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Support for Renewable Energy: The Case of Wind Power

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Support for Renewable Energy: The Case of Wind Power*

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Abstract

The rise of societal goals like climate change mitigation and energy security calls for rapid capacity growth in renewable electricity sources, yet citizens' support is put to a test when such technologies emit negative local externalities. We estimate the impact of wind turbine deployment on granular measures of revealed preferences for renewable electricity in product and political markets. We address potentially endogenous siting of turbines with an IV design that exploits quasi-experimental variation in profitability induced by subsidies. We find that wind turbines significantly reduce citizens' support locally, but this effect quickly fades with distance from the site. We assess policy instruments for enhancing citizens' support for renewable energy in light of our results.

Keywords: renewable energy, wind power, public support, elections, externalities.
JEL: D12, D72, Q42, Q48, Q50

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1 Introduction

Nearly 60 percent of global electricity is generated by burning fossil fuels (IEA, 2025), polluting ambient air and driving global climate change. To mitigate these negative externalities, it is crucial to increase electricity generation from renewable sources. The Intergovernmental Panel on Climate Change (IPCC, 2018) estimates that limiting global warming to 1.5°C requires that the renewable electricity share reach 70–85 percent by 2050. Scenarios of such a clean energy transition invariably attribute a dominant role to wind power because it is cheap and universally available (European Commission, 2018). However, harvesting wind power imposes visual and acoustic externalities on local residents. With a height exceeding 200 meters and rotor diameter of 137 meters, modern wind turbines are perceived as visually disruptive. Wind turbines cast moving shadows into nearby homes in the daytime and are illuminated by blinking lights at night. Noise from a wind turbine 500 meters away is roughly equivalent to a humming refrigerator or buzzing streetlamp (45 decibels). Affected residents say that the low-frequency, swooshing or pulsing sound can be difficult to ignore ("once you hear the noise, you can't un-hear it"; cf. Die Welt, 2018), especially at night.[1] Research has shown that local disamenities of wind turbines not only lower life satisfaction reported by those living in close vicinity to them (Krekel and Zerrahn, 2017) but also lowers the value of their residential properties (e.g. Gibbons, 2015; Jarvis, 2024; Guo et al., 2024).[2]

The discrepancy between local and global effects entails that the deployment of wind turbines is embraced in the abstract (e.g. Renewable Energies Agency, 2016) yet strongly resented by local residents when specific projects are planned—an attitude often referred to as *not-in-my-backyard* (NIMBY). NIMBYism is driven by a rational self-interest to protect one's well-being or property value from the anticipated negative effects of wind turbines. In recent years, resistance to wind energy has been

[1]Some residents claim to be affected by infrasound from turbines, i.e., very low-frequency vibrations below the range of human hearing. The scientific evidence on health impacts of infrasound remains inconclusive, however.

[2]Residents preoccupied with such market capitalization effects sometimes speak of a "de facto expropriation" (Die Zeit, 2022).

amplified by alleged adverse health effects made on social media and elsewhere. In a 2019 speech, U.S. president Donald Trump asserted, without proof, that wind turbines "cause cancer" or "spew toxic fumes" (The Guardian, 2019). Such disinformation has led a growing number of U.S. counties and states to ban renewable investments. President Trump extended this ban to all federal lands on the first day of his current term. Given the vast scale at which wind power is needed to replace conventional generation capacity, the number of citizens that are directly exposed to wind power infrastructure will be growing fast, especially in densely populated countries. To the extent that NIMBY attitudes towards wind turbines scale up with exposure, this might lead to broad opposition towards wind turbine deployment and, hence, threaten the success of the energy transition.

This paper empirically estimates local opposition to wind turbine deployment using data from Germany, a leading country in the uptake of wind energy worldwide. Thanks to a generous and prolonged subsidy program, the share of wind power in Germany's gross electricity consumption grew from 1.7 percent in 2000 to 22.4 percent in 2023 (BMWK, 2024). Total installed capacity in Germany is surpassed only by China and the U.S., though the wind share in the electricity mix is still less than half in those countries.[3] In recent years, the pace of expansion has slowed substantially, threatening to set back Germany's trajectory towards achieving carbon neutrality (Financial Times, 2019; Bloomberg, 2020). Plans to install new wind turbines have been met with substantial opposition from local residents who—organized in more than 1,000 citizens' initiatives across Germany—often launch litigation against new wind energy projects.[4] To understand how the deployment of wind turbines affects citizens' support for green electricity, we analyze two novel measures of revealed preference for renewable energy.

The first measure is based on the premise that citizens who support the development of renewable electricity generation prefer to purchase only this type of electricity.

[3]Wind contributes 6.1 percent to the Chinese and and 8.4 percent to the U.S. total electricity consumption. See China Energy Portal (2021) and U.S. Energy Information Administration (2021).

[4]Approximately 900 of those initiatives are affiliated with the federal association Vernunftkraft.

Using rich data from widely used price comparison web sites, we construct granular measures of how intensely consumers *search* for green electricity tariffs that draw only on renewable sources. Analyzing search instead of purchase decisions sidesteps the issue that prices of green and conventional electricity tariffs differ systematically and drive tariff choices.[5] The search measure disentangles preferences from prices because information on prices is displayed only after consumers have entered their search query. Nonetheless, search queries are an accurate predictor of actual tariff choices, as we show in the data section.

The second measure of citizens' support for renewable energy is the share of votes received by the Green Party in the German federal elections (*Bundestagswahlen*). The transition of the energy sector from conventional generation towards renewable energy is the ideological basis of the Green Party and has been a central issue in their electoral campaigns. Moreover, the Green Party was the junior partner in the 1998-2005 coalition government that jump started the German renewable electricity boom by implementing a generous subsidy scheme. Because of these strong ties, variation in the vote share of the Green Party across municipalities and over time is revealing of citizens' support for renewable energy.

Studying these outcome variables follows the revealed-preference tradition of analyzing observed behavior rather than stated preferences which might be subject to cognitive biases. While much of the revealed-preference literature on renewable-energy sources has focused on housing markets, we analyze two distinct yet highly relevant markets, namely elections – "the market in which votes are exchanged for public-policy outcomes" (Crain, 1977) – and the market for renewable electricity. Doing so provides an important complement to hedonic studies, which have the benefit of providing monetized welfare impacts of new energy infrastructure, but also rely on the strong assumptions that agents are fully informed and move in frictionless housing markets to establish a new hedonic equilibrium (Rosen, 1974; Roback, 1982). To the extent that moving is costly and agents have less costly alternatives to reduce expo-

[5]For a standard two-person household with 3.5 MWh annual electricity consumption green electricity tariffs are on average 4.6 percent more expensive than regular tariffs in our observation period.

sure, welfare impacts are not fully capitalized into housing prices. In our application, this is plausible because the costs of moving away likely outweighs the disamenity value of wind turbines for most affected residents, and because they have the option of launching litigation against projected wind parks.

Our research design exploits variation in the construction of new wind turbines to identify the impact of an additional turbine nearby on the outcome variable. The main threat to identifying a causal relationship is posed by the potentially endogenous siting of wind turbines, e.g because citizens actively block wind power near their homes.[6] Including location fixed effects is only a partial remedy to this problem because unobserved preferences for wind turbines are not necessarily static and might change as citizens learn more about the technology. To address this issue, we exploit spatio-temporal variation in the profitability of wind turbines to construct instrumental variables for their actual deployment. Specifically, the cross-sectional differentiation of federal production subsidies according to local wind potential, combined with multiple adjustments to the overall subsidy rates that occurred over time, have been shifting investment incentives for wind turbines in ways that are plausibly exogenous to local preference dynamics.

We find that the construction of new wind turbines has negative and significant effects on both preferences measures. Using data on more than 35 million individual search queries, we estimate that an additional wind turbine reduces searches for green electricity tariffs in the same postal code by 24 percent. Using data on four federal elections between 2005 and 2017, we estimate that an additional wind turbine in a municipality significantly reduces the vote share of the Green Party by 10 percent. The estimated effect is even larger in elections to the European Parliament, which we attribute to the fact that European elections matter more for protest voters.[7] The magnitude of the treatment effects diminishes rapidly with distance from the wind turbine,

[6]Citizens' initiatives and private persons are involved in 62 percent of all law suits filed against wind projects according to the German Wind Energy Association (BWE), 2019. Environmental associations represent another major opponent in many cases.

[7]European elections tend to be perceived as "second-order-national-contests" where voters are more willing to express dissatisfaction with a party's national politics (Hix and Marsh, 2007).

suggesting that externalities provoking a NIMBY attitude are very local. Treatment effects are substantially larger in locations without any previous generation capacity than at the average location. The estimated effects of wind turbines on tariff searches and election results are robust to functional form assumptions and corroborated by several placebo tests.

Our findings have important policy implications for countries that, like Germany, "are covered by a contiguous and dense mesh of buildings" (Behnisch et al., 2019). To achieve national climate targets under these circumstances, siting new wind turbines closer to buildings will be inevitable and exposes a greater population share to negative externalities. This increases the likelihood that a critical mass of opponents to wind power could stop the energy transition via the legislative channel, making it a victim of its own success. Such a "NIMBY equilibrium" is socially undesirable under the premise that renewable energy is globally welfare-improving. To boost citizen support for wind turbines, policy makers could offer financial compensation to affected communities. We provide first empirical evidence that such a strategy could be effective by showing the negative impact of wind turbines on the Green Party´s vote share decreases by one third once municipalities begin to benefit financially from wind power expansion, following a reform in the local taxation of wind power profits.

Our findings bear policy relevance not only in regards to climate policy, but also in light of the Russian invasion of Ukraine on February 24, 2022, which put an end to the era of cheap fossil fuels in Europe. The EU Commission responded to this on March 8, 2022, by making the deployment of wind turbines a top policy priority and urging member states to "dash into renewable energy at lightning speed".[8] Our quantitative analysis of local preferences casts a spotlight on trade-offs in turbine deployment

[8]EU vice president Frans Timmermans on March 8, 2022, when launching the REPowerEU plan (cf. https://ec.europa.eu/commission/presscorner/detail/en/ip_22_3131, last accessed on December 16, 2022). The REPowerEU Plan (cf. Communication from the Commission to the European Parliament, the European Council, the Council, the European Economic and Social Committee and the Committee of the Regions, COM/2022/230 final), stipulates an amendment to the Renewable Energy Directive to accelerate renewable energy projects (cf. COMMISSION RECOMMENDATION on speeding up permit-granting procedures for renewable energy projects and facilitating Power Purchase Agreements, C/2022/3219 final

which need to be taken into account when designing better instruments to achieve this important policy objective.

The remainder of this paper is structured as follows: Section 2 summarizes related research and describes our contributions in the context of this literature. Section 3 presents the institutional background of wind power deployment in Germany. Our empirical strategy is outlined in Section 4 and the data are described in Section 5. Section 6 summarizes the empirical results, Section 7 investigates the potential for compensation payments, and Section 8 concludes.

2 Literature

A sizable literature has established that renewable energy is generally preferred to fossil energy sources due to its more environmentally-friendly production process but also gives rise to local externalities that reduce welfare. Given the financial challenges associated with the energy transition, one strand of research has focused on stated willingness-to-pay (WTP) for green electricity. Meta-analyses based on 227 WTP estimates taken from 47 studies show that households state a positive WTP for wind and solar electricity, as well as—to a lesser extent—biomass and hydropower (Ma et al., 2015; Sundt and Rehdanz, 2015). WTP is negatively associated with a household's total electricity consumption but correlates positively with the renewables share in that total (Ma et al., 2015). Choice experiments tend to give higher WTP estimates than other methods (Sundt and Rehdanz, 2015).

Studies based on actual decisions rather than stated preferences have attributed green electricity purchases or participation in green electricity programs to environmental concerns, warm glow motives, and other household characteristics (e.g. Menges et al., 2005; Kotchen and Moore, 2007a; Jacobsen et al., 2012).

With respect to externalities of renewable energy technologies, a host of case studies and qualitative analyses shed light on public acceptance and document NIMBY attitudes (see, e.g., Aitken, 2010; van der Horst, 2007). Stated-preferences approaches, such as contingent valuation, are widespread in this area. Mattmann et al. (2016a,b) conduct meta-analyses of the studies pertaining to externalities of wind and hydro power generation. Stated-preferences methods offer the benefit of near-universal applicability, but they have also been criticized for giving unreliable results due to hypothetical biases or framing effects (Hausman, 2012; Kling et al., 2012).

An alternative approach employs self-reported well-being data to quantify the externalities of renewable energy technologies. Krekel and Zerrahn (2017) estimate negative effects of new wind turbines on reported life satisfaction in Germany. von Möllendorff and Welsch (2017) find that well-being externalities associated with biomass are stronger than for wind and solar power.

Revealed-preference estimates of the value of externalities emanating from power plants have been mainly derived in hedonic analyses of housing prices (see, e.g., Davis, 2011; Dastrup et al., 2012; Heintzelman and Tuttle, 2012). These studies have shown that both wind turbines and conventional power plants lead to lower property prices in the surrounding areas. For wind power plants, several studies credibly link such effects to their negative visual impacts in Germany (-9 to -14 percent of asking prices; Sunak and Madlener, 2016), the United Kingdom (-4 to -5 percent of property value within 2km; Gibbons, 2015; Jarvis, 2024), and the U.S. (-1.1 percent of property value within 10km viewshed; Guo et al., 2024). Jensen et al. (2014) disentangle the effect of of wind turbines on nearby property values in Denmark into visual degradation (-3 percent) and noise pollution (-3 to -7 percent).[9] However, while home owners are negatively affected by nearby wind turbines, land owners in windy areas may profit from the capitalization of wind energy subsidies into land prices (Haan and Simmler, 2018).

We contribute to the above literature by bringing revealed-preference data from markets other than real estate markets to bear on this issue. Our analysis of online search queries for renewable electricity tariffs introduces a novel preference measure

[9]Renewable energy sources other than wind can also impose significant costs on nearby populations. In India, large hydroelectric dams—while increasing productivity of downstream agriculture—have been shown to increase flooding, displacement, poverty, and income volatility in upstream communities (Duflo and Pande, 2007).

for renewable electricity technologies, based on the premise that "concern for the environment translates into predictable patterns of consumer behavior" (Kotchen and Moore, 2007b). Our analysis of electoral vote shares for the Green Party speaks to such preferences because this party, after joining the federal government in 1998, paved the way for the rapid diffusion of renewable energy technologies that Germany has seen ever since. While this aspect has not been studied in the economics literature so far,[10] political science research on voting and wind turbines has produced mixed results so far. Looking at provincial elections in Ontario (Canada), Stokes (2016) estimates losses of 4 to 10 percent to the incumbent party in precincts within 3km of a wind turbine. In contrast, analyses of U.S. elections find that the incumbent party benefits electorally from turbine development (Bayulgen et al., 2021; Urpelainen and Zhang, 2022), with the interpretation that any electoral backlash against local wind power is more than offset by economic benefits.[11] Otteni and Weisskircher (2022) use German election data similar to ours and estimate a small positive association between wind turbine deployment and vote shares of the Green Party. Their two-way fixed-effects estimator is predicated on assuming strict exogeneity of turbine deployment w.r.t voting. This assumption is incompatible, however, with the likely presence of measurement error and reverse causality, biasing OLS estimates away from finding a NIMBY effect.[12] We address this issue with a novel identification strategy that exploits both cross-sectional and temporal sources of exogenous variation in profitability to instrument for wind turbine deployment.

In sum, our paper contributes to this strand of literature by challenging the previous finding that wind turbines generate electoral net benefits, by drawing attention

[10]Comin and Rode (2015) study the diffusion of solar photovoltaic systems in Germany and ask: Do households that install on-roof systems become more supportive of the Green Party? Our focus is on wind turbines—a technology with stronger negative externalities—and their effects on preferences of neighboring households.

[11]Direct evidence on economic benefits of wind turbines is scarce. Recent evidence indicates modest increases in employment (Fabra et al., 2024, for Spain) and municipal budgets (Gavard et al., 2025, for Denmark) in the host communities.

[12]Classical measurement error in the distance between turbines and local residents induces attenuation bias in OLS estimates. A reverse causality running from increasing opposition to wind turbines to slower wind power expansion would induce upward bias in the estimates. The latter mechanism is supported by evidence in Jarvis (2021) that local resistance to wind power amounts to the equivalent of a 10-25 percent cost surcharge and hence strongly decreases turbine deployment.

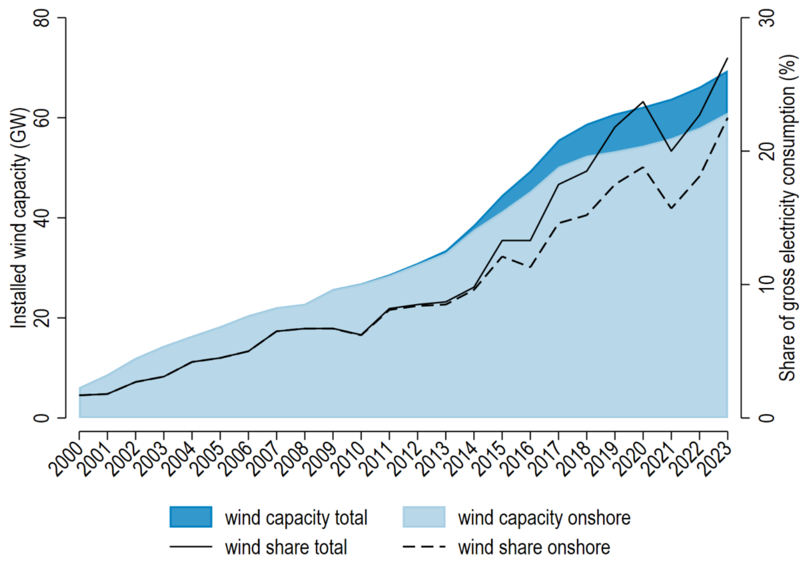


Figure 1: *Development of wind power capacity and contribution in Germany*

Calculation based on data from the German Federal Ministry for Economic Affairs and Energy (BMWK, 2024).

to the issue of endogenous treatment, and by proposing a rigorous econometric approach to address this issue. Our analysis of how preferences for wind power vary with financial participation is new to the literature. By speaking to possible ways of reducing public resistance to accelerated deployment of wind turbines, this contribution bears immediate policy relevance to important societal goals such as climate change mitigation and energy security.

3 Wind Power Subsidies in Germany

Beginning in the early 2000's, Germany embarked on a period of rapid growth in wind energy. Installed onshore wind power capacity soared from 6.1 GW in 2000 to 26.8 GW in 2010 and 61 GW in 2023, respectively. The share of wind energy in gross electricity consumption rose from 1.7 percent in 2000 to 6.2 percent in 2010 and reached 22.4 percent in 2023.[13] Figure 1 illustrates this development.

[13]The second largest renewable energy source in Germany is solar energy with a share of 12.2 percent of total energy consumption as of 2023 (BMWK, 2024).

Much of this expansion has been attributed to government policies, in particular to subsidization of renewable systems through legislated feed-in tariffs. These tariffs guaranteed a fixed price for every kilowatt hour of renewable electricity produced with an eligible technology and fed into the grid. In addition, renewable electricity enjoyed priority feed into the grid. These privileges were granted in the Renewable Energy Sources Act (henceforth referred to by its German acronym, EEG), a federal law enacted in 2000 under the auspices of a government formed by the social democrats and the Green Party (as a first-time junior coalition partner).[14]

Feed-in tariffs were differentiated by technology and size, resulting in different subsidy levels granted for wind, solar photovoltaic, biomass, and other systems. The tariff levels were administratively determined and regularly adjusted for the installation of new systems based on estimates of their electricity generation cost. For an individual system, the nominal tariff that was valid on the date of installation was locked in for the first 20 years of operation. In recent years, tendering of support levels has been introduced for large wind and solar systems. This paper analyzes the period before this reform was introduced.

Feed-in tariffs to wind turbines were also geographically differentiated according to the so-called reference yield model, which granted higher subsidies per unit of electricity generated in locations with low wind potential. By levelling incentives for wind power generation across space, this scheme aimed to mitigate potential grid constraints and to reduce volatility in aggregate wind power generation. The reference yield model consisted of a benchmarking component and a tariff schedule. Locations with different wind potentials were benchmarked by computing 'yields', i.e., the expected power output of a designated turbine type. These location-specific yields were normalized by the 'reference yield', obtained in the same fashion for a designated reference location.[15] Yield ratios in our data range from 0.3 to 2.2. The tariff schedule

[14]The EEG superseded the Electricity Feed-in Law (*Stromeinspeisungsgesetz*) dating from 1991.

[15]More specifically, the law defined the wind power potential of the reference location based on average annual wind speed of 5.5 meters per second at 30 meters above the ground, a logarithmic elevation profile, and a roughness length of 0.1 meters (i.e., the theoretical height above the ground at which the mean wind speed is zero). The conversion of wind potential into electric power was based on the technical characteristics of a pre-specified reference plant.

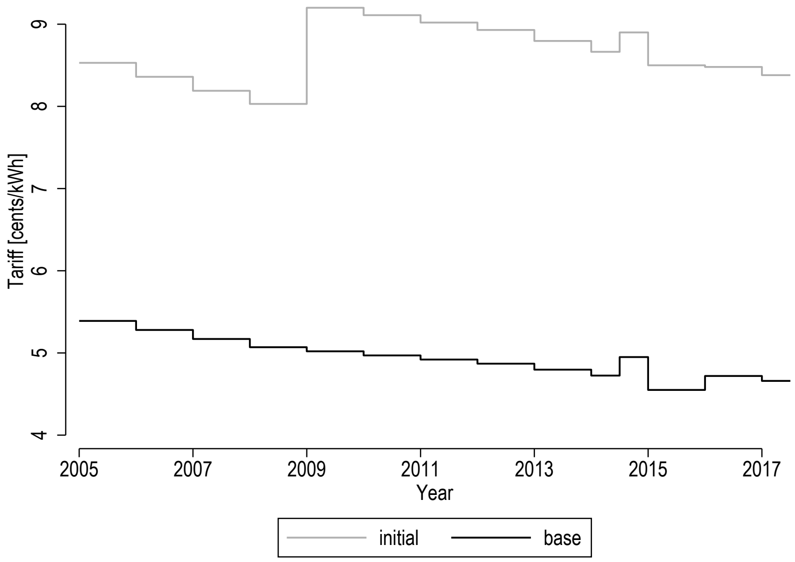


Figure 2: *Development of feed-in tariffs for wind, 2005-2017*

Own illustration based on data from the German Transmission System Operators (2019).

consisted of a high initial tariff, paid at the beginning, and a lower base tariff that applied thereafter. The length of the initial period was at least five years, plus an extension that declined with the yield ratio. Thus, a low-yield location was eligible for the higher initial tariff for a longer period than a high-yield location. This mechanism dampened cross-sectional differences in the profitability of wind turbines. Appendix Table A1 summarizes the tariff rates paid under the EEG law and its amendments.

The identification strategy we propose below exploits the fact that wind power subsidies varied not only across space but also over time. Several amendments to the EEG law between 2000 and 2017 changed both initial and base tariffs. Most amendments stipulated downward adjustments of both tariffs. Others, like the 2009 amendment increased the initial tariff by 17 percent to offset increased resource costs for wind turbines (e.g., higher prices of copper and steel, see Böttcher, 2010). Annual digressive adjustments applied to both tariffs in years without new amendments. Figure 2 plots the resulting variation in the initial and base tariffs pertaining to new wind turbines deployed in each year between 2005 and 2017.

Additional time variation was induced by changes to both the length of the initial period and the tiers of the reference yield distribution which were eligible for such extensions. In 2012, feed-in tariffs were rolled out to all of Germany to further promote the spatial diffusion of this technology in the wake of Germany's nuclear exit decision. Before 2012, locations with less than 60 percent of the reference yield had not been eligible for subsidized feed-in tariffs. The 2014 EEG amendment abolished feed-in-tariffs in favor of the market-premium system; renewable electricity producers had to sell their output on the spot market but received a market premium that compensated for any difference between the market price and a location-specific minimum remuneration, determined by the reference yield system (Bundesministerium der Justiz und für Verbraucherschutz, 2014). Therefore, expected returns derived from the reference yield system remained a critical factor in the economics of wind projects after 2014.

When the principle of output-based subsidies was eventually abandoned in favor of an auction system in the 2017 amendments, wind projects that were already permitted at the time and commissioned by the end of 2018 remained eligible for remuneration according to the reference-yield system (cf. Section 22(2) of the law Bundesministerium der Justiz und für Verbraucherschutz, 2017).

For the subsequent analysis, it is important to clarify that time variation in feed-in tariffs never changes the expected revenue of any given installation. Since feed-in tariffs are locked in at the time of installation, this expectation is taken only with respect to wind power output over the first 20 years of operation at the given location. Therefore, within-location variation in statutory feed-in tariffs affect expected revenue only for wind turbines installed in different years.

4 Research Design

Our aim is to test whether citizens curb their support for renewable electricity when exposed to local externalities associated with its production. For a given revealed-preference measure CS of citizens' support for renewable energy, we implement this test in the regression

$$\log(CS_{it}) = \beta_1 \cdot WT_{it} + \mathbf{X}_{it}' \cdot \beta_2 + \xi_i + \phi_t + \varepsilon_{it}, \tag{1}$$

where the explanatory variable of interest is WT, the number of wind turbines (or, alternatively, the installed wind power capacity). The vector $\mathbf{X}$ contains time variant local socioeconomic characteristics, such as average purchasing power, unemployment rates, age, and population density. Subscript i indicates zip codes in regressions of search queries and municipalities in regressions of vote shares, with ξ_i being the respective location fixed effects. Time t varies at the annual level, ϕ_t is a set of year effects, and ε is an error term.

The main threat to identifying the parameter β_1 is the potential endogeneity of wind turbine deployment. Reaching heights of 150 meters and more, wind turbines can have an invasive impact on townscapes and landscapes which threatens to lower the market value of real estate. Consequently, planned wind power projects are frequently met with local opposition, and citizens' initiatives have been successful in blocking many such projects. If indeed fewer wind turbines are built in areas with weaker support for renewable energy, ignoring this feedback will lead to upward bias in the OLS coefficient on WT in eq. (1). Location and time fixed effects control for unobserved heterogeneity in preferences and profitability across locations, as well as for aggregate shocks to renewable energy supply. Notwithstanding this, WT is likely endogenous for two reasons. First, unobserved preferences for wind turbines are not necessarily stable but might change during the sample period as citizens learn more about the technology. Second, the variable WT is not an exact measure of population exposure to wind turbines. As explained below, we compute WT based on distance to the centroid of a zip code or municipality. This introduces classical measurement error, as the bulk of the population might live elsewhere in the administrative unit.

To address endogeneity, we adopt an instrumental-variable (IV) approach that exploits quasi-experimental variation in the feed-in tariff that shifts the profitability of wind energy within locations and across installation years. For changes in feed-in tar-

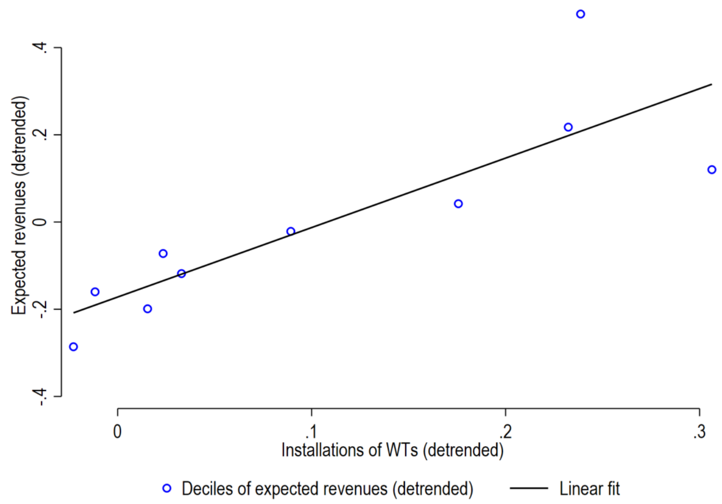


Figure 3: *Expected revenues and new wind turbine installations*

The figure plots expected revenues from the reference yield scheme (defined in eq. (3)*) against the number of newly installed wind turbines, after residualizing both variables with respect to year dummies. This procedure corrects for both cost reductions in wind turbine construction and reductions in the feed-in tariffs over time.*

iffs to be a valid instrumental variable, they must be (i) correlated with local trends in wind power deployment, and (ii) unrelated to unobserved shocks that confound the impact of wind-turbine deployment on the outcome variable. Assumption (i) is reasonable because higher revenues increase the profitability of wind-power investments. A plot of expected revenues against the number of newly installed wind turbines, as in Figure 3, exhibits a strong positive correlation (see also Hitaj and Löschel, 2019, for related evidence). The exclusion restriction (ii) is not testable. In what follows, we discuss this assumption and explain why a correlation between changes in feed-in tariffs and shocks to citizen support for wind power, other than the one mediated by wind turbine deployment, is unlikely to drive results in our setting.

To begin, note that the revenue of a wind power plant is given by the product of electric output and feed-in tariff. Since output depends on wind availability and strength, locations with high wind power potential can generate and sell more electricity than those with low potential. The geographic distribution of wind potential across locations is very uneven (cf. Figure 4a). Feed-in tariffs mitigate the impact of such differences on expected revenues and enhance the profitability of wind energy investments in less favorable locations.[16] The resulting distribution in expected revenues (cf. Figure 4b) is more homogeneous than that of wind potential. Profitability differences persist, however, and might be correlated with unobserved heterogeneity in citizen's support for renewable energy. Using time-variation in feed-in tariffs allows us to break any such correlation and obtain consistent estimates.

A potential threat to identification would arise if policy makers were able to target feed-in tariffs at particular locations in order to manipulate citizens' support. We investigated this but did not find any evidence that would substantiate such concerns. First, the EEG law spells out clearly that the feed-in tariffs were designed and adjusted so as to promote the further deployment of wind power generation capacity in Germany while also incentivizing further technological improvements and cost-cutting measures in the wind industry (EEG, 2004, 2009). The law does not stipulate any targeting beyond the cross-sectional differentiation by wind potential, which we control for.

Second, the policy instruments provided by the EEG law are too blunt to allow legislators to target locations based on characteristics other than wind potential. As discussed above, most amendments changed only two parameters, the initial tariff and the base tariff. The 2012 amendment additionally removed the eligibility threshold for feed-in-tariffs, which again affected a very large group of municipalities in Germany.

Third, a look to the data corroborates the view that granular fine-tuning of subsidies to particular zip codes or municipalities was impossible. Figure 4c displays the variation in expected revenues within locations over the estimation period, expressed in relation to the cross-sectional variation in Germany (cf. Figure 3). The figure shows that most of Germany's inland municipalities exhibit considerable (at least 50%) within variation in expected revenues. Removing the eligibility threshold induced variations of more than 100% in large parts of eastern and southern Germany.

[16]As explained in Section 3, locations with a lower potential received the higher initial tariff for a longer time period than locations with a higher potential. Thus, the former locations obtained a higher average feed-in tariff for wind turbines over their lifetime.

The variation in the instrumental variable thus affects large parts of Germany that can be viewed as representative.

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

$$\begin{aligned} WT_{it} = {} & \gamma_1 \cdot ER_{it} + \gamma_2 \cdot Ineligible_{it} + \gamma_3 \cdot Ineligible_{it} \cdot Potential_i + \\ & \mathbf{X}_{it}^{'} \cdot \gamma_3 + \eta_i + \nu_t + v_{it}, \end{aligned} \tag{2}$$

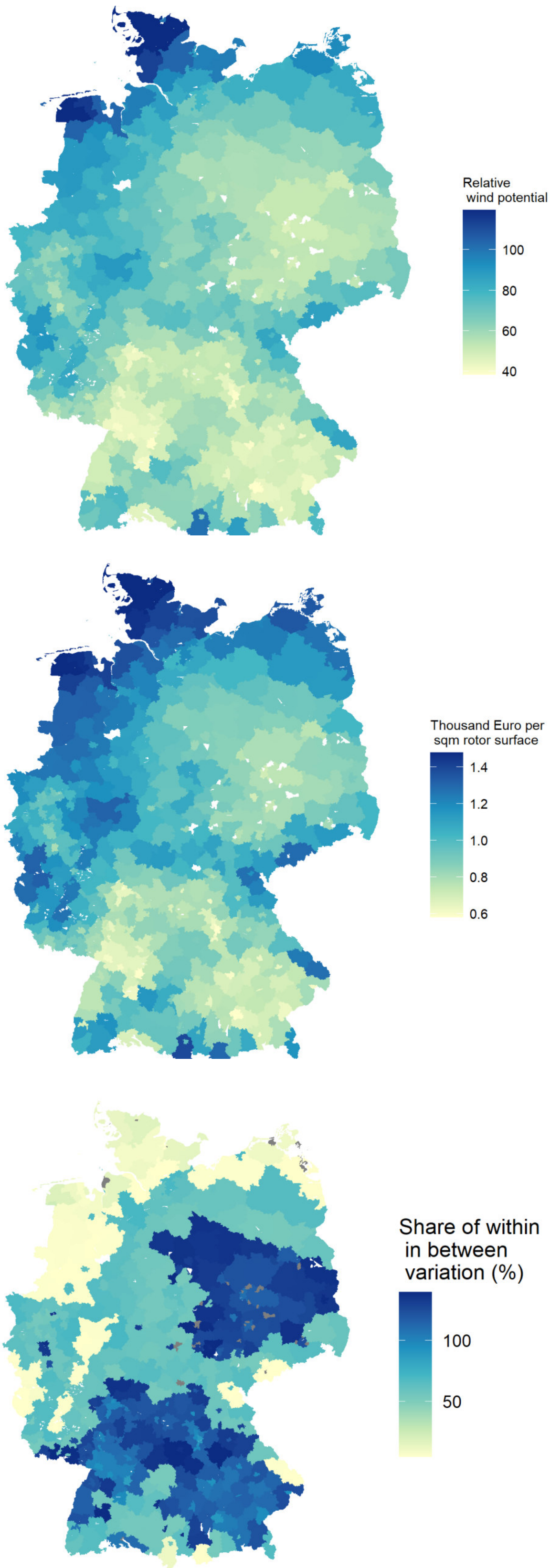
where the instrument $ER_{i,t}$ is the expected revenue of a wind turbine built in location i and year t according to the reference yield model. As was mentioned in Section 3, locations with less than 60 percent of the wind potential at the reference location were ineligible for the reference yield scheme before 2012. In those instances, $ER_{i,t}$ is set to zero and the dummy variable *Ineligible* is set to one. While the model is identified when using $ER_{i,t}$ as the sole instrument variable, adding a separate intercept γ_2 and slope coefficient γ_3 for ineligible municipalities strengthens the first stage by capturing heterogeneity across ineligible locations. Even in the absence of subsidies, locations with higher wind potential ($Potential_i$) provide stronger investment incentives. More details on the construction of the three instruments are given in the next section. The other explanatory variables are analogous to equation (1).

5 Data

Our empirical analysis focuses on two granular, revealed-preference measures of citizens support for renewable electricity. One is based on the corresponding product market and the other one on elections, "the market in which votes are exchanged for public-policy outcomes" (Crain, 1977). We discuss each measure in detail before describing the explanatory variables and summary statistics.

5.1 Search queries for green electricity tariffs

In 1999, Germany liberalized electricity markets by allowing entry to local markets and allowing consumers to freely choose between different electricity retailers and



Wind power potential

The figure plots the estimated wind power output relative to the reference output. The spatial distribution of wind power potential is very uneven.

Expected revenues

The figure shows expected revenues in 2013 based on wind potential and remuneration according to the reference yield model. The reference yield model levels some of the expected revenues over twenty years across regions, but expected revenues remain higher in regions with higher wind potential. To facilitate a visual comparison of the spatial dispersion in profitability before and after subsidies, the color coding in Figures 4a and 4b is based on quantiles of the distributions of wind power potential and expected revenues, respectively.

Within variation in expected revenues

The adjustments in feed-in tariffs and eligibility of regions lead to changes in expected revenues. The figure shows the within variation of expected revenues relative to its between variation measured both by their standard deviations. The figure shows sizeable within variation for the different regions. Regions with values above 100 percent are mainly regions that were ineligible for remuneration under the reference yield system before 2012 due to their low wind potential.

Figure 4: *Wind power potential and reference yield remuneration*

tariffs. This brought about the end of local monopolies and paved the way for massive entry of electricity retailers.[17] Fierce competition for customers is mainly on prices but also on product attributes such as renewable generation. Price comparison websites make it easy for consumers to compare electricity tariffs and switch suppliers. Our first measure of citizens' support is based on the premise that consumers who search and purchase a green electricity tariff via such websites reveal their preference for renewable energy. While we cannot observe the actual purchase decision and contract choice, we do measure how intensely consumers *search* for green electricity tariffs in the pre-contracting stage. This preference measure is based on observed behavior and hence less likely to suffer from cognitive biases than stated preferences.

The German software company *ene't*, an operator of several popular websites for comparing electricity tariffs, provided us with detailed data on search queries conducted between March 2011 and December 2014.[18] Figure A1 shows a screenshot of the search interface on toptarif.de, the most frequented of those platforms. For each search query, we observe the timestamp, the zip code for which information on local electricity tariffs is requested, the (expected) annual consumption entered into the search interface, the type of search query (household or industrial customer), a search session ID indicating the order of the queries of each searching consumer as well as the options ticked by the consumers. These options allow to refine the search query according to the consumer's personal preferences, and to compare results obtained when ticking different options. For instance, consumers can choose whether or not the ranked tariffs include package tariffs or switching premiums, or to only compare tariffs with price guarantees. Key for our analysis is whether a searcher ticked the box "show green tariffs only". As explained above, this is an important step towards

[17]During our sample period, the number of active electricity retailers per zip code ranged from 55 to 192, with an average of 133.

[18]Websites include tariffs including Toptarif.de (top tariff), Stromtipp.de (power tip), Energieverbraucherportal.de (energy consumption portal) and mut-zum-wechseln.de (courage-to-change). Search intensity on those sites and on the main competitor, the *Verivox* platform were strongly correlated with a coefficient of 0.85 in 2014, suggesting that our data are representative for online searches. Research in IO based on the same dataset has examined its representativeness in multiple ways. Gugler et al. (2023) find high correlations between searches on the comparison sites and on google, using keywords such as "Stromwechsel" (change of electricity supplier). Heim (2021) shows that factors influencing household search behavior include age, purchasing power, and the local availability of high-speed internet.

a green tariff purchase and thus speaks to the consumer's preference for renewable energy.

In sum, we have information on 35,855,071 search queries from 17,302,530 search sessions. Since our analysis focuses on households, we drop the 524,316 sessions (3.3 percent) that were conducted by commercial electricity users. Although our data do not tell us exactly how many households use the search tool, the sheer numbers of queries and sessions suggests that the use of price comparison websites was widespread, at least among households looking to switch contracts. In support of this interpretation, market research found that 80 percent of switchers already used price comparison websites in 2011 (A. T. Kearney, 2012). Our measure fails to capture the preferences of households that do not search, evoking a possible sample selection issue that is inevitable in revealed-preference studies. In our context, this issue appears relatively minor when considering that revealed-preference analysis of wages or housing prices is based on actions far more costly than running a search query on a website. Our measure does capture preferences of households that search but do not switch.

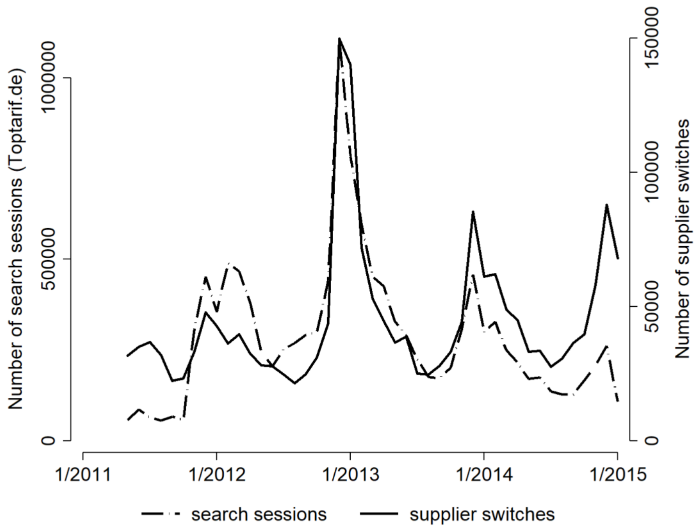
We aggregate the data to the zip code-year level. The yearly aggregation is consistent with households considering a supplier switch at most once a year (if at all), and coincides with the typical length of an electricity contract. Our measure of renewable energy support in zip code i and year t is computed as the share variable

$$CS_{i,t} = \frac{\textit{number of search sessions with box ticked}_{i,t}}{\textit{number of search sessions}_{i,t}},$$

where the numerator counts all search sessions where the "show only green tariffs" option is ticked in at least one query of a search session, and the denominator controls for the overall number of search sessions.

Search activity turns out to be a strong predictor of consumers' contracting decisions, indeed. Figure 5 shows that the number of search sessions from the *ene't* data is strongly and positively correlated with actual switching of electricity suppliers which we obtained from *Verivox*, another major price comparison site for electricity tariffs. The spikes in November stem from the fact that price adjustments typically take place

Figure 5: *Electricity tariff searches and contract switches over time*



in January and have to be announced six week in advance. A substantial price increase took place in 2013. The data suggest that consumers search in reaction to announcements of price changes.

Panel A of Table 1 reports descriptive statistics for the sample of search queries. On average, less than two wind turbines with a capacity of 2.7 MW are installed in a zip code. Almost nine percent of all searching households ticked the "show only green electricity tariffs" box at least once in a search session. Although there is meaningful spatial variation in this variable, visualized in Figure 6a, the vast majority of consumers does not regard this product attribute as central to their search and purchase decisions. Results obtained with this outcome thus speak to a small group of citizens with *strong* preferences for green product attributes. This provides additional motivation for studying an alternative preference measure.

5.2 Election results of the Green Party

Our second measure of citizen's support for renewable energy is the share of votes received by the Green Party in the German federal elections (*Bundestagswahlen*). The Green Party was established in 1980 and has been gaining importance in the German political landscape ever since. The party has been represented in the federal parlia-

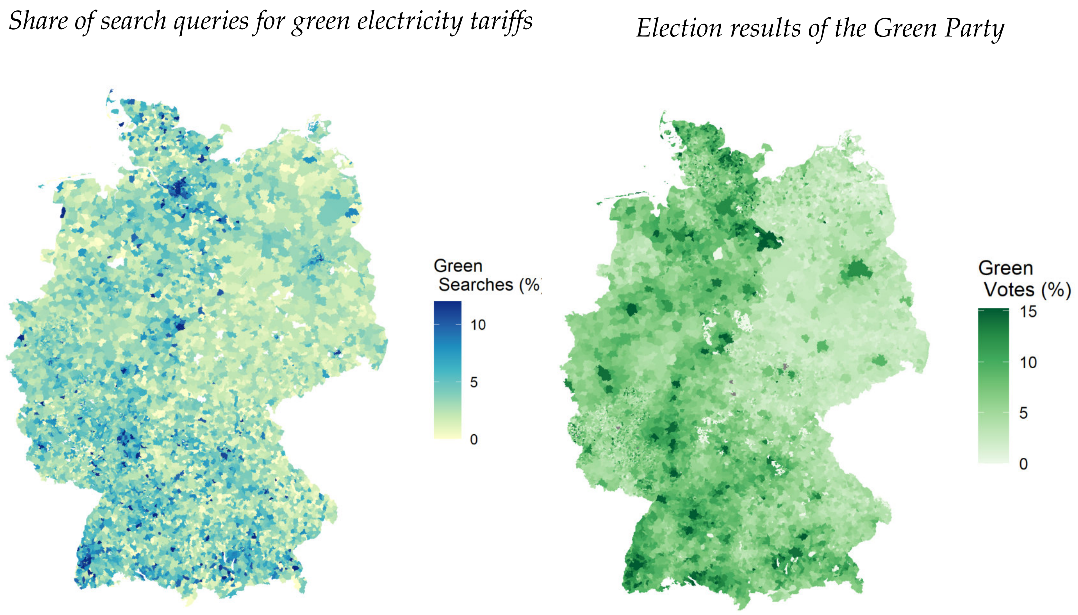


Figure 6: *Spatial distribution of outcome variables in 2013*

ment (the *Bundestag*) since 1983.[19] Between 1998 and 2005, it was part of the first-ever Red-Green federal government coalition partnering with the Social Democratic Party (SPD).

The transition of the energy sector from conventional generation towards renewable energy is the ideological basis of the Green Party and has been a central campaign issue during our sample period. For example, the term "renewable energy" was mentioned 61 times in the party's 2009 election program and 75 times in the 2013 program. The term "energy transition" appeared twice in 2009 and 74 times in 2013.[20] Wind plants in particular were mentioned 11 and 36 times and references to "climate" appeared 151 and 153 times, respectively (see Bündnis 90/Die Grünen, 2009, 2013). This is several times more often than in any of the other parties' election programs (cf. Appendix Table A2). In view of this, election results of the Green Party are well-suited for measuring revealed preferences for renewable energy.

Data on the election outcomes at the municipality level for the Bundestagswahl elections in 2005, 2009, 2013 and 2017 were obtained from the German Federal Return-

[19] A party gets seats in the *Bundestag* if it receives at least 5 percent of all votes.

[20] The 2013 election was the first federal election held after the 2011 nuclear accident in Fukushima (Japan) which triggered Germany's rapid nuclear exit. The gradual phase-out of nuclear energy had been a project of the Red-Green government which was put on hold by Angela Merkel of the Christian-Democratic Party when taking office in 2005.

ing Office.[21] On average, the Green Party received 8.7 percent of votes per municipality during our sample period. The spatial distribution of election results of the Green Party in the 2013 Bundestagswahl is displayed in Figure 6b. Descriptive statistics are reported in Panel B of Table 1.

5.3 Explanatory variables

Wind turbines. The *Marktstammdatenregister*, maintained by the German Transmission System Operators (TSO), provides official and detailed information on all renewable energy plants including the plant type (e.g. wind, solar, hydro etc.), net capacity, geo-coordinates and the date of commissioning.[22] We use this dataset to construct our variables of interest, i.e., the number and capacity of wind turbines located in a given zip code or municipality, as well as in 1 km-wide rings around the centroid, measured in 1 km increments up to 25 km. Figure 7 shows the spatial distribution of the stock of wind turbines in 2005 and 2017. While it is immediately seen that more turbines are installed in the northern half of the country, it is also apparent that the distribution is not a mirror image of that of wind power potential (see Figure 4a). In fact, two decades of subsidization have shaped the distribution of wind turbines in space, as is corroborated by first-stage regressions shown below.

Feed-in tariffs and socio-economic data. We calculate the expected revenue of each wind turbine based on the reference yield model, using data on local wind potential from the German Meteorological Office,[23] as well as information on initial and base tariffs obtained from the German Transmission System Operators.[24] Expected revenue during the 20 years of subsidization is given by

$$ER_{it} = (FIT_{init,t} \cdot n_{init,i} + FIT_{base,t} \cdot n_{base,i}) \cdot Potential_i, \tag{3}$$

[21] Available online at https://www.bundeswahlleiterin.de.
[22] Available online at https://www.marktstammdatenregister.de/.
[23] Available online at https://www.dwd.de/DE/leistungen/winddaten_windenergienutzer/dwd_winddaten_version6_demo.html
[24] See https://www.netztransparenz.de/EEG/Verguetungs-und-Umlagekategorien

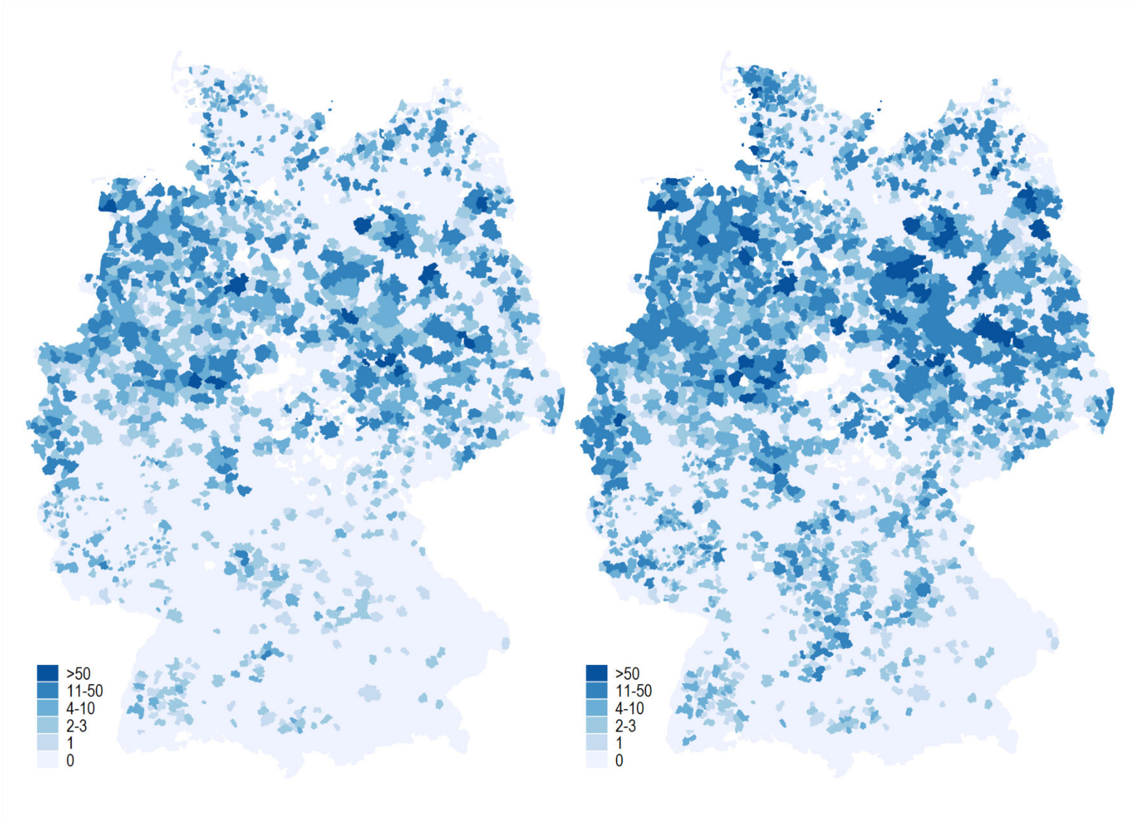


Figure 7: *Diffusion of wind turbines in 2005 and 2017*

where $FIT_{init,t}$ and $FIT_{base,t}$ are the initial and base tariff valid in year t, respectively. The terms $n_{init,i}$ and $n_{base,i}$ refer to the initial and base period in location i, respectively, with $n_{init,i} + n_{base,i} = 20$ years.[25] Annual wind potential is denoted by $Potential_i$. The expected revenue is measured in Euro cents per square meter of rotor surface over the same time frame. Before 2012, locations with less than 60 percent of the reference yield were ineligible for remuneration according to the reference yield scheme. In this case ER_{it} is set to zero, the variable $Ineligible$ is set to one and the interaction term $Ineligible_{it} \times Potential_i$ equals the reference yield at location i, which proxies for profitability. This captures the variation in investment incentives across ineligible locations.

Furthermore, we use socio-economic and demographic data to control for time-varying local changes, e.g., purchasing power, unemployment, population and household age. These data are obtained from Acxiom for the zip code level and from INKAR

[25]See Table A1 for details on the computation of $n_{init,i}$ and $n_{base,i}$.

and the German Federal Statistical Office for the municipality level. Data on commercial taxes of municipalities stem from the German Federal Statistical Office.

5.4 Spatial resolution

The spatial data resolution is at the German zip code level (8,048 zip codes) for the green electricity tariff queries and at the municipality level (10,611) for the election outcomes. For the green electricity tariff queries, we analyze the period 2011 to 2014 (chosen due to data availability and overlap with the period of the reference yield scheme). During these four years, the installed net capacity of wind power plants rose from 26.9 GW in 2010 to 38.6 GW by the end of 2014—a substantial growth by 43 percent. In our analysis of election results, we use data from the *Bundestag* elections in 2005, 2009, 2013, and 2017. We end our analysis period with the 2017 election, since the 2017 amendments to the EEG law replaced the reference-yield system of remuneration with an auction-based mechanism, meaning that our instrumental variable lacks relevance after 2017.

Table 1: *Summary Statistics*

	Mean	SD	Min	Max
Panel A – Search Queries for Green Electricity Tariffs				
Dependent variables				
Share of search sessions for with green tariffs selection (%)	6.04	5.96	0.00	100
– weighted by population	6.94	6.03	0.00	100
Variables of interest				
No. WT within zip code	1.62	4.44	0.00	37.00
Cap. WT within zip code	2.45	7.17	0.00	61.83
Instrument and control variables				
Expected revenue of a WT (in thousand €/m^2 rotor surface)	0.90	0.30	0.20	2.30
Purchasing power (in thousands Euro/year)	43.44	7.38	0.00	111.86
Population density per km^2	941	2,271	1.07	28,046
Young HH (%)	0.30	0.06	0.00	0.68
Zip code area (km^2)	41.92	47.31	0.08	891.94
Obs.	32,125			
Panel B– Election Results of the Green Party				
Dependent variables				
Share of votes for the Green party in federal elections (%)	6.97	3.70	0.00	51.85
– weighted by number of eligible voters	8.66	3.96	0.00	51.85
Variables of interest				
No. WT within municipality	1.01	2.92	0.00	24.00
Cap. WT within municipality	1.53	4.68	0.00	36.02
Instrument and control variables				
Expected revenue of a WT (in thousand €/m^2 rotor surface)	1.01	0.31	0.17	2.41
Employment rate (%)	55.05	7.90	0.00	205.77
Population density	187.8	279.9	3.00	4,682
Young HH (%)	0.02	0.05	0.00	3.75
Muncipality area (km^2)	31.15	36.40	1.00	632
Obs.	42,166			

Panel A presents descriptive statistics of zip-code–year level data in the period 2011 to 2014 Observations are weighted by population in a zip code. Panel B presents descriptive statistics for municipality-year level data covering the federal elections in the years 2005, 2009, 2013, and 2017.

6 Results

6.1 Main results

Green electricity tariffs. Table 2 shows results obtained when the outcome variable is the share of households searching for green electricity tariffs at any query during a search session. Since wind turbines are often built in sparsely populated areas, smaller communities could have a disproportionate influence on the estimation results. To avoid this, we weight regressions by population.[26] Our preferred estimate in Column (1)—obtained via 2SLS estimation of eq. (1)—implies that an additional wind turbine (WT) reduces the preference for green tariffs by approximately 24 percent.[27] Given that the mean share of households searching for green tariffs is 6.9 percent, this effect translates into an absolute decline of about 1.7 percentage points, which is statistically and economically significant. The corresponding OLS coefficient, reported in Column (2), is also negative and precisely estimated, though an order of magnitude smaller. The discrepancy could arise due to endogenous siting of wind turbines, which implies a causal effect that runs from preferences to the number of turbines. Because it ignores this reverse causality, OLS regression underestimates the relationship of interest. Additionally, classical measurement error in WT biases the OLS estimate towards zero.

To further assess the validity of the IV approach, Table 2 reports the first-stage F-statistic which summarizes the relevance of the instruments. As the Stock-Yogo 10 percent critical value is 9.08, our instruments appear to be sufficiently strong to identify local wind power expansion. Furthermore, correcting for endogeneity appears to be in order as the Durbin-Wu-Hausman test clearly rejects exogeneity of WT. Complete first-stage results are reported in Appendix Table A3.

Columns (3) and (4) of Table 2 report the results from IV and OLS regressions using capacity (not number) of wind turbines as the main explanatory variable. The IV coefficient estimates imply that increasing installed capacity in a zip code by 1 MW decreases preferences for green tariffs by 9 percent. Since the average net capacity of a WT is 1.5 MW in our data, the qualitative findings are reasonably similar, regardless of whether the number or the capacity of WTs is the regressor of interest.

[26] Results remain robust but coefficients are larger for regressions estimated without population weights, cf. Appendix Table A4.

[27] Here and below, we use the exponential function to transform coefficients into percentage effects as follows: $e^{-0.279} - 1 = -0.243$.

Table 2: *Effect of wind power expansion on search queries for green electricity tariffs*

Dependent variable is	*log(search queries for green tariffs)*			
	(1) IV	(2) OLS	(3) IV	(4) OLS
No. WT within zip code	-0.279***	-0.014**		
	(0.072)	(0.006)		
Cap. WT within zip code			-0.089***	-0.005**
			(0.027)	(0.002)
Year FE	y	y	y	y
Zip code FE	y	y	y	y
Socioeconomic controls	y	y	y	y
Durbin-Wu-Hausman test	0.00		0.00	
First stage F stat.	45.81		44.05	
Obs.	32,125	32,137	32,125	32,137

The dependent variable is the natural logarithm of the percentage share of households that search for green electricity tariffs in at least one query during a search session. Standard errors clustered at the zip code level in parenthesis. The local adoption rate of wind power is considered endogenous in Columns (1) and (3). The instruments in these specifications are based on expected revenues of a wind turbine according to the reference yield model. Regressions are weighted by population at the zip code-year level. The observation period covers the years 2011-2014. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Negative externalities of wind turbines are local and decay with distance, so the impact on citizens' support should be strongest in the immediate vicinity of the turbine. To test this hypothesis, we re-estimate specification (1) using only WTs located within 1km-wide rings ("donuts") around the zip-code centroid.[28] Figure 8 plots the treatment effects of an additional wind turbine on green electricity searches for donuts at distances of between 1km and 15km from the zip code centroid. The coefficient estimates steeply decline with distance from the turbine, corroborating the conjecture that negative externalities are local. To pin down the exact pattern of this spatial decay would require us to estimate all coefficients in a single regression, which is infeasible for lack of a sufficient number of instrumental variables.[29] However, the fact that the

[28]The average size of a zip code is 42 km^2, an area approximately equal to that of a circle with radius 3.7 km.

[29]The issue is one of omitted-variables bias that arises when the number of WTs in the donut is correlated with the (unobserved) number of WTs in the donut hole. As shown in Figure A2 in the appendix, this correlation is negligible at distances below 5km, indicating that the number of WTs are well stratified across distance rings and hence unlikely to confound the treatment effect. At longer distances, however, the correlation coefficient between measured and omitted WTs increases rapidly and hence more likely induces downward bias. This explains why the estimates in Figure 8 do not fall to zero.

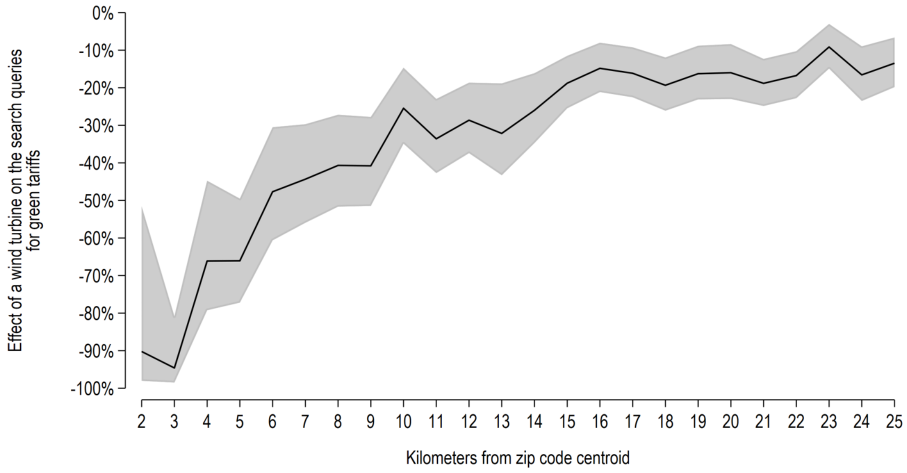


Figure 8: *Effect of the number of wind turbines on search queries for green electricity tariffs – different distances*

The figure plots the IV point estimates transformed into percentage effects ($(e^{\beta} - 1) * 100$) and the corresponding 95 % confidence intervals of the effect of the number of wind turbines within a 1km-wide ring at distance xkm from the zip-code centroid on green electricity tariff searches.

coefficient size more than halves between the 3km and 5km distance bands (where the potential for omitted variables bias is small) supports the qualitative conclusion that the effect on searches for green electricity tariffs quickly fades with distance.

Election results of the Green Party. Turning to vote shares of the Green Party as an alternative measure of citizens' support for renewable energy, we apply our research design to data on municipality-level results in German federal elections held between 2005 and 2017. Regressions are weighted by the number of eligible voters in the respective election. The results are reported in Table 3. The IV estimate in column 1 implies that an additional WT in a municipality reduces election outcomes for the Green Party by 10 percent. Given the average vote share for the Green Party of 8.6 percent, this corresponds to a decrease by approximately 0.9 percentage points. As above, the OLS estimate is strongly biased towards zero. As above, the Durbin-Wu-Hausman test corroborates our working hypothesis that wind turbine deployment is endogenous. The first-stage F-statistic of 26.7 lends support to the relevance of our instruments. Columns (3) and (4) report the estimated effect of adding 1 MW of wind generation capacity in a municipality. This causes a 5 percent decrease in the election results of the Green Party in the IV specification. As above, this lines up closely with the Column (1) estimate for the number of WTs.

Table 3: *Effect of wind power expansion on Green Party vote shares*

Dependent variable is	*log(vote share for the Green Party)*			
	IV (1)	OLS (2)	IV (3)	OLS (4)
No. WT within municipality	-0.105*** (0.015)	-0.004*** (0.001)		
Cap. WT within municipality			-0.045*** (0.008)	-0.002*** (0.001)
Year FE	y	y	y	y
Zip code FE	y	y	y	y
Socioeconomic controls	y	y	y	y
Durbin-Wu-Hausman test	0.00		0.00	
First stage F stat.	26.67		22.29	
Obs.	42,166	42,170	42,166	42,170

The dependent variable is the natural logarithm of the percentage share of votes for the Green Party. Standard errors clustered at the municipality level in parenthesis. The local adoption rate of wind power is considered endogenous in Columns (1) and (3). The instruments in these specifications are based on expected revenues of a wind turbine according to the reference yield model. Regressions are weighted by the number of eligible voters at the municipality-election year level. The observation period covers the federal elections 2005, 2009, 2013 and 2017. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

As is the case with search queries, the impact of WTs on votes for the Green Party rapidly diminishes with distance from a municipality's centroid as shown in Figure 9.[30]

Aggregate political impact. How many votes did the Green Party lose, on aggregate, because of the local externalities of the wind power boom? As a back-of-the-envelope calculation, we multiply, for each municipality, the average treatment effect of a wind turbine by the increment in the number of WTs installed between successive *Bundestag* elections and scale this proportional effect with the total number of votes received by the Green Party. This provides an estimate of the aggregate number of votes lost due to these installations. After dividing this number by the total votes cast nationally,

[30] As explained in footnote 29, spatial correlation likely prevents the effect size from going all the way to zero.

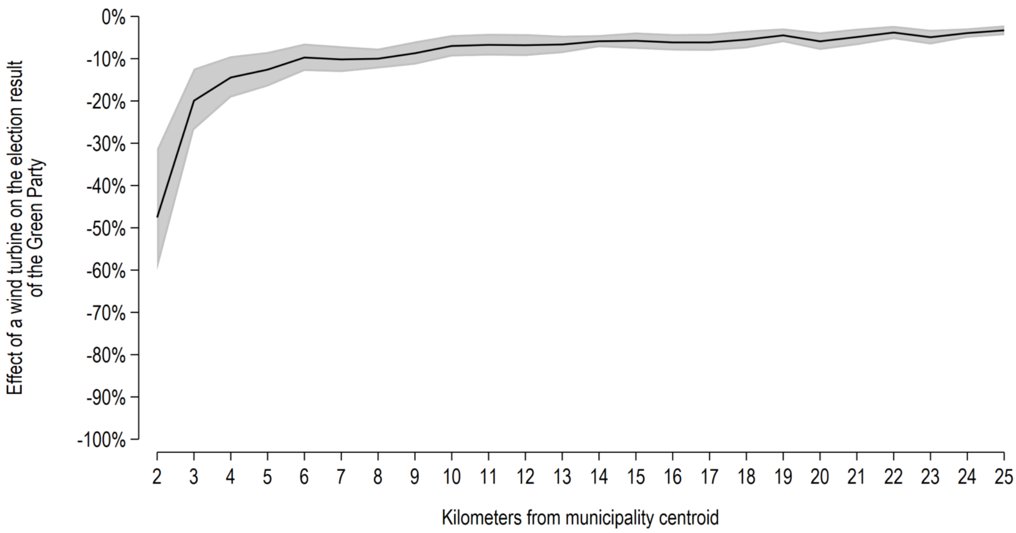


Figure 9: *Effect of the number of wind turbines on Green Party vote shares – different distances*

The figure plots the IV point estimates transformed into percentage effects ($e^{\beta} - 1) * 100$) and the corresponding 95 % confidence intervals of the effect of the number of wind turbines within a 1km-wide ring at distance xkm from the zip-code centroid on the vote share for the Green Party.

we find that the growth of wind power installations between 2005 and 2017 reduced the nationwide vote share of the Green Party by approximately 0.4 percentage points. Relative to the party's average vote share of 8.7 percentage points (ranging from 7.8 in 2005 to 10.4 in 2009), the decline corresponds to roughly a one in 20 votes.[31]

6.2 Robustness

This section shows that our results are robust to a battery of checks w.r.t. functional form assumptions, treatment of outliers, estimation algorithm, as well as alternative choices of covariates and outcome variables. We briefly motivate and describe alternative specifications that we have estimated in this section. Results are relegated to Appendix A.

[31] Because we assume a uniform effect of each turbine across all municipalities, our estimate does not capture potential nonlinearities or compounding effects in areas with multiple turbine installations, which we investigate in Section 6.2. Therefore, it should be interpreted as an approximation rather than a precise measure of the aggregate political impact.

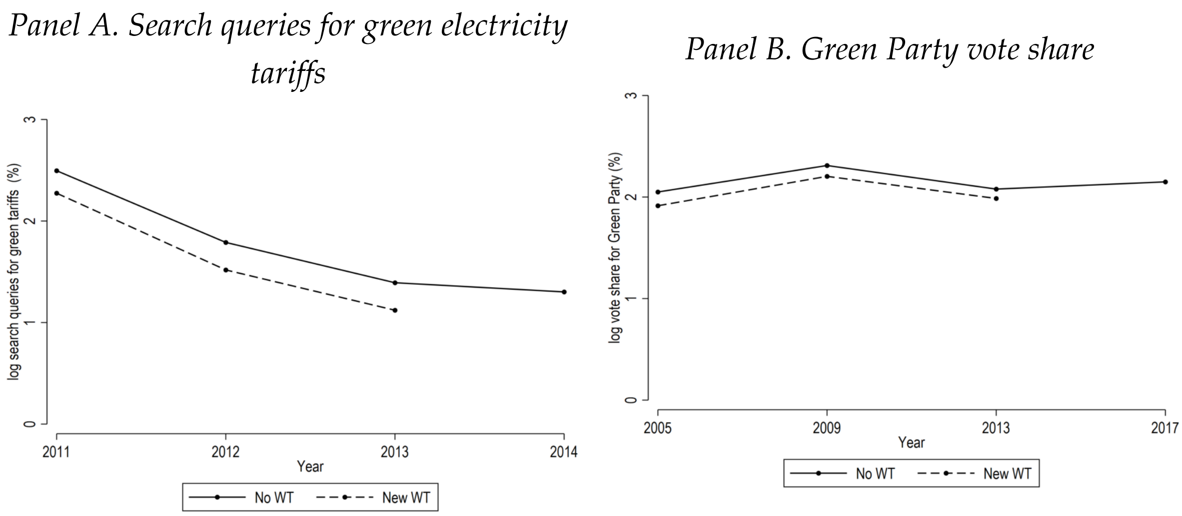


Figure 10: *Pretrends*

Solid lines represent the average yearly outcomes in areas that had no WTs throughout the observation period. Dashed lines represent outcomes in areas that eventually installed at least one WT during the observation period, but only for the years before their first WT was installed. The graph compares these two groups during periods when neither group had any WTs.

Parallel trends. We examine whether our outcome variables differed between locations that, by the end of the sample period, had no wind turbines installed and those that installed their first one during the study period. Figure 10 plots the outcomes for a visual assessment of whether any such differences existed before the installation of the first turbine. For locations that installed the wind turbines during the observation period, only the periods before the first installation are shown. Inspection of these trends suggests that both outcomes followed similar trends in locations that eventually installed wind turbines and those that did not.

Placebo analysis. To assess the possibility that our results are driven by pure chance, we run placebo regressions where the treatment is randomly assigned. For instance, we assign the WT data and the corresponding instrument in zip code i in the years 2011 to 2014 to a randomly selected zip code j for the corresponding years. This procedure ensures relevance of the instruments for WT expansion, as in the original specification, yet there should no longer be a systematic relationship with green tariff searches or election results of the Green Party. We keep the socio-economic control variables in their original location.[32] Estimating the baseline specification (column 1 of Tables 2 and 3) on 1,000 placebo datasets yields distributions of the WT coefficients and their p values (plotted in Appendix Figure A3). For both outcome variables, placebo regressions yields, on average, a precise zero (0.00) effect with $p = 0.5$, and the Durbin-Wu-Hausmann tests no longer reject exogeneity. This is in stark contrast to the negative and highly significant treatment effects obtained in our main findings.

Our second placebo test addresses the concern that the areas that received subsidies might have been building turbines for other reasons. To investigate this, we estimate our baseline model after lagging the dependent variable by one period. Wind energy projects that will be developed only in the future should not affect current preferences for green electricity tariffs or election outcomes for the Green Party. Results in Appendix Tables A7 and A8 confirm this expectation in that the estimated coefficients of future wind turbine developments are four to ten times smaller and statistically indistinguishable from zero. Furthermore, the Durbin-Wu-Hausman test fails to reject, indicating that, as anticipated, endogeneity is no longer an issue when the dependent variable is lagged.

Eligible vs. non-eligible areas. Prior to 2012, areas with wind potentials below a certain minimum threshold were ineligible for remuneration under the reference yield scheme. The 2012 EEG amendment removed this threshold, allowing all locations—including those previously deemed too low in wind potential—to benefit from wind power subsidies. Since our observation period includes this policy change for both outcomes, we can measure the extent to which our instruments—eligibility status and expected revenues—identify treatment effects on locations that became newly eligible after 2012. If the Local Average Treatment Effect (LATE) identified by our IV approach is very specific to initially ineligible locations, this would limit the generalizability of our findings to other locations that were always eligible for feed-in-tariffs.

To investigate this, we augment the baseline model to estimate separate treatment effects for locations that are initially eligible and those that are not. The former effect

[32] Randomizing the socio-economic controls does not change the results of the placebo tests.

is identified only off the variation in ER whereas the latter additionally uses the time variation in $INELIGIBLE$. We test whether these two LATEs yield different estimates. Results reported in Appendix Tables A9 and A10 show that point estimates are slightly larger for the group of initially ineligible locations, but the differences are not statistically significant with p-values of 0.61 and 0.48, respectively.[33] We thus cannot reject the hypothesis that the wind turbines have the same impact on the outcome variables in always-eligible and newly-eligible locations. This mitigates the concern that our LATE estimate might not be representative for a broader subpopulation, enhancing the external validity and robustness of our findings.

Functional form. Our main results are derived from a semi-log specification where we use $\log(y + 0.1)$ as the dependent variable. The log transformation limits the influence of outliers on the results while the addition of 0.1 is necessary to accommodate zero values of y. We examine robustness of the results when addressing potentially influential outliers in alternative ways. As a direct analogue to our main specification, we re-estimate the model after applying the inverse hyperbolic sine transformation (IHS) to the outcome variables. In further regressions, we drop zero-valued observations from the estimation sample, or truncate the sample from the top, dropping observations where the outcome variable exceeds the 99th, 95th or 90th percentiles. As shown in Columns (1)–(5) of Appendix Tables A12 and A13, the results remain qualitatively robust to all these transformations. Column (6) reports results obtained with a Poisson Pseudo Maximum Likelihood (PPML) estimator where the first-stage residuals are included as a control function for endogeneity. This addresses the non-negative nature of the outcome variables more directly and yields results that are very similar to those the baseline 2SLS regressions. Column (7) shows that the results are also robust when applying the approach to deal with zeros in log-linear models recently suggested by Bellégo et al. (2022).

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

Lagged instruments. Given that planning and constructing new wind turbines takes time, the strength of our first-stage relationship between subsidies and *contemporaneous* wind power expansion might surprise. The timing of draft bills across versions of the EEG between 2000 and 2014 was such that investors had between four and eleven months to learn about new subsidies before they entered into force.[34] With a typical construction phase of 12 to 18 months (Fabra et al., 2024), this lead time allowed firms to either speed up (or delay, when subsidies were increased) the completion of projects in order to bring them online in the calendar year of the subsidy change, driving a contemporaneous correlation in the first-stage regressions.

New projects might take more than two years to materialize, suggesting the use of lagged subsidies as instrumental variables. Appendix Tables A14 and A15 show that our results are robust to the timing of the subsidy effect. Including first or second lags of the instrumental variables yields a very similar effect on tariff searches and a somewhat smaller effect on the Green Party vote share. These regressions also suggest that possible serial correlation in subsidies does not bias our results. Lagged instruments reduce the first-stage F statistics, however, and are thus omitted in our preferred specification. Clustering standard errors at the municipality or zip code level makes the inference robust to potential serial correlation.

Spatial correlation. Statistical inference drawn from the above results might be incorrect if there is spatial correlation in the error terms. Following Conley (1999), we account for this by computing standard errors using a weighting function that is the product of one kernel in each dimension (north-south, east-west). The kernel starts at one and declines linearly until it reaches 0 when it exceeds a certain cutoff point. We choose the cutoff points at distances of 10, 25 and 50 kilometers, respectively. Appendix Tables A18 and A19 show that the treatment effect remains statistically significant when allowing the errors to be correlated within geographical areas larger than our cross-sectional units of observation.

[34]For instance, the 2012 EEG amendments, which made low-yield areas eligible for subsidies, were drafted in the wake of the Fukushima nuclear accident in March 2011, passed the Bundestag in June 2011, and entered into force on January 1 of 2012.

Pecuniary vs. non-pecuniary externalities. Wind turbines exert downward pressure on land prices because of negative externalities for residents, or upward pressure because renewable energy subsidies are capitalized into land prices (Haan and Simmler, 2018). Such pecuniary externalities add to—or subtract from—the non-pecuniary externalities that we are interested in measuring. Controlling for land prices might thus yield a more precise measure of non-pecuniary externalities, but due to their endogeneity w.r.t. wind power deployment, we do not include land prices in the main specification. Appendix Tables A16 and A17 report results where we additionally control for local variation in land prices. Our coefficient estimates on WT remain robust to this exercise, which supports our exclusion restriction.

Alternative search measures. Recall that we measure preferences for green electricity in a zip code as the share of search sessions with the filter "show only green tariffs" activated at least once during the session. A potential concern with this interpretation is that salience effects could shift this variable irrespective of green preferences. For example, if wind turbines raise awareness about electricity costs among local residents, this might increase the number of searches. In turn, if turbines raise awareness that green electricity is available for purchase, local consumers might search more directly for such tariffs.[35] The net effect of such mechanisms on the outcome variable is ambiguous. We thus investigate the robustness of our results to using two alternative definitions for green tariff searches in the numerator of the outcome variable. The first is based on searches that ticked the "show only green tariffs" box already in the first query of their search session (4.1 percent). Consumers ticking the box in the first query likely have a strong, lexicographic preference for a green tariff, making them less susceptible to salience or price effects. The second alternative measure counts only search sessions where the "show only green tariffs" option is ticked in the last query (5.7 percent). The appeal of this measure is that, of all three measures, it likely exhibits the strongest correlation with a consumer's final choice. Table A6 reports the estimated effects of wind turbines on the *share of households searching for green electricity tariffs* for

[35]We thank two anonymous referees for pointing out different salience effects to us.

these two alternative definitions. The results are very similar to those from our main specification.

6.3 Extensions

Having established the robustness of our baseline results, we now discuss several extensions that shed light on the factors underlying those results and reveal relevant heterogeneities.

Impact of the first wind turbine. Do new wind turbines have a stronger effect on citizens' support in populations that have not yet been exposed to them? If residents get used to the sight of wind turbines (as suggested by evidence presented in Guo et al., 2024), we would expect a more negative reaction when going from zero to n WTs than when adding those n WTs to an existing stock, especially for $n = 1$. Such cases are quite relevant in our data.[36] To investigate this, we re-estimate the baseline specification while interacting the number of wind turbines with indicator variables for whether a region already had at least one WT at the beginning of the observation period. The results, reported in Appendix Tables A20 and A21, show that the estimated effects are indeed substantially larger for the first installation of a WT. First-time installation in a zip code reduces the share of green tariff queries by as much as 42 percent. In contrast, adding another WT to a zip code that already hosts some reduces green tariff searches by only 20 percent. Similarly, Green Party vote shares drop by 14 percent when the first WT is installed in a municipality, while an additional WT reduces the vote share by only 7 percent in areas where WTs are already present. The result that the first wind turbine causes a notably stronger decline in local support for green energy compared to the more modest effects of subsequent installations is consistent with a habituation effect over time.

[36]Out of 10,874 municipalities, 9,165 had not a single WT installed by 2005, and 6,011 out of 8,039 zip codes had no wind turbine installed by 2011. At the end of the respective sample periods, 984 municipalities and 303 zip codes had seen the installation of the first WT on their territory.

Does size matter? To assess whether the local disamenity effects of wind turbines vary by turbine size, disaggregate the number of WTs in a location into separate counts for above- and below median height. Because turbine sizes have increased over time, using an overall median would over-represent additions to the WT stock in later years in the "large turbine" category. Instead, we use year-specific, nationwide median turbine height when classifying new turbines as "large". We generate two variables: one that equals the number of wind turbines multiplied by an indicator that the average turbine height is less than or equal to the year-specific median and another for turbines above the median. To address potential endogeneity concerns, we also interact our instruments with these size-specific dummies. The results reported in Appendix Tables A22 and A23 suggest that the effect does not differ significantly regardless of whether wind turbines are somewhat smaller or larger.

Voter migration and turnout. Mechanically, our main result that WT installations reduce the Green Party's vote share can be driven by voter migration, changes in turnout, or both. To abstract from turnout, we estimate our model using the Green Party's vote share among all eligible voters rather than among all votes cast, finding a slightly larger treatment effect of -12 percent instead of -10 percent in our original specification (see Table A24). This suggests that the decline in Green Party support is primarily driven by voters switching to other parties rather than by lower turnout among Green Party supporters. Consequently, the election outcomes of other parties must be affected—*cui bono*?

To answer this, we examine patterns of voter migration in response to WT deployment. We start with effect on vote shares of the ruling coalition parties, as they are widely perceived as 'in charge' of implementing large-scale policies such as the renewable energy expansion.[37] We examine the electoral performance of these parties to assess the political cost of wind power expansion imposed on the ruling coalition as a whole as well as the burden on the individual governing parties. The results,

[37] The ruling coalitions were, in chronological order: SPD and Green Party (1998-2005), CDU and SPD (2005-09), CDU and FDP (2009-13), CDU and SPD (2013-17).

reported in Column (1) of Table A25, indicate that there is virtually no effect of WT deployment on the combined vote share of the ruling coalition parties (the coefficient is close to zero and not statistically significant). Voters do not seem to punish the governing coalition as a whole for negative local impacts of WT deployment. However, they may shift their support based on their broader ideological stance on renewable energy policies.

To explore this further, we classify the six major political parties into "pro-wind" and "anti-wind" camps based on the preferences of their voter bases. Using survey data from the Social Sustainability Barometer, Otteni and Weisskircher (2022, Figure 3) find that voters of the CDU, FDP, and AfD tend to be skeptical of renewable energy projects in general and wind turbines in particular, forming the "anti-wind" camp. In contrast, voters of the SPD, Green Party, and Die Linke are generally supportive of renewable energy projects, constituting the "pro-wind" camp. We estimate that the deployment of new WTs leads to a 3.8 percent increase in vote share for the "anti-wind" parties and a 3.2 percent decrease for the "pro-wind" parties, as reported in Columns 2 and 3 of Appendix Table A25. This corroborates our main results in that WT deployment not only reduces Green Party support but also shifts local political dynamics in favor of parties whose voter bases are more critical of renewable energy projects and, in particular, wind turbines.

To complete our analysis, we estimate the direct effect of WT deployment on voter turnout. Results in Appendix Table A26 indicate that, on average, an additional WT installed lowers turnout by a modest but statistically significant 1.4 percent. This is consistent with an interpretation whereby dissatisfaction or a perceived lack of political responsiveness leads some voters to not participate in the election.

Other elections. So far we have focused on how WTs affect the local voting behavior in federal elections. This is reasonable as the course of Germany's energy transition is basically set at the federal level. Local externalities might affect local elections as well, but an empirical investigation of such spillovers is complicated by several factors. First and foremost, the Green Party did not run candidates for the municipal council in 66 percent of German municipalities.[38] Second, so-called independent voters' associations, formed by citizens who unite to pursue local objectives despite having very heterogeneous ideological stances, compete with established parties in local elections. In Baden-Württemberg, where the Green Party leads the state government, independent voter groups have been dominating the municipal councils since the nineties and accounted for 38% of the votes in the municipal elections 2009 and 2014 (Statistisches Landesamt Baden-Wuerttemberg, 2014). Another reason for us to refrain from analyzing local elections is that party positions at the municipality and state levels often deviate in non-negligible ways from the position at the federal level. Partly, such discrepancies can be seen as a reaction to fierce competition from independent voter associations.

It is possible, however, to estimate the impact of WTs on the outcomes of elections to the European Parliament (EP). These elections are commonly perceived as less important and hence could be used as "second-order-national-contests" where voters express their dissatisfaction with a party's national politics (Hix and Marsh, 2007). The logic behind this is that long-term supporters of a political party are reluctant to express their disenchantment by voting for another party at a first-order (e.g., a federal) election, but are willing to cast a vote of dissatisfaction with their party in a second-order election. In line with this hypothesis we find somewhat larger effects when re-estimating the model on EP election data, as reported in Appendix Table A27. The coefficient estimates imply that an additional WT reduces the votes of the Green Party by 14 percent (compared to 10 percent in the *Bundestag* elections).

Local electricity prices. The expansion of wind turbines lowers wholesale electricity prices, which are determined at the national market level. In principle, more wind power could also increase retail electricity prices locally via increased grid fees. These fees are collected to cover the costs of connecting wind turbines to the grid, upgrading

[38]Own calculations based on official data on municipal elections by the statistical offices of the German states.

infrastructure, and managing imbalances caused by the variability of wind energy generation. Adjustments to grid fees are subject to administrative delays and thus unlikely to be simultaneous with wind power deployment. To shed light on this, we estimate the impact of wind turbines on electricity prices charged by basic suppliers (*Grundversorger*) for a typical two-person household with an annual consumption of 3,500 kWh. Our regression results, reported in Appendix Table A28, indicate that the installation of wind turbines do not significantly affect local retail electricity prices. Therefore, it seems unlikely that local price effects are driving the substantial decline in Green Party vote shares or in searches for green electricity tariffs.

7 Financial Participation and Support for Renewables

As shown by the analysis above, proximity to wind turbines lowers revealed-preference measures of citizens' support for renewable energy. Hence, minimum distance requirements for new wind turbines—introduced in German federal and state laws—could help sustain local acceptance of wind power expansion. At the same time, however, such requirements directly slow down the energy transition by reducing the number of suitable sites. Industry representatives blame Bavaria's "10H rule", which required turbines to be set back from residential areas by a distance of at least ten times the turbine's hub height, for bringing wind-power development in Bavaria to a near-standstill after 2014 (Bayrischer Rundfunk, 2024). A nationwide study commissioned by the German Federal Environment Agency finds that raising the minimum distance from 800 m to 1,200 m reduces the available land area for wind turbines to only one quarter of the original potential; at a distance of 2,000 m from residential areas, the remaining land potential drops to a mere 0.4 percent of Germany's total land area (Umweltbundesamt, 2013).

The concern that strict distance regulations are in conflict with meeting renewable-energy targets has motivated interest in alternative policy instruments that avoid these trade-offs. Financial participation, which seeks to compensate nearby residents for the local externalities of renewable electricity generation, has received particular attention as a potential remedy for NIMBYism. Our data and setting provide a unique opportunity to examine whether such an approach can be successful. We test this by comparing citizens' support for wind power before and after a policy change that transferred more tax revenues from wind power plants to the municipalities where they operate. Profits from wind power plants are subject to the commercial tax (*Gewerbesteuer*), which constitutes a major source of municipal tax revenues (along with property taxes). Firms operating in multiple municipalities pay commercial taxes in proportion to the share of labor costs incurred in each municipality. Since turbines incur rather low labor costs once operational, municipalities hosting wind turbines did not benefit financially from them under this arrangement. A tax reform in 2009 sought to change this by allocating 70 percent of commercial tax revenues from wind turbines based on the book value of tangible fixed assets, and only 30 percent according to labor costs.

To analyze whether the tax reform had the desired effect, we first determine whether wind turbines were locally owned. We do so using registered addresses of WT operators, available from the *Marktstammdatenregister* for 94 percent of the WTs in our sample. We find that only 26 percent of these turbines were located in the same zip code as their operators. Classifying the remaining WTs as not locally owned ($LOCAL = 0$), we test whether the tax reform increased tax revenues from those WTs. We implement this in a cross-sectional IV regression of the change in the log tax base between 2008 and 2010 on the total number of WTs in 2008 and its interaction with $(1 - LOCAL)$. Our empirical test focuses on the commercial tax *base* instead of tax *revenues* to avoid the possibility that municipalities might adjust their commercial tax multipliers in response to wind power expansion.[39]

Results reported in Appendix Table A29 imply that the post-reform tax base increased by 5.2 percent per WT in municipalities where WTs are not locally owned. The effect is consistent with the intended effect of the reform to shift tax revenues from

[39]German municipalities set a local multiplier on top of a standardized base tax rate (*Hebesatz*), thereby determining the final tax burden and revenue potential. Because municipalities may adjust their multiplier in response to local developments, it is potentially endogenous (see, e.g., Langenmayr and Simmler, 2021).

municipalities that host company headquarters towards those that host only wind turbines. Relative to the mean tax base in 2008, the estimated coefficient corresponds to an economically significant increase of 85 thousand euros.[40]

We exploit the differential effect of the 2009 reform on municipal tax bases to examine how financial participation moderates the impact of a wind turbine on vote shares for the Green party. Unobserved heterogeneity in the response to WT deployment could vary in systematic ways with tax revenues from WTs. The tax reform breaks any such correlation by raising the tax base in those municipalities that hosted wind turbines but not the operator's headquarters. To map this quasi-experiment to the data, we define a dummy variable $TREAT$ for municipalities that host only WTs with owners in a different zip code and estimate the equation

$$\begin{aligned}\log(CS_{it}) = \beta_1 \cdot WT_{it} + \beta_2 \cdot WT_{it} \cdot TREAT_i + \beta_3 \cdot WT_{it} \cdot TREAT_i \cdot POST_t \\ + \mathbf{X}'_{it}\beta_5 + \xi_i + \phi_t + \varepsilon_{it}.\end{aligned} \tag{4}$$

where $POST_t$ is a dummy for years 2009 and later.

The results, summarized in Table 4, are consistent with the reform mitigating the negative impact of WTs on the Green party's vote share. Across specifications, the estimated $\hat{\beta}_3$ is significant and implies a reduction of the negative treatment effect of WT by one to two thirds. Smaller moderating effects arise when estimating separate pre-reform coefficients; those coefficients imply that treated municipalities more strongly rejected WTs prior to the reform. However, the inclusion of three endogenous variables is quite demanding on the strength of the instrumental variables, as indicated by low Kleibergen-Paap statistics. The point estimates are robust to allowing the reform to have differential impact on citizen support in municipalities that do not host any WTs (but may host headquarters of WT operators); the estimated β_3 is somewhat smaller but remains statistically significant. In sum, the estimation results support the conclusion that the negative effect of wind turbines on the vote share for the Green

[40] This likely overstates the average treatment effect on the treated because it is relative to all other municipalities, some of which lose tax base after the reform. For our purposes, however, it is sufficient to verify that the relative effect is positive.

Party is mitigated by at least one third once municipalities are enabled to financially benefit from wind power profits via commercial taxes.

Table 4: *Effect of wind turbines on citizens' support and the role of local commercial tax revenues*

Dependent variable is	*log(vote share for the Green Party)*				
	(1)	(2)	(3)	(4)	(5)
No. WT within municipality	-0.105***	-0.142***	-0.140***	-0.108***	-0.114***
	(0.015)	(0.035)	(0.035)	(0.025)	(0.026)
$\times$ *TREAT*				-0.180**	-0.173**
				(0.083)	(0.084)
$\times$ *TREAT* $\times$ *POST*		0.089***	0.075***	0.124***	0.094**
		(0.021)	(0.029)	(0.033)	(0.044)
$\mathbb{I}\{WT = 0\} \times POST$			0.027		0.114
			(0.099)		(0.105)
Year FE	y	y	y	y	y
Zip code FE	y	y	y	y	y
Socioeconomic controls	y	y	y	y	y
Durbin-Wu-Hausman test	0.00	0.00	0.00	0.00	0.00
First stage F stat. WT	26.67	38.75	9.29	32.06	10.04
First stage F stat. $WT \times TREAT$				9.47	4.98
First stage F stat. $WT \times TREAT \times POST$		35.44	8.98	28.88	8.75
Kleibergen Paap F stat.	26.67	14.62	8.22	4.29	5.45
Obs.	42,166	42,166	42,166	42,166	42,166

The dependent variable is the natural logarithm of the percentage share of votes for the Green Party. WT denotes the number of wind turbines in a municipality, $TREAT$ is dummy for municipalities hosting only WTs that are not owned by a local company, $POST$ is a dummy for years after 2008, and $\mathbb{I}\{WT = 0\}$ is a dummy for all municipalities that have not a single wind turbine at the end of 2017. The local adoption rate of wind power and its interactions terms are considered endogenous. The instruments in these specifications are based on expected revenues of a wind turbine according to the reference yield model. For the interaction terms the instruments are interacted with the respective indicator variables (Treat, Treat $\times$ Post). The observation period covers the federal elections 2005, 2009, 2013 and 2017. Standard errors clustered at the municipality level in parenthesis. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

This finding is consistent with a mechanism by which (i) additional commercial tax revenue from wind turbines is used to either provide more local amenities or lower other taxes *and* (ii) citizens being aware that the additional tax revenue came from wind turbines. Anecdotal evidence supports this mechanism in that local officials and WT operators frequently emphasize these fiscal benefits in public discourse, thereby raising residents' awareness of how turbine revenues finance visible local improvements. For instance, some rural municipalities have used such revenues to build new playgrounds, upgrade street lighting, and expand broadband internet (Der Spiegel, 2016; Märkische Allgemeine, 2021).[41] Moreover, electricity companies advertise the resulting tax revenues and quantify by how much host municipalities could property taxes for their residents (EnBW, 2024). Towns like Lichtenau (2024) publicly disclose how much income they obtain from wind turbines.

Overall, these empirical results support the notion that greater local participation in wind power profits can mitigate the negative impact of nearby wind turbine installations on citizens' support for renewable energy. While more research is needed to corroborate the strength of this effect and to identify the mechanism underlying it, the policy implication is that directly compensating municipalities for installing wind turbines will have a positive impact on the energy transition. Germany has recently introduced this possibility in the 2021 amendment of the renewable energy support act.

8 Conclusion

Model scenarios unequivocally show that mitigating global climate change requires a dramatic expansion of renewable energy in the years and decades to come. In liberal societies, the success of such a strategy crucially depends on public acceptance and citizen's support for renewable energy. While opinion polls consistently find broad support for renewable energy among citizens, actual projects are often met by fierce local opposition. The NIMBY phenomenon is particularly wide-spread in the context of wind power plants and poses a serious obstacle for a successful energy transition.

In this paper, we have estimated the impact of increasing wind power exposure on citizen's support for renewable energy using Germany as a case study. We propose two granular measures of citizen's support: local preferences for renewable energy electricity tariffs and election results of the Green Party. We have found that search queries for renewable energy tariffs made on price comparison websites drop by around 24 percent when a wind turbine is installed in the zip code. Similarly, we

[41] Gavard et al. (2025) document that budgets of Danish municipalities increase following the installation of new turbines.

have found that votes for the Green Party in German federal elections decrease by about 10 percent with each new wind turbine in a municipality. These findings indicate that even strong and active proponents of renewable energy, i.e. consumers who actively search for green electricity and voters of the Green Party, significantly reduced their support when exposed to nearby wind turbines.

An alternative interpretation might attribute our empirical findings to moral licensing, in the sense that people living close to a wind turbine are less inclined to shop for a green electricity tariff or to cast their vote for a pro-environmental party because they feel that they have "done their part" for the environment. Although we cannot rule out such an effect, we find this explanation less convincing in light of our results on voting behavior where declining support for the Green Party coincides with increasing support for parties that are more antagonistic towards wind power. This is consistent with other forms of opposition often observed in affected communities, such as protests and efforts to block further installations. Both types of behavior indicate an active backlash against tangible negative externalities of wind turbines, such as noise and visual disruption, rather than a passive sense of having earned moral credit. Our finding that affected voters "punish" the Green Party also in elections for the EU Parliament—whose influence on (local) environmental policies is much weaker compared to the *Bundestag*—further supports this interpretation.

From a policy point-of-view, our results emphasize the urgency of bringing society on board with continued renewable energy expansion in order to achieve climate targets and energy security objectives. Our analysis contributes evidence pertaining to two solutions that have been proposed in the policy debate. The first one is to enforce minimum distances between wind parks and populated areas. Our results support the view that minimum distance requirements are effective at mitigating negative effects on citizen's support. Minimum-distance policies are controversial, however, because they drastically limit the available space for building new wind turbines onshore. An alternative solution is to provide financial compensation to residents living close to wind turbines. We have investigated such a mechanism under the assumption that revenues from local wind power projects are redistributed among residents via existing schemes of commercial taxation. According to our analysis, wind energy expansion has significantly increased tax revenues from such schemes, and this has been associated with smaller negative effects of wind turbines on citizens' support. In line with this result, our policy recommendation is to enhance financial participation in the economic benefits from wind projects in order to consolidate citizens' support for renewable energy in the affected communities.

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A Appendix

A.1 Additional tables

Table A1: *Structure of feed-in tariffs at the time of enactment*

EEG amendments	**Initial tariff** [cts. / kWh]	**Base tariff** [cts. / kWh]	**Extension of initial tariff**
EEG 2000 (effective 04/2000)	9.10	6.19	2 months per -0.75% deviation from 150% of reference yield
EEG 2004 (effective 08/2004)	8.70	5.50	2 months per -0.75% deviation from 150% of reference yield
EEG 2009 (effective 01/2009)	9.20	5.02	2 months per -0.75% deviation from 150% of reference yield
EEG 2012 (effective 01/2012)	8.93	4.87	2 months per -0.75% deviation from 150% of reference yield
EEG 2014 (effective 08/2014)	8.90	4.95	2 months per -0.36% deviation from 130% of reference yield + 1 month per -0.48% deviation from 100% of reference yield

*EEG is the German acronym for the Renewable Energy Sources Act (*Gesetz für den Ausbau erneuerbarer Energien*).*

Table A2: *Mentions of keywords in election programs*

	2005			2009		
	Green	SPD	CDU	Green	SPD	CDU
Wind	6	1	3	11	2	3
Energy transition	0	0	0	2	1	0
Renewable energy	22	8	1	61	24	16
Climate	20	5	8	151	22	44
	2013			**2017**		
	Green	SPD	CDU	Green	SPD	CDU
Wind	36	5	7	11	1	2
Energy transition	74	33	11	22	13	8
Renewable energy	75	33	13	36	6	5
Climate	153	21	24	141	35	21

Table A3: *First-stage regression of the analysis of search queries for green elecricity tariffs*

Dependent variable is	*No. WT within zip code*
Expected revenues of a WT	0.678***
	(0.151)
Ineligible	0.539***
	(0.060)
Ineligible × wind potential	0.064
	(0.059)
Year FE	y
Zip code FE	y
Socioeconomic controls	y
Obs.	32,125

The dependent variable is the number of wind turbines in a zip code. Standard errors clustered at the zip code level in parenthesis. Coefficients and standard errors of Expected revenues of a WT are divided by 100,000 and coefficients and standard errors of Ineligible × wind potential by 1,000 for better readability. Regressions are weighted by population at the zip code-year level. The observation period covers the years 2011–2014. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A4: *Effect of wind power expansion on search queries for green electricity tariffs – unweighted regressions*

Dependent variable is	*log(search queries for green tariffs)*			
	(1) IV	(2) OLS	(3) IV	(4) OLS
No. WT within zip code	-0.405***	-0.011		
	(0.101)	(0.007)		
Cap. WT within zip code			-0.144***	-0.002
			(0.038)	(0.003)
Year FE	y	y	y	y
Zip code FE	y	y	y	y
Socioeconomic controls	y	y	y	y
Durbin-Wu-Hausman test	0.00		0.00	
First stage F stat.	76.28		72.53	
Obs.	32,103	32,115	32,103	32,115

The dependent variable is the natural logarithm of the percentage share of households that search for green electricity tariffs in at least one query during a search session. Standard errors clustered at the zip code level in parenthesis. The local adoption rate of wind power is considered endogenous in Columns (1) and (3). The instruments in these specifications are based on expected revenues of a wind turbine according to the reference yield model. The observation period covers the years 2011–2014 $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A5: *Effect of wind power expansion on Green Party vote shares – unweighted regressions*

Dependent variable is	*log(vote share for the Green Party)*			
	IV (1)	OLS (2)	IV (3)	OLS (4)
No. WT within municipality	-0.071***	0.001		
	(0.014)	(0.001)		
Cap. WT within municipality			-0.023***	0.001
			(0.006)	(0.001)
Year FE	y	y	y	y
Zip code FE	y	y	y	y
Socioeconomic controls	y	y	y	y
Durbin-Wu-Hausman test	0.00		0.00	
First stage F stat.	148.02		133.15	
Obs.	42,166	42,170	42,166	42,170

The dependent variable is the natural logarithm of the percentage share of votes for the Green Party. Standard errors clustered at the zip code level in parenthesis. The local adoption rate of wind power is considered endogenous in Columns (1) and (3). The instruments in these specifications are based on expected revenues of a wind turbine according to the reference yield model. The observation period covers the federal elections 2005, 2009, 2013 and 2017. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A6: *Effect of wind power expansion on search queries for green electricity tariffs – alternative measures*

Dependent variable is	*log(search queries for green tariffs)*	
	(1) – in the first search query	(2) – in the last search query
No. WT within zip code	-0.291***	-0.217***
	(0.067)	(0.057)
Year FE	y	y
Zip code FE	y	y
Socioeconomic controls	y	y
Durbin-Wu-Hausman test	0.00	0.00
First stage F stat.	69.72	69.72
Obs.	32,328	32,328

The depenedent variable in our main specifications is the natural logarithm of the share of households that search for green electricity tariffs at least once in a search session. In Columns (1) and (2) of the above table we instead use two alternative measures. In Column (1) we use the share of households that already search for green electricity tariffs in their first search query while in Column (2) we use the share of households that search for green electricity tariffs in their last search query. Standard errors clustered at the zip code level in parenthesis. Estimation by 2SLS. Construction of wind turbines is considered endogenous. Instruments based on expected revenues of a wind turbine according to the reference yield model. Regressions are weighted by population at the zip code-year level. The period under investigation covers the years 2011–2014. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A7: *Placebo - Effect of wind power expansion on lagged search queries for green electricity tariffs*

Dependent variable is	*Lagged log(search queries for green tariffs)*
No. WT within zip code	-0.073
	(0.049)
Year FE	y
Zip code FE	y
Socioeconomic controls	y
Durbin-Wu-Hausman test	0.21
First stage F stat.	33.98
Obs.	31,846

The dependent variable is the natural logarithm of the percentage share of households that search for green electricity tariffs in at least one query during a search session, lagged by one period. Standard errors clustered at the zip code level in parenthesis. Estimation by 2SLS. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. Regressions are weighted by population at the zip code-year level. The observation period covers the years 2011–2014. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A8: *Placebo - Effect of wind power expansion on lagged Green Party vote shares*

Dependent variable is	*Lagged log(vote share for the Green Party)*
No. WT within municipality	-0.013
	(0.008)
Year FE	y
Municipality FE	y
Socioeconomic controls	y
Durbin-Wu-Hausman test	0.08
First stage F stat.	17.01
Obs.	42,074

The dependent variable is the natural logarithm of the percentage share of votes for the Green Party, lagged by one period. Standard errors clustered at the municipality level in parenthesis. Estimation by 2SLS. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. Regressions are weighted by the number of eligible voters at the municipality-election year level. The observation period covers the elections 2005, 2009, 2013 and 2017. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A9: *Effect of wind power expansion on search queries for green electricity tariffs – Always eligible vs newly eligible locations*

Dependent variable is	*log((search queries for green tariffs)*
No. WT within municipality × always eligible	-0.313***
	(0.075)
No. WT within municipality × not always eligible	-0.372**
	(0.157)
Year FE	y
Zip code FE	y
Socioeconomic controls	y
Durbin-Wu-Hausman test	0.00
First stage F stat. *always eligible*	54.53
First stage F stat. *not always eligible*	14.68
Kleibergen Paap F stat.	15.75
F-test (p-val): *always eligible = not always eligible*	0.61
Obs.	32,125

The dependent variable is the natural logarithm of the percentage share of households that search for green electricity tariffs in at least one query during a search session. Standard errors clustered at the zip code level in parenthesis. The local adoption rate of wind power is interacted with dummy variables indicating whether a location was always eligible to the reference yield scheme or not. Both interaction terms are considered endogenous. The instruments in these specifications are based on expected revenues of a wind turbine according to the reference yield model, interacted with dummy variables indicating whether a location was always eligible to the scheme or not. Regressions are weighted by population at the zip code-year level. The observation period covers the years 2011–2014. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A10: *Effect of wind power expansion on Green Party vote shares – Always eligible vs non-eligible locations*

Dependent variable is	*log(vote share for the Green Party)*
No. WT within municipality × always eligible	-0.096***
	(0.015)
No. WT within municipality × not always eligible	-0.112***
	(0.027)
Year FE	y
Zip code FE	y
Socioeconomic controls	y
Durbin-Wu-Hausman test	0.00
First stage F stat. *always eligible*	58.31
First stage F stat. *not always eligible*	15.23
Kleibergen Paap F stat.	16.13
F-test (p-val): *always eligible = not always eligible*	0.48
Obs.	42,166

The dependent variable is the natural logarithm of the percentage share of votes for the Green Party. Standard errors clustered at the municipality level in parenthesis. The local adoption rate of wind power is interacted with dummy variables indicating whether a location was always eligible to the reference yield scheme or not. Both interaction terms are considered endogenous. The instruments in these specifications are based on expected revenues of a wind turbine according to the reference yield model, interacted with dummy variables indicating whether a location was always eligible to the scheme or not. Regressions are weighted by the number of eligible voters at the municipality-election year level. The observation period covers the federal elections 2005, 2009, 2013 and 2017. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A12: *Effect of the number of wind turbines on search queries for green electricity tariffs – alternative transformations*

	(1) IHS	(2) Zeros excluded	(3) >99% excluded	(4) >95% excluded	(5) >90% excluded	(6) PPML	(7) i2SLS
No. WT within zip code	-0.267***	-0.259***	-0.304***	-0.280***	-0.249***	-0.186***	-0.188**
	(0.068)	(0.068)	(0.074)	(0.072)	(0.073)	(0.030)	(0.094)
Control function						0.173***	
						(0.030)	
Year FE	y	y	y	y	y	y	y
Zip code FE	y	y	y	y	y	y	y
Socioeconomic controls	y	y	y	y	y	y	y
Durbin-Wu-Hausman test	0.00	0.00	0.00	0.00	0.00		
First stage F stat.	45.81	45.04	44.50	41.95	36.00		
Obs.	32,125	30,176	31,801	30,493	28,836	32,050	32,050

The dependent variable is the natural logarithm of the percentage share of households that search for green electricity tariffs in at least one query during a search session. In Column (1) we transform it using the inverse hyperbolic sine transformation (IHS) (instead of $log(x+0.1)$). In Column (2) we use $log(x)$ transformation, i.e. observations where the share of green electricity searches is zero are excluded. In Columns (3)-(5) we apply the baseline transformation $log(x+0.1)$ and in addition remove the smallest and largest 1 percent, 5 percent and 10 percent, respectively, of the green electricity searches. Standard errors are clustered at the zip code level in parenthesis. Estimation by 2SLS. Construction of wind turbines is considered endogenous. Instruments based on expected revenues of a wind turbine according to the reference yield model. Regressions are weighted by population at the zip code-year level. The observation period covers the years 2011 to 2014. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A13: *Effect of wind power expansion on Green Party vote shares – alternative transformations*

	(1) IHS	(2) Zeros excluded	(3) >99% excluded	(4) >95% excluded	(5) >90% excluded	(6) PPML	(7) i2SLS
No. WT within municipality	-0.113***	-0.105***	-0.069***	-0.058***	-0.052***	-0.107***	-0.065**
	(0.016)	(0.015)	(0.014)	(0.014)	(0.015)	(0.010)	(0.029)
Control function						0.106***	
						(0.010)	
Year FE	y	y	y	y	y	y	y
Zip code FE	y	y	y	y	y	y	y
Socioeconomic controls	y	y	y	y	y	y	y
Durbin-Wu-Hausman test	0.00	0.00	0.00	0.00	0.00		
First stage F stat.	26.67	26.69	146.56	140.41	127.86		
Obs.	42,166	41,883	41,944	40,874	39,092	42,138	42,138

The dependent variable is the vote share of the Green Party. In Column (1) we transform it using the inverse hyperbolic sine transformation (IHS) (instead of $log(x+0.1)$). In Column (2) we use the $log(x)$ transformation, i.e. observations where the share of votes for the Green Party is zero are excluded. In Columns (3)-(5) we apply the baseline transformation $log(x+0.1)$ and in addition remove the smallest and largest 1 percent, 5 percent and 10 percent, respectively, of the election result of the Green Party. Standard errors clustered at the municipality level in parenthesis. Estimation by 2SLS. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. Regressions are weighted by the number of eligible voters at the municipality-election year level. The observation period covers the elections 2005, 2009, 2013 and 2017. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A14: *Effect of the number of wind turbines on search queries for green electricity tariffs– Lagged instruments*

Dependent variable is	*log(search queries for green tariffs)*	
	(1)	(2)
No. WT within zip code	-0.266***	-0.251***
	(0.058)	(0.057)
Year FE	y	y
Zip code FE	y	y
Socioeconomic controls	y	y
Durbin-Wu-Hausman test	0.00	0.00
First stage F stat.	24.55	17.98
Obs.	32,103	32,103

The dependent variable is the natural logarithm of the percentage share of households that search for green electricity tariffs in at least one query during a search session. Standard errors clustered at the zip code level in parenthesis. Estimation by 2SLS. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. In column(1) we add instruments lagged by one year, in column (2) we further add instruments lagged by 2 years. Regressions are weighted by population at the zip code-year level. The observation period covers the years 2011-2014. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A15: *Effect of wind power expansion on Green Party vote shares – Lagged instruments*

Dependent variable is	*log(vote share for the Green Party)*	
	(1)	(2)
No. WT within municipality	-0.075***	-0.072***
	(0.010)	(0.009)
Year FE	y	y
Municipality FE	y	y
Socioeconomic controls	y	y
Durbin-Wu-Hausman test	0.07	0.03
First stage F stat.	23.59	17.73
Obs.	42,166	42,166

The dependent variable is the natural logarithm of the percentage share of votes for the Green Party. Standard errors clustered at the municipality level in parenthesis. Estimation by 2SLS. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. In column(1) we add instruments lagged by one year, in column (2) we further add instruments lagged by 2 years. Regressions are weighted by the number of eligible voters at the municipality-election year level. The observation period covers the federal elections 2005, 2009, 2013 and 2017. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A16: *Effect of the number of wind turbines on search queries for green electricity tariffs – controlling for land prices*

Dependent variable is	*log(search queries for green tariffs)*
No. WT within zip code	-0.255***
	(0.071)
(log)land price	0.034
	(0.042)
Year FE	y
Zip code FE	y
Socioeconomic controls	y
Durbin-Wu-Hausman test	0.00
First stage F stat.	43.97
Obs.	28,912

The dependent variable is the natural logarithm of the percentage share of households that search for green electricity tariffs in at least one query during a search session. Standard errors clustered at the zip code level in parenthesis. Estimation by 2SLS. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. Regressions are weighted by population at the zip code-year level. The observation period covers the years 2011–2014. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A17: *Effect of wind power expansion on Green Party vote shares – controlling for land prices*

Dependent variable is	*log(vote share for the Green Party)*
No. WT within municipality	-0.109***
	(0.016)
(log)land price	0.023
	(0.027)
Year FE	y
Zip code FE	y
Socioeconomic controls	y
Durbin-Wu-Hausman test	0.00
First stage F stat.	24.22
Obs.	37,974

The dependent variable is the natural logarithm of the percentage share of votes for the Green Party. Standard errors clustered at the municipality level in parenthesis. Estimation by 2SLS. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. Regressions are weighted by the number of eligible voters at the municipality-election year level. The observation period covers the federal elections 2005, 2009, 2013 and 2017. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A18: *Effect of the number of wind turbines on search queries for green electricity tariffs – Conley standard errors with spatial correction*

Dependent variable is	*log(search queries for green tariffs)*		
	(1)	(2)	(3)
No. WT within zip code	-0.279***	-0.279***	-0.279**
	(0.084)	(0.108)	(0.132)
Year FE	y	y	y
Zip code FE	y	y	y
Socioeconomic controls	y	y	y
Conley cluster distance	10km	25km	50km
First stage F stat.	48	30	17
Obs.	32,135	32,135	32,135

The dependent variable is the natural logarithm of the percentage share of households that search for green electricity tariffs in at least one query during a search session. Standard errors adjusted for spatial correlation (Conley, 1999) within different thresholds. Estimation by 2SLS. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. Regressions are weighted by population at the zip code-year level. The observation period covers the years 2011 to 2014. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A19: *Effect of the number of wind turbines on election results of the Green Party – Conley standard errors with spatial correction*

Dependent variable is	*log(vote share for the Green Party)*		
	(1)	(2)	(3)
No. WT within municipality	-0.105***	-0.105***	-0.105***
	(0.014)	(0.016)	(0.019)
Year FE	y	y	y
Municipality FE	y	y	y
Socioeconomic controls	y	y	y
Conley cluster distance	10km	25km	50km
First stage F stat.	7.99	5.30	3.75
Obs.	42,214	42,214	42,214

Effect of wind power expansion on Green Party vote shares. Standard errors adjusted for spatial correlation (Conley, 1999) within different thresholds. Estimation by 2SLS. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. Regressions are weighted by the number of eligible voters at the municipality-election year level. The observation period covers the federal elections 2005, 2009, 2013 and 2017. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A20: *Effect of the first wind turbine on search queries for green electricity tariffs – First vs additional WTs*

Dependent variable is	*log(search queries for green tariffs)*
No. WT in municipality × first WT	-0.545***
	(0.163)
No. WT in municipality × not first WT	-0.233***
	(0.042)
Year FE	y
Zip code FE	y
Socioeconomic controls	y
Durbin-Wu-Hausman test	0.00
First stage F stat. *First WTs*	19.71
First stage F stat. *Additional WTs*	25.35
Kleibergen Paap F stat.	12.71
Obs.	32,294

The dependent variable is the natural logarithm of the percentage share of households that search for green electricity tariffs in at least one query during a search session. Standard errors clustered at the zip code level in parenthesis. Estimation by 2SLS. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. Regressions are weighted by population at the zip code-year level. The observation period covers the years 2011–2014. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A21: *Effect of wind power expansion on Green Party vote shares – first vs additional WTs*

Dependent variable is	*log(vote share for the Green Party)*
No. WT in municipality × first WT	-0.153***
	(0.025)
No. WT in municipality × not first WT	-0.069***
	(0.011)
Year FE	y
Zip code FE	y
Socioeconomic controls	y
Durbin-Wu-Hausman test	0.00
First stage F stat. *First WTs*	22.38
First stage F stat. *Additional WTs*	22.68
Kleibergen Paap F stat.	15.97
Obs.	42,162

The dependent variable is the natural logarithm of the percentage share of votes for the Green Party. Standard errors clustered at the municipality level in parenthesis. Estimation by 2SLS. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. Regressions are weighted by the number of eligible voters at the municipality-election year level. The observation period covers the federal elections 2005, 2009, 2013 and 2017. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A22: *Effect of turbine size on search queries for green electricity tariffs*

Dependent variable is	*log(search queries for green tariffs)*
No. WT in zip code × average WT height<median	-0.356***
	(0.073)
No. WT in zip code × average WT height>median	-0.295***
	(0.061)
Year FE	y
Zip code FE	y
Socioeconomic controls	y
Durbin-Wu-Hausman test	0.00
First stage F stat. *below median*	29.54
First stage F stat. *above median*	36.48
Kleibergen Paap F stat.	29.94
Obs.	32,103

The dependent variable is the natural logarithm of the percentage share of households that search for green electricity tariffs in at least one query during a search session. Standard errors clustered at the zip code level in parenthesis. Estimation by 2SLS. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. Regressions are weighted by population at the zip code-year level. The observation period covers the years 2011–2014. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A23: *Effect of wind power expansion on Green Party vote shares – differentiation by turbine sioze*

Dependent variable is	*log(vote share for the Green Party)*
No. WT in municipality × average WT height<median	-0.108***
	(0.014)
No. WT in municipality × average WT height>median	-0.099***
	(0.015)
Year FE	y
Municipality FE	y
Socioeconomic controls	y
Durbin-Wu-Hausman test	0.00
First stage F stat. *below median*	44.84
First stage F stat. *above median WTs*	64.02
Kleibergen Paap F stat.	13.37
Obs.	42,166

The dependent variable is the natural logarithm of the percentage share of votes for the Green Party. Standard errors clustered at the municipality level in parenthesis. Estimation by 2SLS. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. Regressions are weighted by the number of eligible voters at the municipality-election year level. The observation period covers the federal elections 2005, 2009, 2013 and 2017. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A24: *Effect of wind power expansion on Green Party votes as a share of all eligible voters*

Dependent variable is	*log(Green Party votes as share of all eligible voters)*
No. WT within municipality	-0.125***
	(0.018)
Year FE	y
Zip code FE	y
Socioeconomic controls	y
Durbin-Wu-Hausman test	0.00
First stage F stat.	26.67
Obs.	42,166

The dependent variable is the natural logarithm of the Green Party votes as share of all eligible voters. Standard errors clustered at the municipality level in parenthesis. Estimation by 2SLS. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. Regressions are weighted by the number of eligible voters at the municipality-election year level. The observation period covers the federal elections 2005,2009, 2013 and 2017. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A25: *Effect of the number of wind turbines on voter migration*

	(1)	(2)	(3)
Dependent variable is *log(vote share)* of	*Ruling coalition*	*Anti wind parties*	*Pro wind parties*
No. WT within municipality	0.008	0.038***	-0.032***
	(0.011)	(0.007)	(0.007)
Year FE	y	y	y
Zip code FE	y	y	y
Socioeconomic controls	y	y	y
Durbin-Wu-Hausman test	0.01	0.00	0.00
First stage F stat.	26.67	26.67	26.67
Obs.	42,166	42,166	42,166

The dependent variable is the natural logarithm of the combined percentage share of votes received by either the parties in the ruling coalition (column1), the anti-wind parties (column 2) or the pro-wind parties (column 3). Standard errors clustered at the municipality level in parenthesis. Estimation by 2SLS. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. Regressions are weighted by the number of eligible voters at the municipality-election year level. The observation period covers the federal elections 2005, 2009, 2013 and 2017. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A26: *Effect of the number of wind turbines on voter turnout*

Dependent variable is	*log(voter turnout)*
No. WT within municipality	-0.014***
	(0.003)
Year FE	y
Zip code FE	y
Socioeconomic controls	y
Durbin-Wu-Hausman test	0.00
First stage F stat.	26.67
Obs.	42,167

The dependent variable is the natural logarithm of voter turnout (actual voters as a share of eligible voters). Standard errors clustered at the municipality level in parenthesis. Estimation by 2SLS. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. Regressions are weighted by the number of eligible voters at the municipality-election year level. The observation period covers the elections 2005,2009, 2013 and 2017. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A27: *Effect of wind power expansion on Green Party vote shares in elections to the European Parliament*

Dependent variable is	*log(vote share for the Green Party)*
No. WT within municipality	-0.146***
	(0.020)
Year FE	y
Zip code FE	y
Socioeconomic controls	y
Durbin-Wu-Hausman test	0.00
First stage F stat.	50.40
Obs.	20,650

The dependent variable is the natural logarithm of the percentage share of votes for the Green Party at the elections to the European Parliament. Standard errors clustered at the municipality level in parenthesis. Estimation by 2SLS. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. Regressions are weighted by the number of eligible voters at the municipality-election year level. The observation period covers the elections 2009 and 2014. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A28: *Effect of wind power expansion on retail electricity prices*

Dependent variable is	*log(incumbent base price)*
No. WT within zip code	-0.004
	(0.003)
Year FE	y
Zip code FE	y
Socioeconomic controls	y
Durbin-Wu-Hausman test	0.05
Kleibergen Paap F stat.	26.7
Obs.	31,015

The dependent variable is the natural logarithm of the local incumbent's base tariff for a household with an annual electricity consumption of 3,500kWh. Standard errors clustered at the zip code level in parenthesis. The local adoption rate of wind power is considered endogenous. The instruments are based on expected revenues of a wind turbine according to the reference yield model. Regressions are weighted by population at the zip code-year level. The observation period covers the years 2001–2014. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A29: *Local commercial tax base and wind power expansion*

Dependent variable is	*Δlog(taxbase)*
No. WT within municipality	0.011
	(0.011)
$\times(1 - LOCAL)$	0.052***
	(0.017)
Durbin-Wu-Hausman test	0.00
First stage F stat. WT	34.88
First stage F stat. $WT \times (1 - LOCAL)$	44.44
Kleibergen Paap F stat.	22.18
Obs.	9,682

Results from cross-sectional regressions of the change in $\log(taxbase)$ *between 2008 and 2010 on WT in 2008 and its interaction with* $(1 - LOCAL)$*, a dummy indicating that WTs are not locally owned. The number of wind turbines* WT *and its interactions are considered endogenous and instrumented with expected turbine revenues according to the reference yield model (ER) and its interaction with* $(1 - LOCAL)$*. Regressions are weighted by the number of eligible voters at the municipality-election year level. Robust standard errors in parenthesis.* $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

A.2 Additional figures

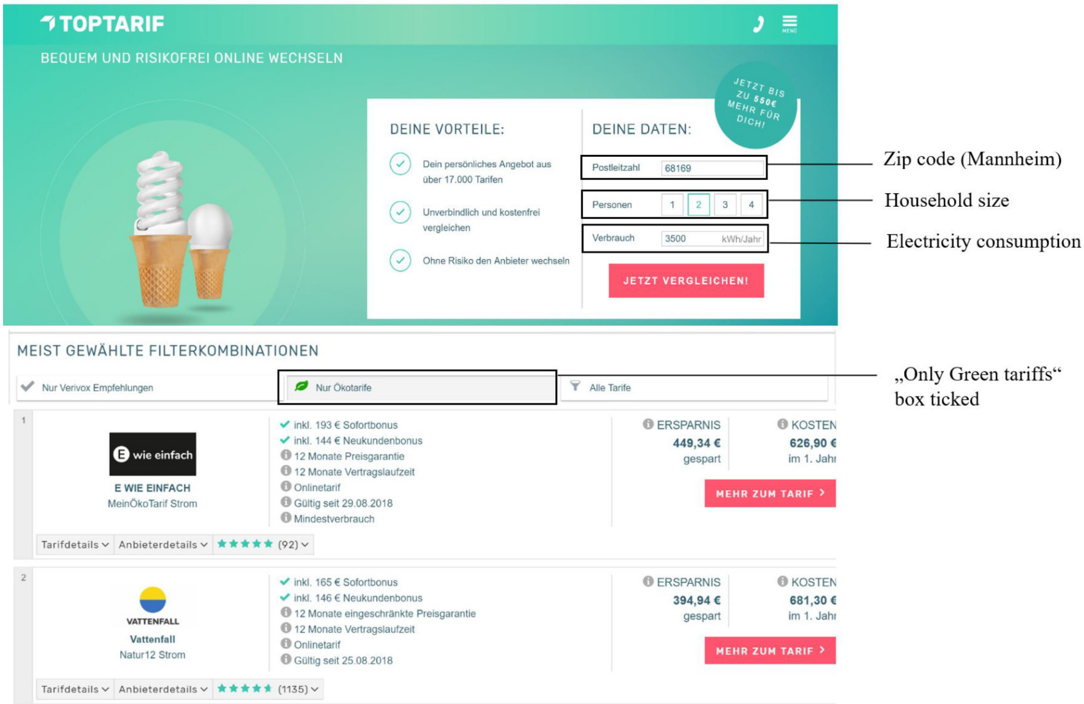


Figure A1: *Interface of the price comparison website "Toptarif"*

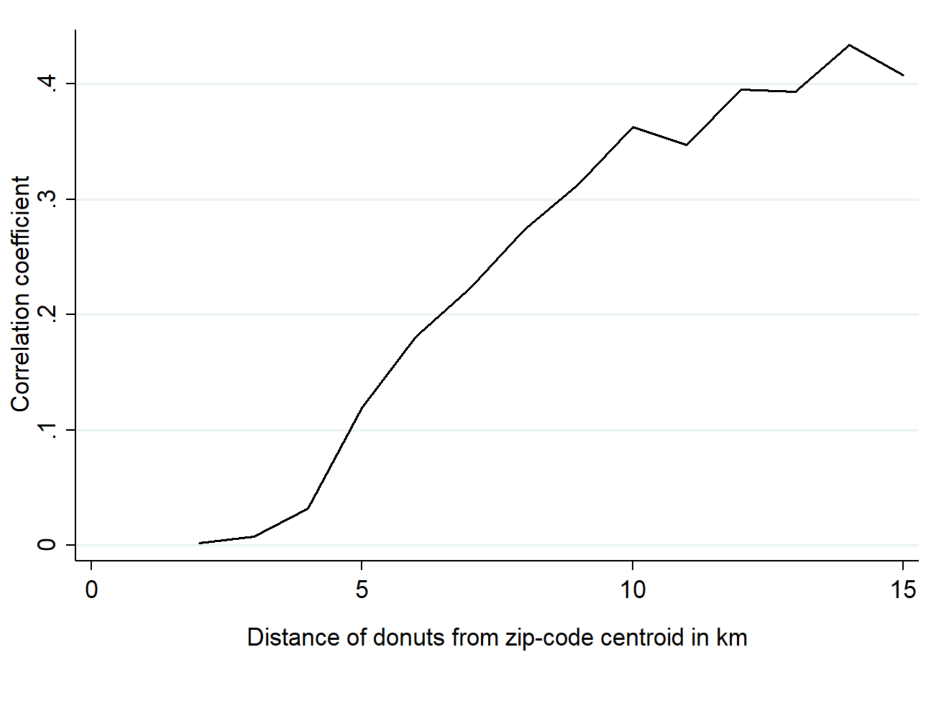
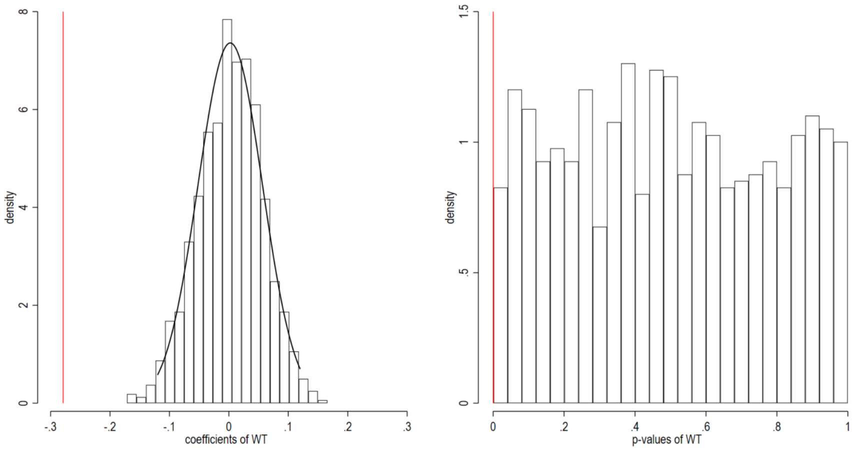
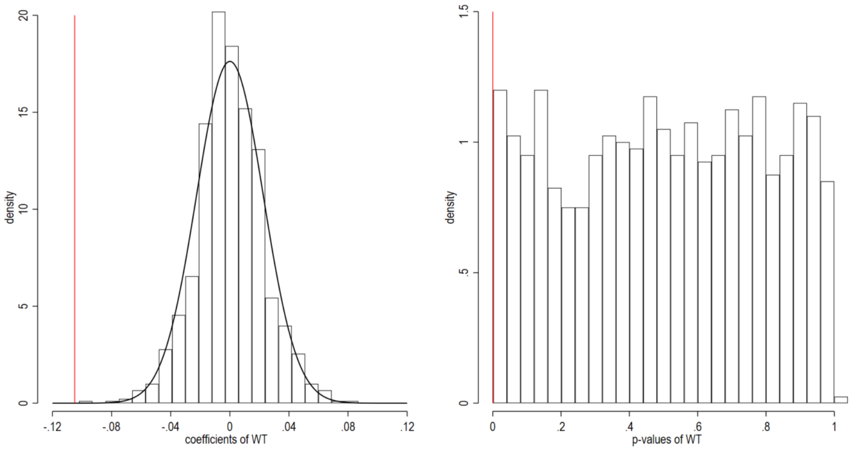


Figure A2: *Spatial correlation in the number of WTs*

The figure plots the correlation coefficient between the number of WTs within 1km-wide rings ("donuts") around the zip-code centroid at distances of xkm, and the number of WTs inside the "donut hole".



(a) Search queries for green tariffs



(b) Vote share for the Green Party

Figure A3: *Distribution of placebo estimates for the effect of wind power expansion on (a) search queries for green electricity tariffs and (b) vote share for the Green Party.*

The panels show the distribution of treatment coefficients and p-values from placebo estimations. The red vertical lines indicate estimation results from the Column (1) in Table 2 and 3, respectively: -0.279 ($p = 0.00$) for search queries for green tariffs (Panel a) and -0.104 ($p = 0.00$) for the vote share for the Green Party (Panel b). The black lines represent normal distributions. Durbin-Wu-Hausman p-values are 0.49 (Panel a) and 0.50 (Panel b).