity targets. The scenario in Column (2) allows wind turbines to be located anywhere in Germany. The scenarios in (3) and (4) ensure that each state achieve its specific wind energy capacity goal. To make sure that all states have sufficient area available, scenario (3) reduces the minimum distance between wind turbines and residential area from 1000 to 600 meters and scenario (4) allows that wind turbines can be placed in at most ten percent of the state's forest area and in at most five percent of the state's protected area. Figure A.10 shows the distribution of wind turbines in all scenarios for reference. Welfare costs are calculated using the quantitative spatial general equilibrium model. The share of wind turbines in disadvantaged municipalities is defined as the share of wind turbines in municipalities below the median in terms of the per capita income, share of high-skilled, and population density distribution.

The scenarios achieve the lower welfare costs by deliberately placing wind turbines in neighborhoods with low willingness-to-pay. As a consequence, they concentrate turbines more strongly, and especially in rural, low-income, and low-education areas. Comparing the turbine distribution in 2017 and the additional installations in the scenarios for 2022 to 2030, the share of wind turbines in municipalities below median income increases by 3 to 8 percentage points, the share of turbines in municipalities below the median share of high-skilled residents increases by 3 to 8 percentage points, and the share of turbines in municipalities below median population density increases by 12 to 14 percentage points.

As a consequence, the low-cost scenarios for wind turbine development may be especially unattractive for disadvantaged regions, as well as for a social planner that cares about both aggregate welfare and inequality. To make the wind turbine scenarios incentive-compatible for all municipalities, I calculate the budget-balanced transfers that smooth the costs across municipalities. As before, transfers are calculated based on Equation (26) and as derived in Appendix E.4. Figure A.11 in the Appendix shows the net transfers aggregated at the municipality level.

8 Conclusion

Against the backdrop of climate change, countries around the world engage in policies that aim to reduce emissions and mitigate climate change. These policies may ultimately bring large welfare benefits, but they may also create local costs and thereby increase inequality.

In this paper, I study one particularly important climate change mitigation policy, the transition to renewable energy. While the transition to renewable energy will ultimately increase welfare due to cheaper electricity and lower emissions, this paper documents that renewable energy infrastructure has important local costs, too. Using a revealed preference argument, I show that residents would be willing-to-pay between 0.9 and 1.4 percent of their income to avoid an addition wind turbine close to their home.

Understanding the costs of renewable energy infrastructure and other climate mitigation policies is important for a successful climate transition. Douenne and Fabre (2022) and Dechezleprêtre et al. (2022) show that the (perceived) costs and fairness of climate policies are important determinants of public support for the climate transition. In the case of renewable energy infrastructure, the reduced support of local communities may lead to an inefficiently low investment in wind energy production and delay the energy transition (Jarvis, 2022).

In response to these concerns, this paper suggests that allocating renewable energy infrastructure in communities with lower willingness-to-pay may substantially reduce welfare costs. However, such turbine allocations also put the burden disproportionally in rural, poorer, and less educated communities. For policy-makers that care about aggregate welfare, inequality, and a rapid transition, the results highlight the importance of compensating communities affected by wind turbine development, either through federal transfers or by sharing the economic profits of local wind turbines, to keep the welfare costs and inequality impacts of wind turbine development low.

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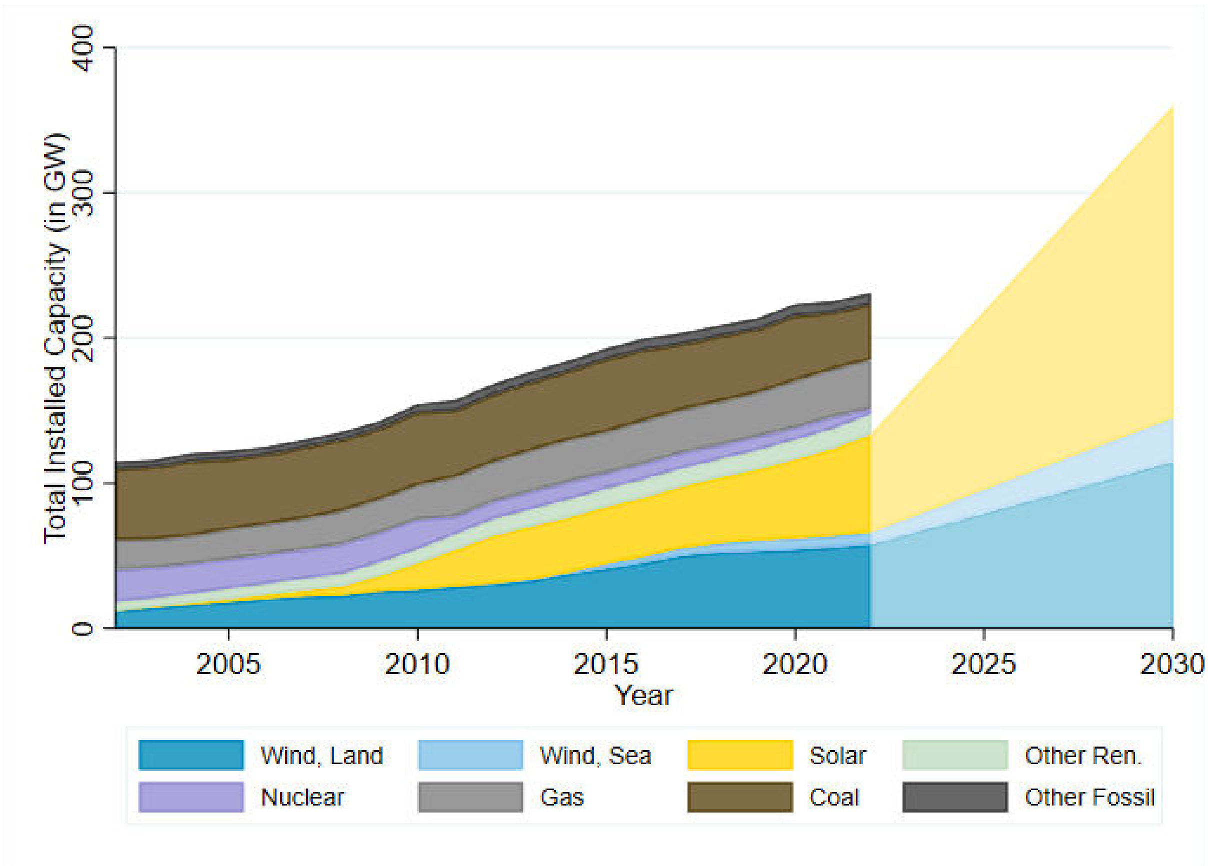
Appendices

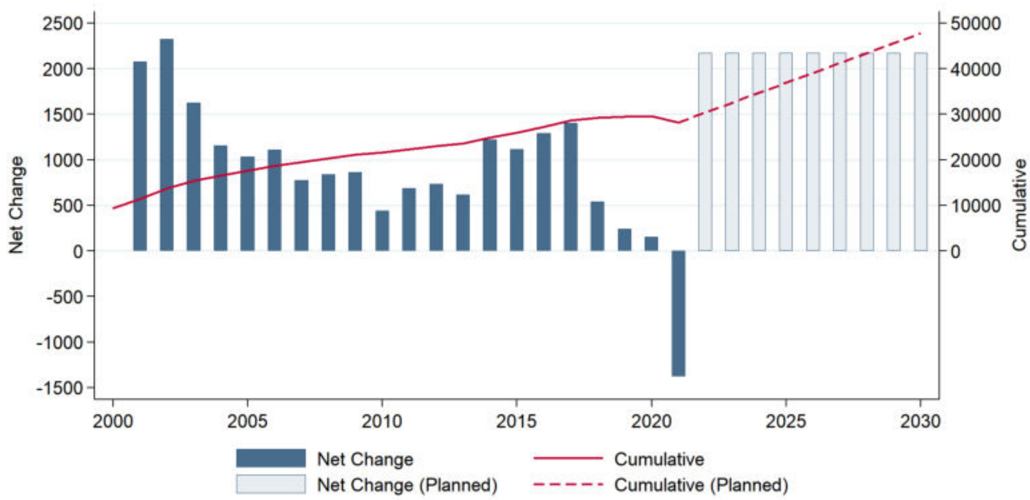
A Additional Figures and Tables

Figure A.1: *Current Installed Electricity Capacity and Plan Until 2030*



Notes: Figure A.1 shows the evolution of electricity mix between 2002 and 2022, as as well as government's goals until 2030. Over the time, the installed wind energy capacity at land rises from 12 GW in 2002, to 32 GW in in 2012, to 55 GWW in 2022. With the Renewable Energy Act 2023, the government plans to increase the capacity to 115 GW until 2030, a 98 percent increase in capacity in eight years. Source: Own calculation based on data provided by the project Energy Charts operated by the Fraunhofer Institute for Solar Energy Systems ISE (for 2002-2022) and the government's expansion goals enacted with the Climate Act 2023.

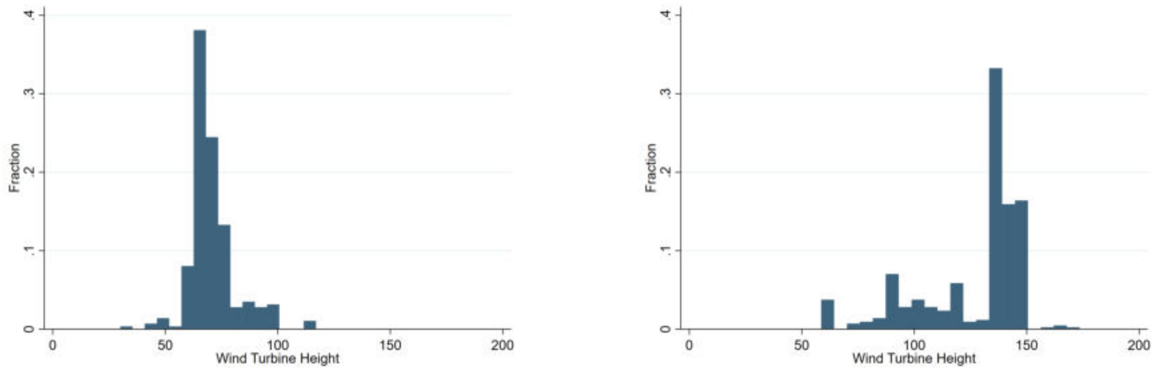
Figure A.2: *Past Wind Turbine Construction and Plan Until 2030*



Notes: Figure A.2 shows the evolution of wind turbine construction in Germany. The blue bars indicate the number of new constructed turbines, net of old turbines that were taken off the grid. The red line shows the cumulative number of wind turbines. The light blue bars in 2022 to 2030 show the number of new turbines that would be necessary to reach the government's capacity goal, 115 GW until 2030. The government does not name an explicit goal for the number of wind turbines. In translating wind capacity goals to annual turbine, I assume that capacity per wind turbine continues to increase at the same rate as in the past and that the same number of wind turbines is installed each year. Source: Own calculation based on data from the Bundesverband Windenergie (for 2000-2021) and the government's expansion goals enacted with the Climate Act 2023.

Figure A.3: *Distribution of Turbine Heights*

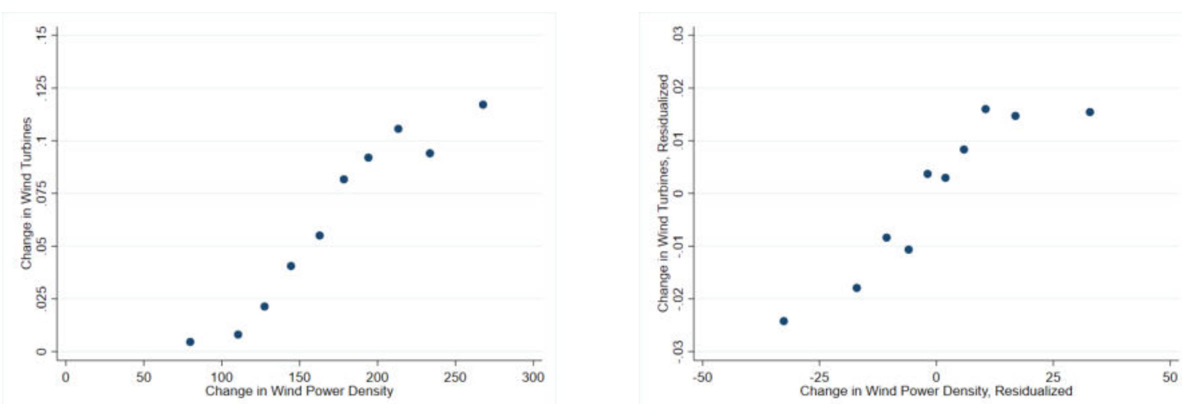
(a) Turbines constructed in 2000 (b) Turbines constructed in 2017



Notes: Figure A.3 shows the distribution of wind turbine heights. Panel **??** plots the distribution in 2000, Panel **??** plots the distribution in 2017. Source: Own calculation based on data from The Wind Power.

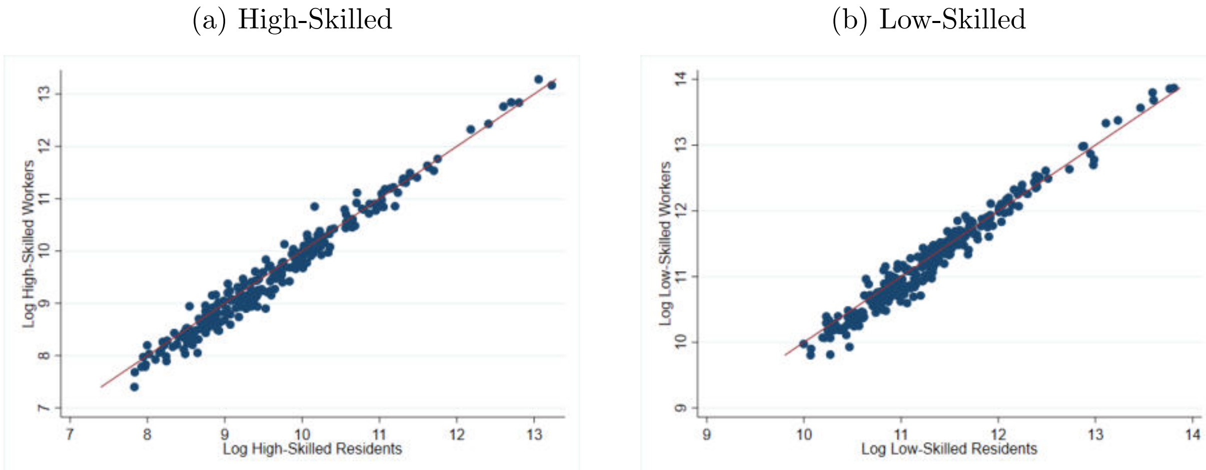
Figure A.4: *Changes in Wind Power Density and Turbines, 2000-2017*

(a) Raw Variation (b) Residual Variation



Notes: Figure A.4 shows the change in wind turbines between 2000 and 2017 for deciles in the change of wind power density (in kg/s^3) over the same period. Panel A.4a uses the raw variation of both variables. Figure A.4b uses the residual variation that remains after controlling for district fixed effects as well as geographic controls including altitude, terrain ruggedness, slope and the share of land that is covered by buildings, agriculture, forests, and water. Source: Own calculation using data on wind turbines from The Wind Power and data on wind power density from the Global Wind Atlas.

Figure A.5: *Balance Residents and Workers Across Labor Markets*

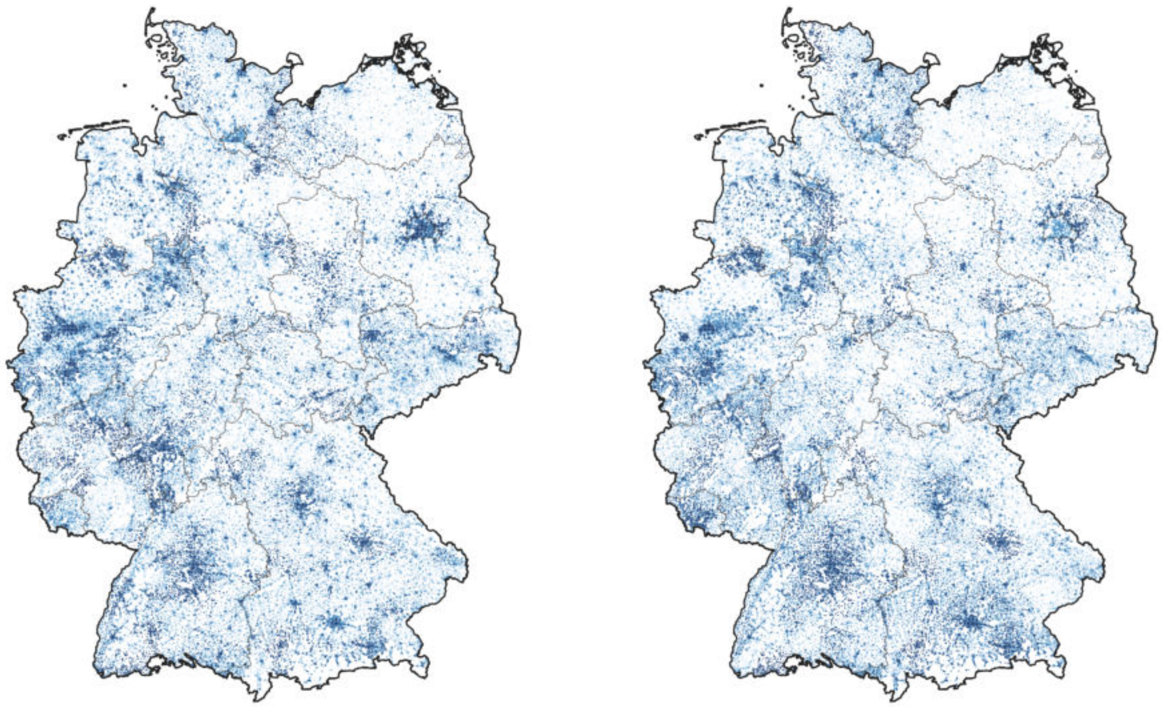


Notes: Figure A.5 plots the log number of residents against the log number of each workers. Each dot represents one of 257 labor markets. The red line represents the 45 degree line.

Figure A.6: *Amenities*

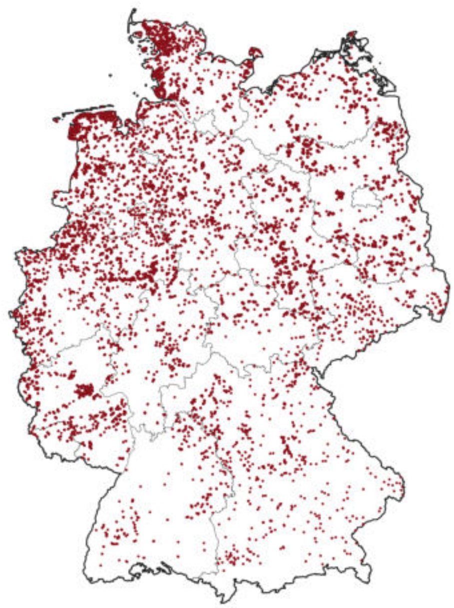
(a) High-Skilled

(b) Low-Skilled



Notes: Figure A.6 shows the model-implied amenities in 2017. Panel A.6a shows amenities for high-skilled residents, Panel A.6b for low-skilled residents. The variation is grouped into quintiles. Dark quintiles indicate high amenities, light quintiles indicate low amenities.

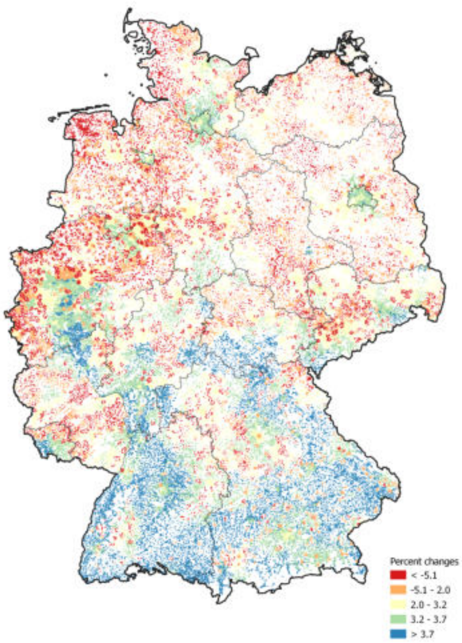
Figure A.7: *Geographic Distribution of Wind Turbines Active in 2017*



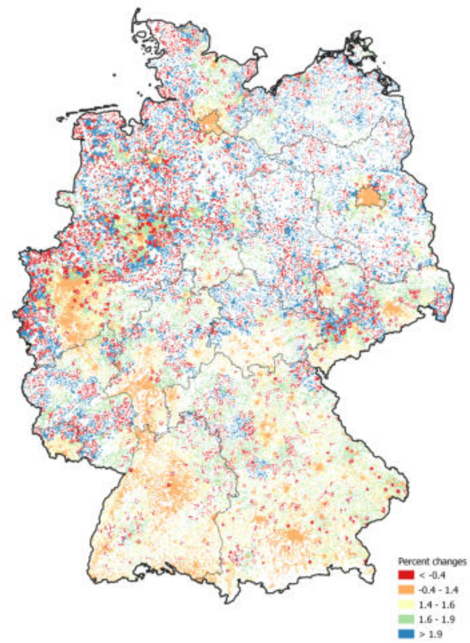
Notes: Figure A.7 shows the geographic distribution of active wind turbines in 2017.

Figure A.8: Effects of Wind Turbines on Population and Employment

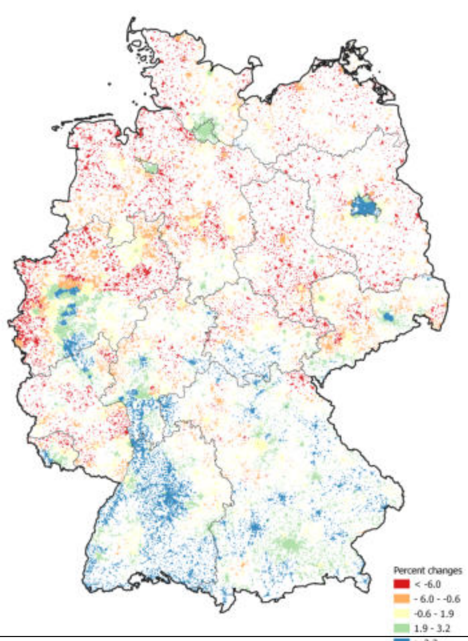
(a) High-Skilled Population



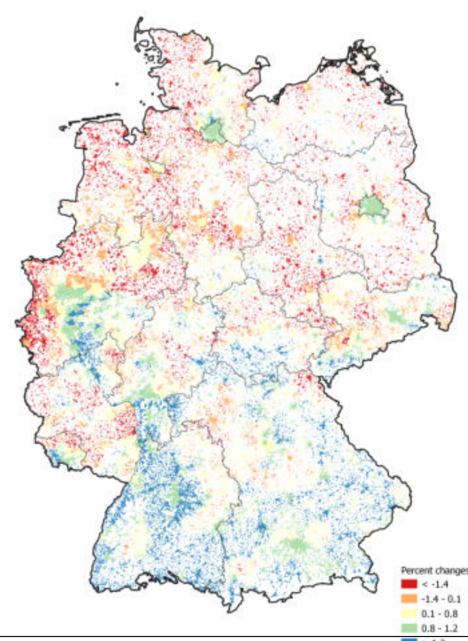
(b) Low-Skilled Population



(c) High-Skilled Employment



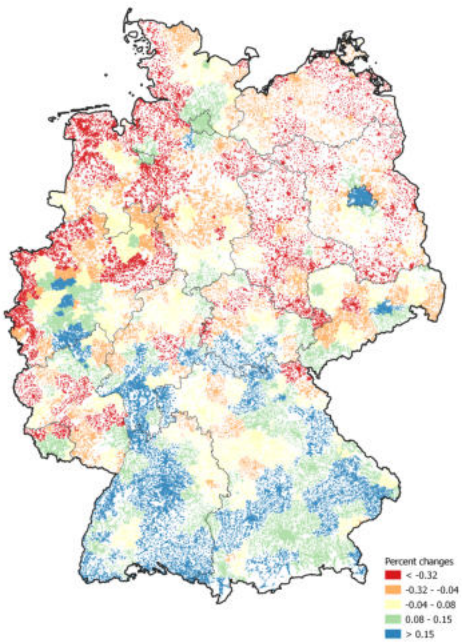
(d) Low-Skilled Employment



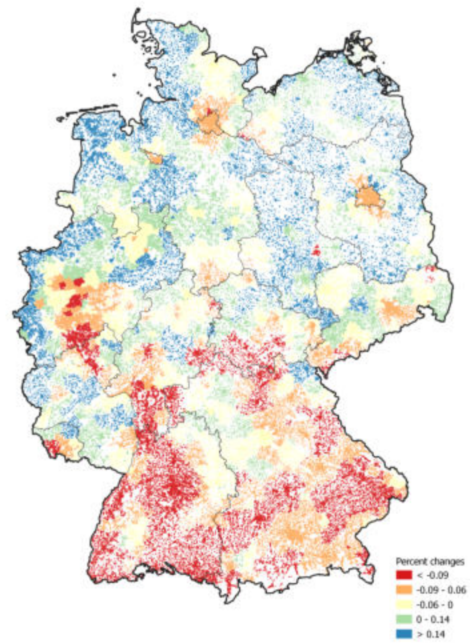
Notes: Figure A.8 shows the general equilibrium effects of wind turbine development on population and employment. Changes are calculated as percent changes, comparing the variables observed in the data in 2017 with the model counterfactual assuming the absence of wind turbines. Panels (a) and (b) show the changes in high- and low-skilled residents, respectively. Panels (c) and (d) show the changes in high- and low-skilled workers, respectively. The variation is grouped into quintiles, ranging from the most negative changes in red to the most positive changes in blue.

Figure A.9: Effects of Wind Turbines on Income and Wages

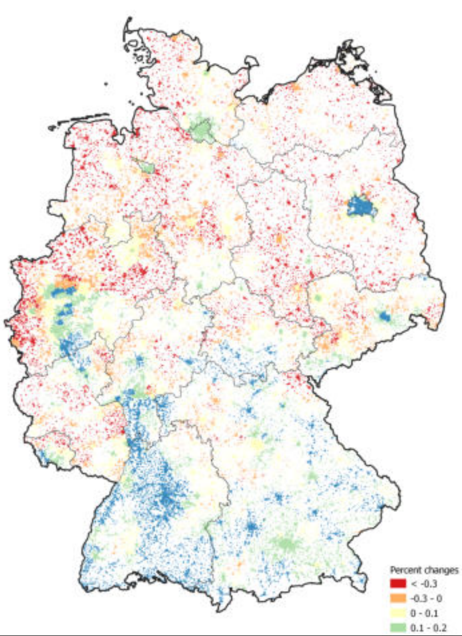
(a) High-Skilled Income



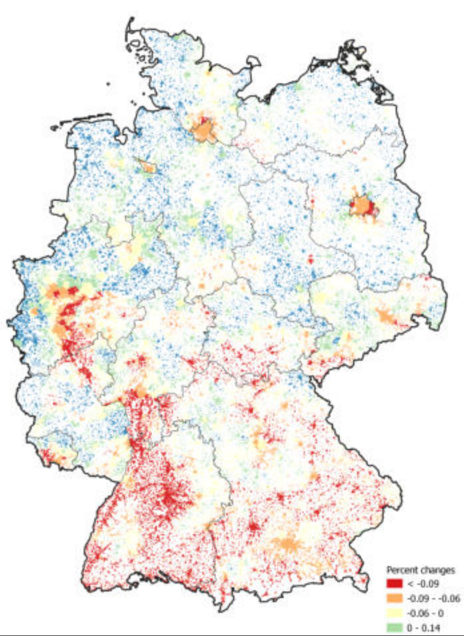
(b) Low-Skilled Income



(c) High-Skilled Wages



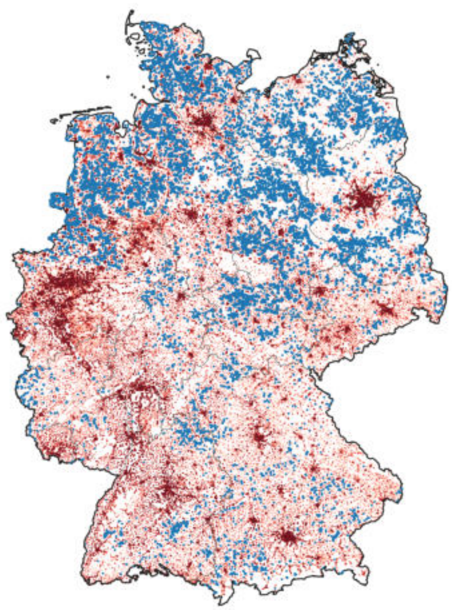
(d) Low-Skilled Wages



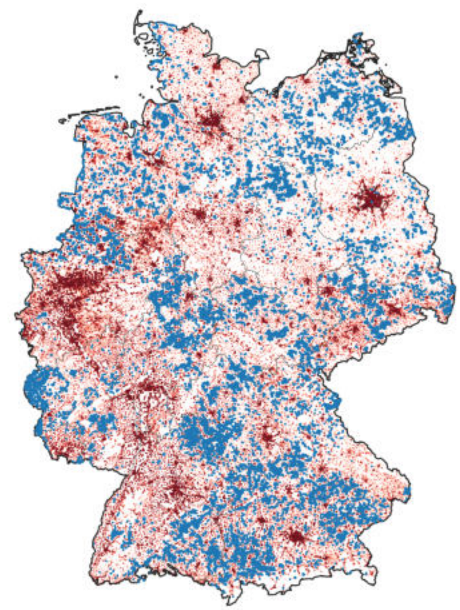
Notes: Figure A.9 shows the general equilibrium effects of wind turbine development on income and wages. Changes are calculated as percent changes, comparing the variables observed in the data in 2017 with the model counterfactual assuming the absence of wind turbines. Panels (a) and (b) show the changes in high- and low-skilled income, respectively. Panels (c) and (d) show the changes in high- and low-skilled wages, respectively. The variation is grouped into quintiles, ranging from the most negative changes in red to the most positive changes in blue.

Figure A.10: Wind Turbine Scenarios, 2022-2030

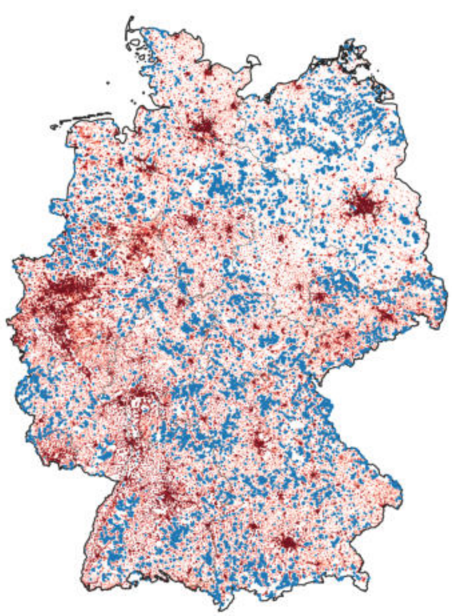
(a) Scenario 1: National



(b) Scenario 2: State, Distance



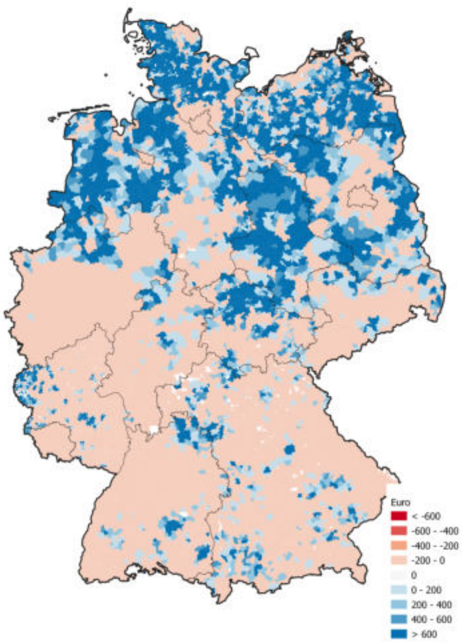
(c) Scenario 3: State, Forests



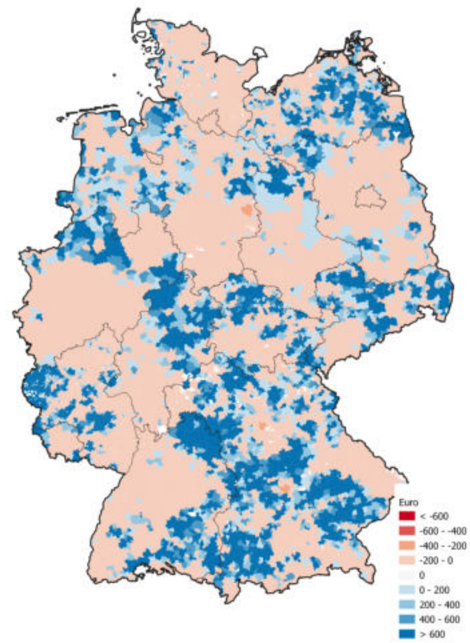
Notes: Figure 7 shows three scenarios for wind turbine development between 2022 and 2030. Wind turbines are depicted in blue, the population density in 2017 is depicted in red. Density is divided into quintiles and darker tones indicate larger density. The three scernarios are derived from the cost-minimizing problem in Equation (25) under different constraints. Panel (a) shows the scenario that meets the national wind energy capacity goal, while ignoring any state-specific goals. Panel (b) maintains state-specific goals and lowers the minimum distance between residential areas and wind turbines from 1000 to 600 meters. Panel (c) maintains state-specific goals and allows wind turbine development in up to ten percent of each state's forest area as well as in up to five percent of each state's protected area ('Lanschaftsschutzgebiet').

Figure A.11: Compensatory Transfers, 2022-2030

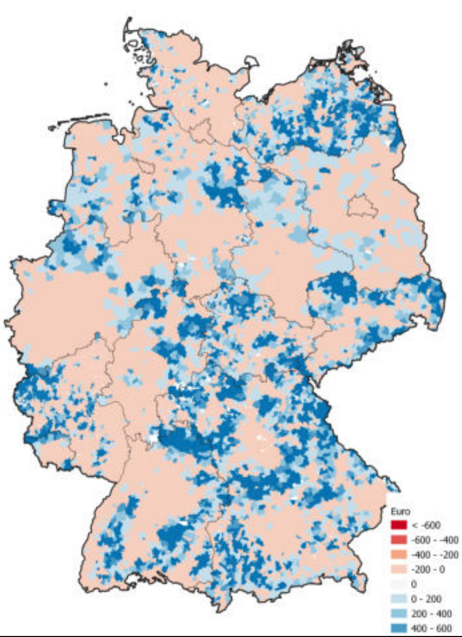
(a) Scenario 1: National



(b) Scenario 2: State, Distance



(c) Scenario 3: State, Forests



Notes: Figure A.11 shows budget-balanced transfers (in Euro per capita, aggregated at the municipality level) that compensate residents close to wind turbines for their welfare loss. On net, municipalities in blue receive transfers, municipalities in red pay transfers. Each Panel shows the transfers for one wind turbine development scenario between 2022 and 2030, as shown in Figure A.10. Transfers are calculated based on Equation (26) and as derived in Appendix E.4.

Table A.3: *Labor Demand Estimation, First-Stage*

	(1) $\Delta ln(L_i^h)$	(2) $\Delta ln(L_i^l)$	(3) $\Delta ln(L_i^h)$	(4) $\Delta ln(L_i^l)$
$\Delta B_i^h/L_{i,2000}^h$	0.097***	0.006	0.094***	0.004
	(0.009)	(0.003)	(0.009)	(0.003)
$\Delta B_i^l/L_{i,2000}^l$	-0.062***	0.050***	-0.087***	0.052***
	(0.013)	(0.014)	(0.026)	(0.023)
2nd-Stage Dep. Var.	$\Delta ln(w_i^h)$	$\Delta ln(w_i^h)$	$\Delta ln(w_i^l)$	$\Delta ln(w_i^l)$
Kleibergen-Paap F-Statistic	9.6	9.6	4.4	4.4
Observations	35,918	35,918	32,539	32,539

Notes: Table A.3 shows the first-stage results for the labor demand estimation. Columns (1) and (2) show the first-stage where the outcome of the second-stage are high-skilled wages. Columns (3) and (4) show the first-stage where the outcome of the second-stage are low-skilled wages. The standard errors are clustered at the level of 401 districts.

B Additional Details on the Data

B.1 Area Available for Wind Turbines (Placebo Check)

I construct the share of land within three kilometers of a neighborhood that is theoretically available for wind turbine construction. The variation serves two purposes. First, I use it as a placebo check, to confirm that changes in wind power density do not affect the outcome variables for neighborhood where wind turbine development is physically impossible or forbidden. Second, I interact the variation in land available with changes in wind power density to increase the power of my instrument.

To make the placebo check useful, I make sure to only exclude areas where wind turbine development is definitely impossible. First, I obtain data on land use in Germany in 1990, before the start of wind turbine development, from the German Federal Environment Agency.

Table A.1: *Robustness House Prices and Residential Sorting*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Δ Log House Prices								
Δ Wind turbines	-0.021***	-0.020***	-0.020***	-0.18***	-0.021***	-0.021***	-0.021***	-0.021***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
Observations	79,573	79,573	79,573	79,573	79,573	79,573	79,573	79,573
Panel A: Δ Share High-Skilled Residents								
Δ Wind turbines	-0.006***	-0.008***	-0.005***	-0.005***	-0.006***	-0.006***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	128,209	128,209	128,209	128,209	128,209	128,209	128,209	128,209
Additional control(s)		Socio-economic	Demographic	Industry	Wind power density at baseline	Coordinates	Shock to other locations instrument	Shock to other locations pred. turbines

Notes: Table A.1 shows additional robustness results for the IV effect on house prices (in Panel A) and residential sorting (in Panel B). Column (1) repeats the baseline specification estimated in Table 2 Column (3) and Table 3 Column (3). The other columns use the baseline specification and add different control variables. Column (2) adds population density, income per capita and the share of high-skilled residents in 2000. Column (3) adds the share of female residents, the share of residents aged 15-25, 26-35, 36-45, 46-55, and above 55, and the share of foreign residents in 2000. Column (4) adds the share of residents that work in each of 21 industries in the WZ 2008 classification. Column (5) adds wind power density in 2000. Column (6) adds the longitude and latitude of the neighborhood. Column (7) adds a distance-weighted average of the change in wind power density in surrounding neighborhoods as proposed by Borusyak et al. (2023). Column (8) adds a distance-weighted average of the change in wind turbines predicted using the change in wind power density and its interaction with land available, again, as proposed by Borusyak et al. (2023). The standard errors are clustered at the level of 401 districts.

Table A.2: *Robustness High- and Low-Skilled Amenities*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Δ Log Amenities, High-Skilled								
Δ Wind turbines	-0.014***	-0.022***	-0.014***	-0.16***	-0.013***	-0.014***	-0.014***	-0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	76,497	76,497	76,426	76,426	76,497	76,497	76,417	76,417
Panel A: Log Amenities, Low-Skilled								
Δ Wind turbines	-0.009***	-0.010***	-0.008***	-0.008***	-0.009***	-0.009***	-0.009***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	76,497	76,497	76,426	76,426	76,497	76,497	76,417	76,417
Additional control(s)		Socio-economic	Demographic	Industry	Wind power density at baseline	Coordinates	Shock to other locations instrument	Shock to other locations pred. turbines

Notes: Table A.2 shows additional robustness results for the IV effect on high-skilled amenities (in Panel A) and low-skilled amenities (in Panel B). Column (1) repeats the baseline specification estimated in Table 5 Column (1). The other columns use the baseline specification and add different control variables. Column (2) adds population density, income per capita and the share of high-skilled residents in 2000. Column (3) adds the share of female residents, the share of residents aged 15-25, 26-35, 36-45, 46-55, and above 55, and the share of foreign residents in 2000. Column (4) adds the share of residents that work in each of 21 industries in the WZ 2008 classification. Column (5) adds wind power density in 2000. Column (6) adds the longitude and latitude of the neighborhood. Column (7) adds a distance-weighted average of the change in wind power density in surrounding neighborhoods as proposed by Borusyak et al. (2023). Column (8) adds a distance-weighted average of the change in wind turbines predicted using the change in wind power density and its interaction with land available, again, as proposed by Borusyak et al. (2023). The standard errors are clustered at the level of 401 districts.

I exclude urban areas (CLC codes 111 and 112), industrial areas (121), road infrastructure (122), green urban araes (141) and sport and leisure facilities (142). Moreover, I exclude 400 meter bands around urban areas (CLC codes 111 and 112) as minimum required distance between residential areas and wind turbine development. Minimum distance rules have changed over time, and are heterogeneous across German states. I decide to take 400 metersas it is the bare minimum enacted by the vast majority of states (FA Wind, 2022).[18] Moreover, I exclude all water bodies (CLC codes starting with 4 or 5).

Secondly, I obtain maps on conservation areas from Germany's Federal Agency for Nature Conservation. In line with the placebo argument, I only exclude conservation areas where turbine development is strictly or almost always prohibited. Following a report by the German Federal Environment Agency (2013) on the availability of land for wind energy, I exclude nature reserves (Naturschutzgebiete, § 23 BNatSchG), national parks and monuments (Nationalparke und Nationale Naturmonumente, § 24 BNatSchG), the core areas of bioshphere reserves (Kern- und Pflegezone der Biosphärenreservate, § 25 BNatSchG), flora and fauna protection areas (FFH Gebiete), and wetlands basd on the RAMSAR convention (RAMSAR Feuchtgebiete).

B.2 Commuting Times

To calibrate commuting costs in the model, I calculate the approximate travel times τ_{ni} for all neighborhood pairs ni. Since there are 133,339 neighborhoods and more than 10^{10} pairs, I simplify the problem as follows: for neighborhood pairs in different municipalities, I approximate the travel time by using the travel time between population-weighted centroids of both municipalities. I calculate these travel times using data from OpenStreetMap and the routing algorithm developed by Huber and Rust (2016). For neighborhood pairs within the same municipality, I calculate the distance as-the-crow-flies and translate distances to travel times by assuming a commuting speed of 50 kilometers per hour.

To estimate the commuting gravity equation (for which I draw on district pair level commuter shares), I aggregate travel times at the district pair level by taking the population-weighted average of the travel times across all municipality pairs within the district pair.

[18] 13 out of 16 states have minimum distance rules of at least 400 meter. Bavaria has a minimum distance rule equal to the height of the turbine times factor ten, which in practice is always larger than 400 meter. Baden-Württemberg and the Saarland use case-by-case minimum distance rules.

B.3 Commuter Data

In Section 6.2, I estimate the commuting cost semi-elasticity using a commuting gravity equation. To do so, I draw on individual level data from the SIAB, a two percent random sample of workers in the IEB. I restrict the sample to all individuals between 25 and 65 years. Moreover, I follow Monte et al. (2018) and exclude all commutes longer than 120 kilometersone-way. These commutes are likely to arise from measurement error in the data. For example, when I plot commuting share against distance the relationship is clearly negative below 120 kilometer, suggesting that residents dislike longer commuters, but turns flat for commutes above 120 kilometer. Finally, I calculate the mean commuting shares over the entire sample period, 2000 to 2017, to reduce year-to-year measurement error and improve the reliability of the data.

B.4 Migration Data

In Section 6.2, I estimate the the labor demand elasticities using a shift-share design exploiting the geographic distribution of migrants of different origin across Germany at baseline and national trends in migration over the sample period.

Specifically, I calculate the shift share instrument

$$\Delta B_i^\theta = \sum_{g \in G} \left(R^\theta_{g,2017,-i} - R^\theta_{g,2000,-i} \right) \cdot \frac{R_{ig,2000}}{R_{g,2000}} \tag{27}$$

where $R^\theta_{g,2017,-i} - R^\theta_{g,2000,-i}$ is the national change in immigrants of skill θ from country group g between 2000 and 2017, leaving out migrants to i to avoid a mechanic effect, and $R_{ig,2000}/R_{g,2000}$ is the share of immigrants of group g that live in i among all immigrants of group g in Germany.

As the groups $g \in G$, I use the following six country groups (determined by the GridAB data). West-European and North American countries (Austria, Belgium, Canada, Denmark, Finland, France, Greece, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States), East European countries based on the expansion of the European Union in 2004 (Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, Slovenia), East European countries based on the expansion of the European Union in 2007 and later (Bulgaria, Croatia, Romania), Balkan countries not in the European Union (Albania, Bosnia and Herzegovina, Serbia and Montenegro, Macedonia, Kosovo), ex-Soviet countries (Armenia, Azerbaijan, Belarus, Kazakhstan, Kirghistan, Moldavia, Russia, Tajikistan, Turkmenistan, Uzbekistan, Ukraine, Georgia), and countries that are historic origins of the refugee population in Germany (Afghanistan, Eritrea, Iraq, Iran, Nigeria, Pakistan, Somalia, Syria).

I obtain the migration distribution at baseline $R_{ig,2000}/R_{g,2000}$ from the GridAB data. For the national trends $R^{\theta}_{g,2017,-i} - R^{\theta}_{g,2000,-i}$, I use individual data from the SIAB. I define high-skilled individuals as those with college education, and low-skilled individuals as everyone else. Since the SIAB is a 2 percent sample, I multiply the numbers with 50 to obtain the total number of residents from each country. I aggregate the numbers by the origin groups of the GridAB data, and calculate the national change in migrants in each origin group between 2000 and 2017. To avoid any mechanic positive correlation, I subtract the number of residents of the specific origin country group in each neighborhood when constructing the nationwide trends.

C Additional Details on the Amenity Mapping

In Section 5.1 I derive the mapping between amenities and population, house prices, and wages for the location choice in the Rosen-Roback framework, in which residents only choose a place of residence (in which they also work). Here, I derive the general mappping for the standard quantitative urban model by Ahlfeldt et al. (2015), in which residents choose a place of residence and a workplace, and pay cost for commuting between them.

Residence and workplace choice. Individuals choose a residence neighborhood n and a workplace i given the amenities A'^{θ}_n in the residential neighborhood, the wages w'^{θ}_i paid at the workplace, the commuting cost d^{θ}_{ni} between n and i, house prices Q_n in the residence, and a residence-workplace pair specific individual taste shock $\varepsilon^{\theta}_{ni}(\omega)$. Their corresponding indirect utility is

$$v^{\theta}_{ni}(\omega) = \frac{A'^{\theta}_n w'^{\theta}_i}{d^{\theta}_{ni} Q^{\alpha^{\theta}}_n} \varepsilon^{\theta}_{ni}(\omega) \tag{28}$$

For each residence-workplace pair individuals draw an idiosyncratic preference shock from a Frechet distribution such that $\varepsilon^{\theta}_{ni}(\omega) \sim F(\varepsilon) = exp(-D^{\theta}_{n}E^{\theta}_{i}\varepsilon^{-\kappa^{\theta}})$. The shape parameter κ^{θ} controls the dispersion of the taste shock distribution and can be interpreted as the labor supply elasticity. The scale parameters D^{θ}_{n} and E^{θ}_{i} determine the average utility of living in n and working in i, respectively. Empirically, they are used to match the spatial distribution of residents and workers in the data.

Using the properties of the Frechet distribution, we can write the share of individuals that live in n and work in i as

$$\lambda^{\theta}_{ni} = \frac{D^{\theta}_{n}E^{\theta}_{i}\left(\frac{A'^{\theta}_{n}w'^{\theta}_{i}}{d^{\theta}_{ni}Q^{\alpha^{\theta}}_{n}}\right)^{\kappa^{\theta}}}{\sum_{r=1}^{N}\sum_{s=1}^{N}D^{\theta}_{r}E^{\theta}_{s}\left(\frac{A'^{\theta}_{r}w'^{\theta}_{s}}{d^{\theta}_{rs}Q^{\alpha^{\theta}}_{r}}\right)^{\kappa^{\theta}}} = \frac{\left(\frac{A^{\theta}_{n}w^{\theta}_{i}}{d^{\theta}_{ni}Q^{\alpha^{\theta}}_{n}}\right)^{\kappa^{\theta}}}{\sum_{r=1}^{N}\sum_{s=1}^{N}\left(\frac{A^{\theta}_{r}w^{\theta}_{s}}{d^{\theta}_{rs}Q^{\alpha^{\theta}}_{r}}\right)^{\kappa^{\theta}}} \tag{29}$$

The scale parameters for the average utility D^{θ}_{n} and the amenities A'^{θ}_{n} enter isomorphically and cannot be identified separately. To simplify notation I denote $A^{\theta}_{n} \equiv (D^{\theta}_{n})^{1/\kappa^{\theta}}A'^{\theta}_{n}$ as adjusted amenities. Similarly, average utility at the workplace E^{θ}_{i} and wages w'^{θ}_{i} enter isomorphically. I denote $w^{\theta}_{i} \equiv (E^{\theta}_{i})^{1/\kappa^{\theta}}w'^{\theta}_{i}$ as adjusted wages.

Summing the bilateral commuting shares over workplaces yields the share of residents and multiplying by total labor in the economy L^{θ} yields the number of residents.

$$R^{\theta}_{n} = L^{\theta}\frac{\left(\frac{A^{\theta}_{n}}{Q^{\alpha^{\theta}}_{n}}\right)^{\kappa^{\theta}}\sum_{i=1}^{N}\left(\frac{w^{\theta}_{i}}{d^{\theta}_{ni}}\right)^{\kappa^{\theta}}}{\sum_{r=1}^{N}\sum_{s=1}^{N}\left(\frac{A^{\theta}_{r}w^{\theta}_{s}}{d^{\theta}_{rs}Q^{\alpha^{\theta}}_{r}}\right)^{\kappa^{\theta}}} \tag{30}$$

Solving for A^{θ}_{n} and taking logs, we obtain

$$ln\left(A^{\theta}_{n}\right) = \frac{1}{\kappa^{\theta}}\cdot ln\left(R^{\theta}_{n}\right) + \alpha^{\theta}\cdot ln\left(Q_{n}\right) - ln\left(\left(\sum_{i=1}^{N}\left(\frac{w^{\theta}_{i}}{d^{\theta}_{ni}}\right)^{\kappa^{\theta}}\right)^{1/\kappa^{\theta}}\right) + c^{\theta} \tag{31}$$

where $c^{\theta} \equiv 1/\kappa^{\theta}\left(ln\left(\sum_{r=1}^{N}\sum_{s=1}^{N}\left(\frac{A^{\theta}_{r}w^{\theta}_{s}}{d^{\theta}_{rs}Q^{\alpha^{\theta}}_{r}}\right)^{\kappa^{\theta}}\right) - ln\left(L^{\theta}\right)\right)$. The mapping differs from the mapping in the Rosen-Roback framework in two ways. First, the constant sums across all residence-workplace pairs. Second, and more importantly, the income term depends on wages in all possible workplaces, weighted by the commuting cost between the neighborhood and each workplace. In the Rosen-Roback location choice where commuting costs are assumed to be one if $n = i$ and infinite if $n \neq i$, this commuting-cost weighted wage term collapses to wages paid in the neighbourhood w_n^θ.

D Additional Details on the Model Inversion

D.1 Adjusted Wages

In the first step, I use the commuter market clearing, data on residents R_n^θ, workers R_n^θ and estimated commuting costs information on d_{ni}^θ as well as the parameter κ^θ to infer adjusted wages w_n^θ. Specifically, the model implies the following commuter market clearing.

$$L_i^\theta = \sum_{i=1}^{N} \frac{\left(w_i/d_{ni}^\theta\right)^{\kappa^\theta}}{\sum_{s=1}^{N} \left(w_s/d_{ns}^\theta\right)^{\kappa^\theta}} R_n^\theta \tag{32}$$

Workplaces with zero employment (L_i^θ) have zero adjusted wages. For the rest of locations with strictly positive employment, Section S.3.1.1 in the Online Appendix of Ahlfeldt et al. (2015) shows that the recovered wages are unique (up to a normalization).

D.2 Adjusted Amenities

In the second step, I use the location choice Equation (29) and data on residents R_n^θ, house prices Q_n, adjusted wages w_n^θ and estimated commuting costs d_{ni}^θ as well as the parameters κ^θ and α^θ to infer adjusted amenities A_n^θ. From the location choice equation, we have

$$\lambda_{ni}^\theta = \frac{\left(\frac{A_n^\theta w_i^\theta}{d_{ni}^\theta Q_n^{\alpha^\theta}}\right)^{\kappa^\theta}}{\sum_{r=1}^{N} \sum_{s=1}^{N} \left(\frac{A_r^\theta w_s^\theta}{d_{rs}^\theta Q_r^{\alpha^\theta}}\right)^{\kappa^\theta}} \tag{33}$$

Summing across workplaces, solving for A_n^θ, and dividing by the same equation for the first equation yields

$$\tilde{A}_n^\theta = \left(\tilde{R}_n^\theta\right)^{1/\kappa^\theta} \tilde{Q}_n^{\alpha^\theta} / \tilde{W}_n^\theta \tag{34}$$

where $\tilde{X}_n = X_n/X_1$ and $W_n = \sum_i w_i^\theta/d_{ni}^\theta$. From this mapping, one can calculate the unique (up to a normalization) vector $\tilde{A}_n^\theta$. With further information on β^θ and T_n, one can further infer fundamental amenities $\tilde{a}_n^\theta$.

D.3 Productivity Fundamentals

In the third step, I use the labor demand Equations (12) and (13), data on employment L_i^θ, and the labor demand elasticities γ^{hh}, γ^{hl}, γ^{lh}, and γ^{ll} to infer adjusted productivity fundamentals z_n^θ. Solving the labor demand equations for productivity, we obtain high-skilled fundamental productivity

$$z_i^h = ln(w_i^h) - \gamma^{hh} ln(L_i^h) + \gamma^{lh} ln(L_i^l) \tag{35}$$

and low-skilled fundamental productivity

$$z_i^l = ln(w_i^l) - \gamma^{hl} ln(L_i^h) + \gamma^{ll} ln(L_i^l) \tag{36}$$

When employment of both types is zero, I assume a fundamental productivity of zero. When employment of one type is zero, I add 10^{-6}, to calculate approximate productivity. With these additions, the inferred vector of fundamental productivity are unique.

D.4 Housing Fundamentals

In the fourth step, I use data on adjusted wages and commuting costs to calculate adjusted income

$$\bar{v}_n^\theta = \sum_{i \in N} \lambda_{ni|n}^\theta w_i^\theta = \sum_{i \in N} \frac{\left(w_i^\theta/d_{ni}^\theta\right)^{\kappa^\theta}}{\sum_{s \in N} \left(w_s^\theta/d_{ns}^\theta\right)^{\kappa^\theta}} w_i^\theta \tag{37}$$

Then, I use the housing market clearing in Equation (18), data on house prices, residents, and income and the estimated housing supply elasticities η_n to solve for housing fundamentals $\bar{H}_n$. Specifically,

$$\bar{H}_n = \frac{R_n^h \bar{v}_n^h \alpha^h + R_n^l \bar{v}_n^l \alpha^l}{Q_n^{1+\eta_n}} \tag{38}$$

yields the unique housing fundamentals $\bar{H}_n$.

E Additional Details on Turbine Scenarios

E.1 Cost Benefit

While the quantified model suggests large costs for residents, there are also important benefits of wind energy that are outside of the model. First, wind energy is Germany's largest source of electricity, and it is becoming increasingly cheap. Second, wind energy avoids greenhouse gas emissions and mitigates climate change. Third, wind energy avoids the air pollution costs that come from fossil sources such as coal energy. I discuss these three benefits in turn.

First, wind energy is Germany's largest source of electricity and it is getting increasingly cheap. Figure 1 in the Appendix reports projections on the levelized cost of electricity (LCOE)[19] of different types of energy reported by DNV (2023). While wind energy has historically been more expensive than fossil sources, advances in turbine technology have decreased its price substantially. An onshore wind turbine installed in 2022 provides electricity for 49 USD per MWh, compared to coal, gas, and nuclear electricity provided at around 75 USD. Multiplying the price difference by total electricity produced by onshore wind energy in 2022, about 99 TWh, saves 2.6 billion USD, or about 0.07 percent of GDP. By 2050, the LCOE is projected to fall to 27 USD, while the LCOE of coal, the source that is most likely to be replaced by wind energy, will increase to around 125 USD. Given this cost differential, wind energy production of 99 TWh may save up to 9.7 billion USD, or about 0.26 percent of GDP.

Secondly, Germany wind energy replaces fossil sources of energy and leads to lower emis-

[19] The LCOE measures the net present cost of electricity of a plant installed in a given year, taking into account the plant's fixed and variable cost as well as the total electricity produced over its lifetime.

sions. The German Environment Agency estimates that onshore wind energy production in 2018 decreased emissions by 63 million CO2 equivalent tons (Umweltbundesamt, 2019). Moreover, the agency estimates welfare benefits between 207 USD and 721 USD per avoided ton of CO2 (Federal Environment Agency, 2020).[20] Together with the total emissions estimates, the price implies that onshore wind energy production in 2018 increased welfare by between 0.35 and 1.22 percent. Nevertheless, there is substantial methodological uncertainty around pricing the welfare costs of Carbon emissions, and previous estimates have often seen upward corrections over time. For example, a special report of the Intergovernmental Panel on Climate Change suggests that limiting global warming to 1.5 degrees above pre-industrial temperatures would require a social of cost of carbon between 135 USD and 5500 USD (IPCC, 2018). This wider range of estimates implies that onshore wind energy production in 2018 increased welfare by between 0.23 and 9.39 percent.

Thirdly, electricity production from wind energy avoids air pollution that fossil sources of energy create. The reduced air pollution following the German phaseout of coal energy is estimated to increase welfare by about 0.12 percent (Böhringer and Rosendahl, 2022).

The discussion suggests that there is meaningful methodological uncertainty around the benefits of wind energy. Nevertheless, the estimates imply that the benefits are very likely to be larger than the residential costs estimated in this study, especially as the costs of wind energy technology continue to fall, and as policy-makers are becoming more ambitious in their climate policies.

E.2 Minimization Problem

To find a low-cost alternative turbine distribution, I minimize the log-linearized first-order welfare costs. Denote Υ_0 short for the baseline wind turbine scenario (possibly, but not necessarily, the absence of any wind turbines) and Υ_1 short for the new distribution of turbines $\{T_n\}_n$, and denote $[X]_{\Upsilon_0}$ and $[X]_{\Upsilon_1}$ the outcome of a variable X under each scenario, respectively.

For worker ω of type θ, who lives in n and works in i under Υ_0, the log change in utility is $ln(\big[v^{\theta}_{ni}(\omega)\big]_{\Upsilon_0}) - ln(\big[v^{\theta}_{ni}(\omega)\big]_{\Upsilon_1})$ where

[20]The German Environment Agency reports benefits between 190 Euro and 680 Euro per ton of CO2 equivalents. I translate the costs to USD using the recent exchange rate of 1.06 USD per Euro (October 2023).

$$v^{\theta}_{ni}(\omega) = \frac{A'^{\theta}_{n} w'^{\theta}_{i}}{d^{\theta}_{ni} Q^{\alpha^{\theta}}_{n}} \varepsilon^{\theta}_{ni}(\omega) \tag{39}$$

Since I am minimizing the first-order impact on residents, I assume that residents are required to continue living in n and working in i, and hence $[X]_{\Upsilon_0} = [X]_{\Upsilon_1}$ for all X except A^{θ}_{n}. The minimization problem thus becomes

$$\underset{\{T_n\}_n}{\text{minimize}} \quad \sum_{n=1}^{N} \mu^h \left[R^h_n\right]_{\Upsilon_0} ln \left(\left[A'^h_n\right]_{\Upsilon_0} \Big/ \left[A'^h_n\right]_{\Upsilon_1} \right) + (1-\mu^h) \left[R^l_n\right]_{\Upsilon_0} ln \left(\left[A'^l_n\right]_{\Upsilon_0} \Big/ \left[A'^l_n\right]_{\Upsilon_1} \right) \tag{40}$$

I set the relative weights μ^h and $1-\mu^h$ that the policy-maker places on the welfare of high- and low-skilled residents equal, so that they scale total utility and do not affect the solution of the minimiation problem. Next, note that

$$ln\left(A'^{\theta}_{n}\right) = ln\left(a'^{\theta}_{n} \cdot exp\left(\beta^{\theta} \cdot T_n\right)\right) = ln\left(a'^{\theta}_{n}\right) + \beta^{\theta} \cdot T_n = \begin{cases} ln\left(a'^{\theta}_{n}\right) + \beta^{\theta} \cdot [T_n]_{\Upsilon_0} & \text{under } \Upsilon_0 \\ ln\left(a'^{\theta}_{n}\right) + \beta^{\theta} \cdot [T_n]_{\Upsilon_1} & \text{under } \Upsilon_1 \end{cases} \tag{41}$$

and so the minimization problem simplifies to

$$\underset{\{T_n\}_n}{\text{minimize}} \quad \sum_{n=1}^{N} \left(\beta^h \cdot \left[R^h_n\right]_{\Upsilon_0} + \beta^l \cdot \left[R^l_n\right]_{\Upsilon_0}\right) \cdot \left([T_n]_{\Upsilon_1} - [T_n]_{\Upsilon_0}\right) \tag{42}$$

E.3 Areas Available for Wind Turbine Development

To identify potential areas for alternative wind turbine allocations, as well as areas for future wind turbines, I draw on maps published by Agora Energiewende (2021), and the accompanying method report (Reiner Lemoine Institute, 2022). The maps start with a base map of Germany and exclude all areas in which wind turbine development is forbidden or physically impossible. Table E.4 lists all excluded areas, as well as the buffer zone around each area. The method report Reiner Lemoine Institute (2022) explains in detail why areas are excluded, and links to further documentation on the legal regulation of wind turbine development in each area type.

Table E.4: *Areas Excluded from Wind Turbine Development - Scenarios*

Area	Excluded	Buffer (in meter)
Settlements and Infrastructure:		
Industrial parks	Yes	0
Residential areas	Yes	Depends
Freeways	Yes	40
Other roads	Yes	20
Railroads	Yes	50
Other train infrastructure	Yes	0
Airports	Yes	5000
Airfields	Yes	1760
Power lines	Yes	141
Military exclusion zones	Yes	0
Aviation communication beacons	Yes	3000
Environmental Protection Areas:		
National parks	Yes	0
Protected areas (Naturschutzgebiet)	Yes	0
Bird protection areas	Yes	0
Wetlands (Ramsar)	Yes	0
Nature reserves (Biosphärenreservat, Kern- und Pflegezone)	Yes	0
Protected areas (Landschaftsschutzgebiet)	Depends	0
Fauna and flora habitats (FFH)	Yes	0
Drinking water protection areas	Yes	0
Other Areas:		
Forests	Depends	0
Water bodies, standing	Yes	5
Water bodies, running	Yes	50
Flood plains	Yes	0
Steep terrain (slope larger than 30 degrees)	Yes	0

Notes: The table shows all areas that are excluded from wind turbine development. For further details, see Reiner Lemoine Institute (2022).

E.4 Compensatory Transfers

The goal is to find compensatory transfers $\{\tau_n^\theta\}_n$ and a uniform tax τ^θ that allow the social planner to implement any allocation of wind turbines without changing the relative welfare across locations. Again denote $\Upsilon_0$short for the baseline wind turbine scenario and Υ_1 short for new distribution of wind turbines $\{T_n\}_n$, and denote $[X]_{\Upsilon_0}$ and $[X]_{\Upsilon_1}$ the outcome of a variable X under each scenario, respectively. The proportional tax $\tau_n^\theta = 1/exp(-\beta^\theta \cdot ([T_n]_{\Upsilon_1} - [T_n]_{\Upsilon_0}))$ compensates residents and preserves the relative welfare in all locations since

$$\tau_n^\theta \cdot \left[A_n^{\prime\theta}\right]_{\Upsilon_1} = \frac{\left[A_n^{\prime\theta}\right]_{\Upsilon_1}}{exp\left(-\beta^\theta \cdot ([T_n]_{\Upsilon_1} - [T_n]_{\Upsilon_0})\right)} = a_n^{\prime\theta} \cdot \frac{exp\left(-\beta^\theta \cdot [T_n]_{\Upsilon_1}\right)}{exp\left(-\beta^\theta \cdot ([T_n]_{\Upsilon_1} - [T_n]_{\Upsilon_0})\right)} = \left[A_n^{\prime\theta}\right]_{\Upsilon_0} \tag{43}$$

Moreover, since the financing tax τ^θ is the same for all neighborhoods, the relative ordering of neighborhoods is preserved for all individuals. τ^θ balances the budget if

$$\sum_{n=1}^{N}\sum_{i=1}^{N} \lambda_{ni}^\theta \cdot w_i^{\prime\theta} \cdot \tau^\theta = \sum_{n=1}^{N}\sum_{i=1}^{N} \lambda_{ni}^\theta \cdot w_i^{\prime\theta} \cdot \tau_n^\theta \tag{44}$$

and, substituting in τ_n^θ and solving for τ^θ,

$$\tau^\theta = \frac{\sum_{n=1}^{N}\sum_{i=1}^{N} \lambda_{ni}^\theta \cdot w_i^{\prime\theta}}{\sum_{n=1}^{N}\sum_{i=1}^{N} \lambda_{ni}^\theta \cdot w_i^{\prime\theta} \cdot exp\left(-\beta^\theta \cdot ([T_n]_{\Upsilon_1} - [T_n]_{\Upsilon_0})\right)} \tag{45}$$

Finally, since the taxes that preserve relative welfare are proportional, the absolute taxes depend on the income in the neighborhood. Specifically, the total absolute payment that a neighborhood receive is

$$\pi_n = \sum_{\theta \in \{h,l\}} R_n^\theta \cdot v_n^\theta \cdot (\tau_n^\theta - \tau^\theta) \tag{46}$$

where income is $v_n^\theta = \sum_{i=1}^{N} \lambda_{ni|n}^\theta \cdot w_i^{\prime\theta}$