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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*

Robert Germeshausen† Sven Heim‡ Ulrich J. Wagner§

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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 Classification: D12, D72, Q42, Q48, Q50

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1 Introduction

A defining characteristic of liberal societies is that public policies are based on the consent of its citizens. While the values and objectives behind such policies often find broad consensus, their actual implementation is more contentious because it creates winners and losers. By denying their consent, losers may delay or block a policy even though it has a large positive impact on aggregate welfare. Establishing a broad consensus is thus crucial for the successful implementation of transformative policies.

The energy transition – defined here as the process of transforming the energy infrastructure so as to curb its detrimental impacts on the environment – is an important case in point. The global power sector heavily depends on fossil fuels that pollute ambient air and drive global climate change. Increasing the share of renewable energy sources like wind, solar or hydro power in total electricity generation is the key to mitigating both these negative externalities. The Intergovernmental Panel on Climate Change (IPCC) estimates that limiting global warming to 1.5°C requires that the renewable electricity share reach 70–85 percent by 2050 (IPCC, 2018). Wind power has been attributed a dominant role in such scenarios, due to its low cost and universal availability (European Commission, 2018). Despite those virtues, harvesting wind power gives rise to negative externalities locally. Wind turbines can lower the aesthetic value of a landscape, interfere with wildlife, generate noise emissions, and reduce local property values (BWE, 2015; Rudolph et al., 2019). The discrepancy between local and global effects leads to a situation in which 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). 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 18.7 percent in 2020 (BMWi, 2021). 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.[1] 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 often launch litigation against them.[2] 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. 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.[3] 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

[1] 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).

[2] There are more than 1,000 organized citizens' initiatives against wind turbine projects in Germany, 900 of them in the federal association Vernunftkraft.

[3] 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.

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. In the context of renewable energy sources, revealed-preference studies have thus far been limited to hedonic analysis of housing markets. Our study breaks new ground on this by analyzing preferences revealed in 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. In so doing, we provide 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 exposure, welfare impacts are not fully capitalized into housing prices. In our particular 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.[4] Including location fixed effects is only a partial remedy to this problem because unobserved preferences for wind turbines are not necessarily static and might

[4]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.

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 37 percent. Using data on results from the federal elections in 2009 and 2013, we estimate that an additional wind turbine in a municipality significantly reduces the election results of the Green Party by 17 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.[5] The magnitude of the treatment effects decreases rapidly when we increase the radius around the wind turbines, suggesting that externalities provoking a NIMBY attitude are very local. Analysis of treatment heterogeneity across demographic groups shows that the effect is largest in rural areas and where the economy is sound. We further show that treatment effects are substantially larger in locations without any previous generation capacity than at the average location. The negative treatment effects of wind turbines on tariff searches and election results are robust to functional form assumptions and corroborated by placebo tests in which wind turbines are randomly assigned to other areas.

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

[5]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).

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 suggestive evidence that such a strategy could be effective by showing that (i) wind power expansion leads to higher commercial tax revenues at the regional level, and that (ii) the negative effects of wind power on both outcomes are substantially smaller in regions that benefited from higher tax revenues after a change 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".[6] Our quantitative analysis of local preferences casts a spotlight on trade-offs in turbine deployment 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 those literatures. 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.

[6]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

2 Literature

A sizable literature seeks to identify the preferences for renewable energy based on both stated and revealed preferences. Two key findings of that literature are 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. In what follows, we summarize this literature and describe this paper's precise contribution to it.

Renewable electricity generation is often more costly than generation from conventional sources and thus commands higher prices. This fact has motivated researchers to estimate the 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 green electricity, with differing values across the specific renewable energy technologies (Ma et al., 2015; Sundt and Rehdanz, 2015). WTP estimates are higher for solar and wind electricity than for electricity generated from hydro power and biomass. In addition, WTP is positively related to the share of renewable electricity generation in current energy consumption (Ma et al., 2015). In regards to household characteristics, Ma et al. (2015) find that WTP estimates are negatively associated with electricity consumption. Sundt and Rehdanz (2015) identify individual knowledge about renewable energy technologies, income, and education as important shifters of WTP estimates. Moreover, these studies highlight uncertainties stemming from the use of different valuation methods. Sundt and Rehdanz (2015) find that choice experiments are associated with higher WTP estimates. Ma et al. (2015) conclude that the characteristics of the study design "explain a large proportion of the variation in WTP values across studies".

Studies on actual decisions to consume green electricity - rather than stated preferences - are much more rare. They reveal that decisions to purchase green electricity or to participate in green electricity programs depend on factors such as household characteristics, environmental concerns, and warm glow motives (e.g. Menges et al., 2005; Kotchen and Moore, 2007a; Jacobsen et al., 2012).

When it comes to externalities of renewable energy technologies, there is a host of case studies and qualitative analyses that 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 (see Hausman, 2012; Kling et al., 2012, for more detailed discussions).

One strand of literature uses self-reported well-being data to quantify the externalities of renewable energy technologies. Krekel and Zerrahn (2017) find negative effects of new wind turbines on reported life satisfaction in Germany. In a comparative analysis of different technologies, 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 negative external effects from wind turbines and conventional power plants lead to lower property prices in the surrounding areas. Sunak and Madlener (2016) find that asking prices for properties that looked onto newly installed wind turbines in Germany experienced a drop of between 9 and 14 percent. Similarly, Gibbons (2015) and Jarvis (2021) provide evidence from the United Kingdom that wind farm visibility reduced local house prices, leading to substantial environmental costs. Jensen et al. (2014) disentangle the effect of visual pollution and noise pollution of wind turbines in Denmark. They estimate a negative effect on residential property prices of up to 3 percent for the former and between 3 and 7 percent for the latter externality. However, while house prices are negatively affected by nearby wind turbines, land owners in windy areas may profit from the capitalization of wind energy subsidies into land prices, as shown by 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 is the first of its kind and introduces a novel preference measure for renewable electricity technologies, which is based on the premise that "concern for the environment translates into predictable patterns of consumer behavior" (Kotchen and Moore, 2007b).

Our complementary 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. This aspect of our paper has not been studied in the economics literature so far.[7] An emerging political science literature has analyzed voting and wind turbines, with mixed results so far. Using Canadian data from provincial elections in Ontario, Stokes (2016) estimates losses of 4 to 10 percent to the incumbent party in precincts within 3km of a turbine. In contrast to this, two studies on 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.[8] These studies reach different conclusions about which party (Democrats or Republicans) benefits more from this effect. Another two studies have analyzed European data. Umit and Schaffer (2022) estimate no significant effect of wind turbine deployment on self-reported voting behavior in Switzerland, based on data from a large randomized survey experiment. Using German data similar to ours, Otteni and Weisskircher (2022) estimate that an additional wind turbine is positively associated with vote shares of the Green Party in OLS regressions with two-way fixed effects. A casual interpretation would require turbine deployment to be strictly exogenous. We believe that this is too strong an assumption given the likely presence of measurement error, endogenous

[7]An earlier economics paper by Comin and Rode (2015) studies the diffusion of solar photovoltaic systems with regard to a different research question: Do households that install on-roof systems become more supportive of the Green Party? Our focus here is on wind turbines, a technology with much stronger negative externalities, and their effects on preferences of neighboring households.

[8]Direct evidence on economic benefits of wind turbines is rare though. For a recent study on employment employment effects of renewable energy see Fabra et al. (2022).

siting of turbines, and reverse causality in this setting.[9] To obtain more credible estimates, we propose a novel identification strategy that exploits both cross-sectional and temporal sources of exogenous variation in profitability to instrument for wind turbine deployment. Our finding of a negative relationship highlights that two-way fixed effects estimates of the coefficient of interest, as in Otteni and Weisskircher (2022), can be severely biased, to the point of changing the sign. 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 to the issue of endogenous treatment, and by proposing a rigorous econometric approach to address this issue.

Finally, 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 Institutional Background of Wind Power in Germany

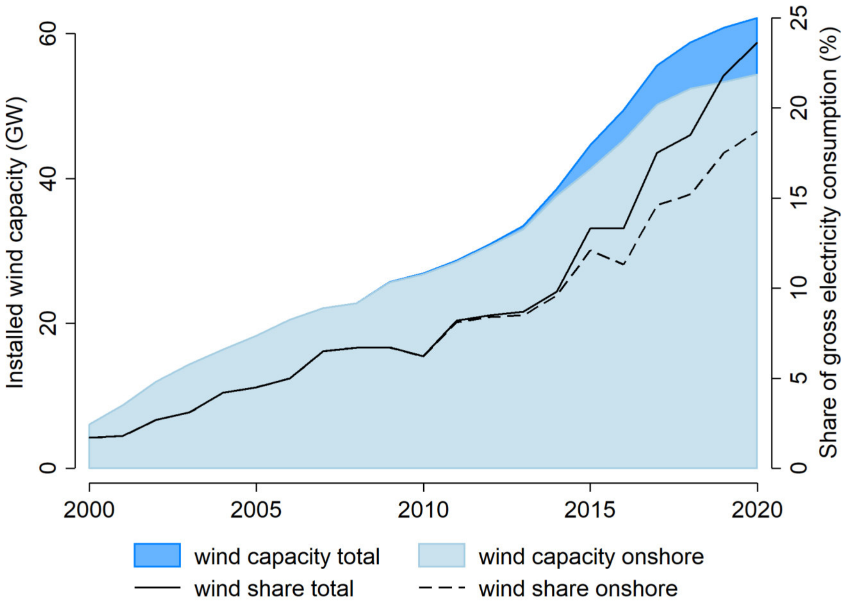
Beginning in the early 2000's, Germany embarked on a period of rapid growth in wind energy. Installed onshore wind power capacity soared from 6.1 GW in 2000 to 26.8 GW in 2010 and 54.4 GW in 2020, respectively. The share of wind energy in gross electricity consumption rose from 1.7 percent in 2000 to 6.2 percent in 2010 and reached 18.7 percent in 2020.[10] Figure 1 illustrates this development.

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

[9]For example, Jarvis (2021) shows that local resistance to wind power amounts to the equivalent of a 10-25 percent cost surcharge and hence strongly decreases turbine deployment.

[10]The second largest renewable energy source in Germany is solar energy with a share of 9.2 percent of total energy consumption as of 2020 (BMWi, 2020).

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



Notes: Calculation based on data from the German Federal Ministry for Economic Affairs and Energy (BMWi, 2020).

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).[11]

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

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

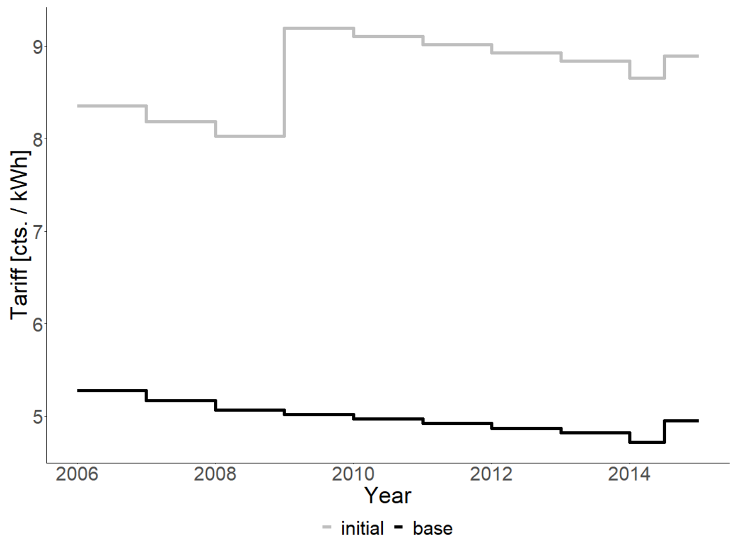
power generation across space, this scheme aimed to mitigate potential grid constraints and to reduce volatility in aggregate wind power generation. The reference yield model consisted of a benchmarking component and a tariff schedule. Locations were benchmarked against a reference location with an expected power output (reference yield) for specific technologies.[12] Yields at any given location were divided by the reference yield, i.e., the yield computed for a benchmark wind potential stipulated in the EEG law. This yield ratio ranges from 0.3 to 2.2 in our data.

The tariff schedule under the reference yield model 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 2014 changed both initial and base tariffs. Most amendments stipulated downward adjustments of both tariffs some. Others, like the 2009 amendment increased the initial tariff so as to offset increased resource costs for wind turbines (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 2006 and 2014. Additional time variation was induced by the 2012 amendment, when feed-in tariffs were rolled out to all of Germany in order to further promote the spatial diffusion of this technology. Before 2012, locations with less than 60 percent of the reference yield had not been eligible for subsidized feed-in tariffs.

[12]More specifically, the wind power potential of the reference location was defined by law 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, 2006-2014



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

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

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

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 key threat to identifying the parameter β_1 is the potential endogeneity of wind turbine deployment. Reaching heights of 100 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.

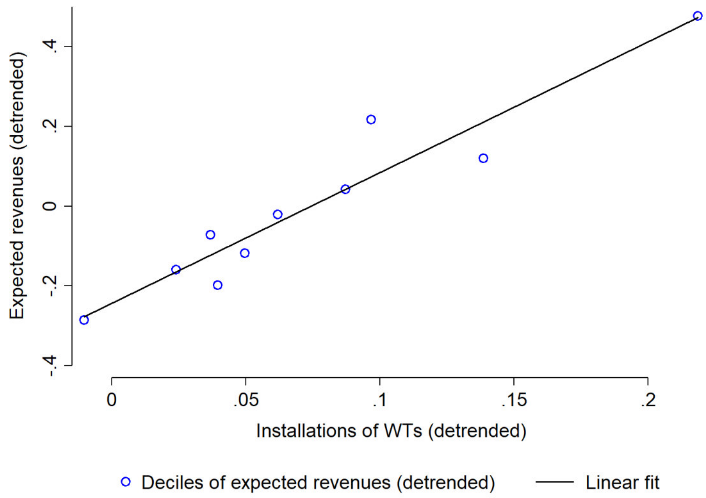
To address endogeneity, we adopt an instrumental-variable (IV) approach that exploits quasi-experimental variation in the feed-in tariff that shifts the profitability of wind energy within locations and across installation years. To be a valid instrumental variable, those changes in feed-in tariffs must 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.[13] 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.

[13]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.

Figure 3: Expected revenues and new wind turbine installations

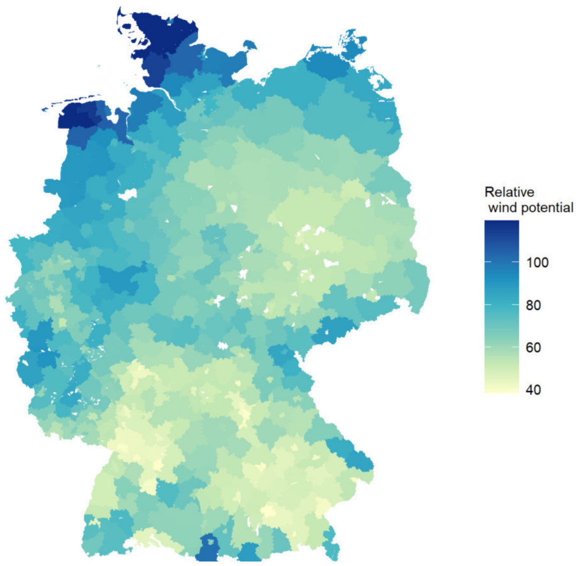


Notes: The figure plots expected revenues from the reference yield scheme (defined in eq. (3)) against the number of newly installed wind turbines, after residualizing both variables with respect to year dummies. This procedure corrects for both cost reductions in wind turbine construction and reductions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

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.

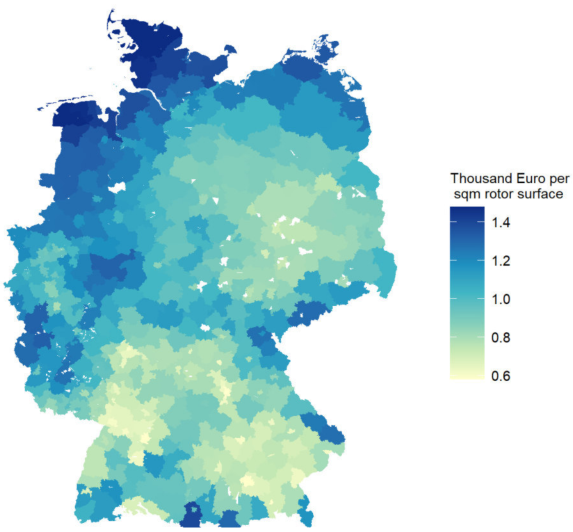
Third, a look to the data corroborates the view that granular fine-tuning of subsidies to particular zip codes or municipalities was impossible. Figure 4c displays the variation in expected revenues within locations over the estimation period, expressed in relation to the cross-sectional variation in 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. The variation in the instrumental variable thus affects large parts of Germany that can be viewed as representative.

Figure 4: Wind power potential and reference yield remuneration



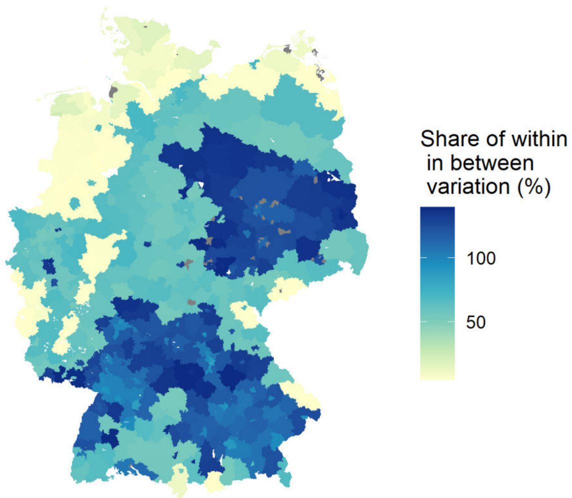
(a) Wind power potential

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



(b) Expected revenues

Notes: 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.



(c) Within variation in expected revenues

Notes: 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.

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

$$\begin{aligned} WT_{it} = \; & \gamma_1 \times ER_{it} + \gamma_2 \times INELIGIBLE_{it} + \gamma_3 \times INELIGIBLE_{it} \times POTENTIAL_i + \\ & \mathbf{X}'_{it} \times \gamma_3 + \eta_i + \nu_t + \upsilon_{it}, \end{aligned} \tag{2}$$

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, the dummy variable $INELIGIBLE$ is set to one, and its interaction with the corresponding wind potential ($POTENTIAL$) captures heterogeneous investment incentives in ineligible locations. More details on the construction of the three instruments are given in the next section. Notation for the other explanatory variables is the same as above.

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 in 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 tariffs. This brought about the end of local monopolies and paved the way for massive entry of electricity retailers.[14] Fierce competition for customers is mainly on prices but

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

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. This preference measure is based on observed behavior and hence less likely to suffer from cognitive biases than stated preferences. In principle, we could use the purchase decision as an outcome, but this would also require us to control for prices and product characteristics in the consumers choice set, which is a formidable task and not feasible with our data. As an alternative, we measure how intensely consumers *search* for green electricity tariffs. In so doing, we sidestep the pricing issue while preserving the benefits of measuring observed behavior and actual decisions taken by consumers in the pre-contracting stage.

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

[15]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).

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. These numbers show that the use of price comparison websites was widespread, and this is particularly true of households looking to switch contracts. According to an early study, 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.

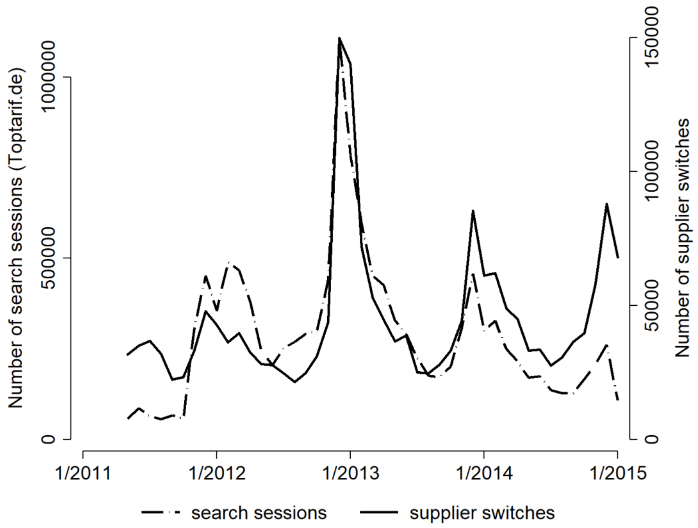
We aggregate the data to the zip code-year level. The yearly aggregation is consistent with households considering a supplier switch at most once a year (if at all), and coincides with the typical length of an electricity contract. Our measure of renewable energy support in zip code i and year t is computed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

Figure 5: Electricity tariff searches and contract switches over time



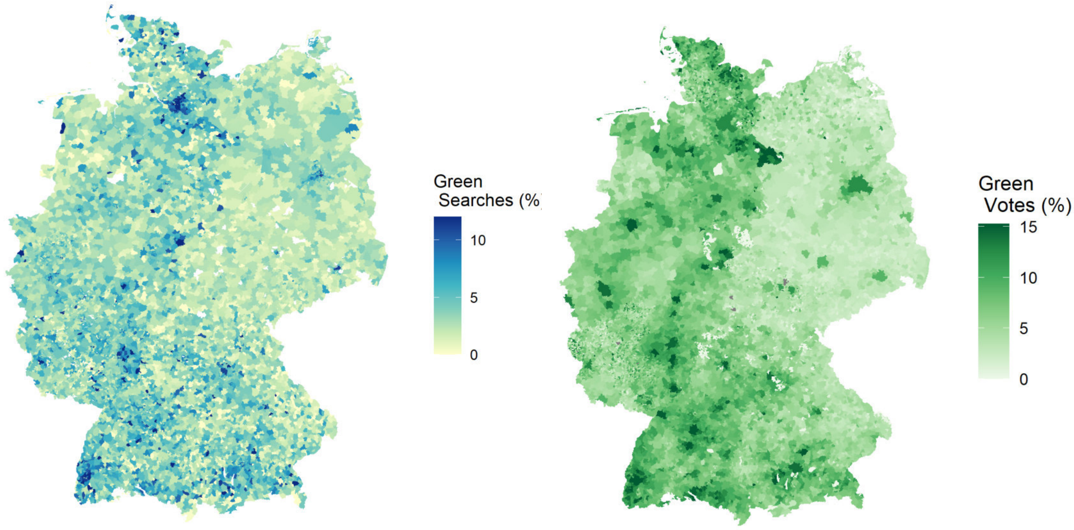
As reported in Table 1, a little more than six percent of all searching households ticked the "show only green electricity tariffs" box at least once in a search session. That is, the vast majority of consumers does not regard this product attribute as very central to their search and purchase decisions. 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. On average, 2 wind turbines are installed in a zip code. The regional distribution of the share of green tariff queries for 2013 is shown in Figure 6a.

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 parliament (the *Bundestag*) for the last 25 years.[16] Between 1998 and 2005, it was part of the first-ever Red-Green federal government coalition partnering with the Social Democratic Party (SPD).

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

Figure 6: Spatial distribution of outcome variables in 2013



(a) Share of search queries for green electricity tariffs

(b) Election results of the Green Party

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 in many elections – in particular 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.[17] 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 2009 and 2013 Bundestagswahl were obtained from the German Federal Statistical Office. On average, the Green Party received 8.6 percent of votes per municipality in 2009 and 6.5 percent

[17]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.

in 2013. The spatial distribution of election results of the Green Party in the 2013 Bundestagswahl is displayed in Figure 6b.

5.3 Explanatory variables

Wind turbines. The energymap project (`energymap.info`) provides detailed information on renewable energy plants including the plant type (e.g. wind, solar, hydro etc.), net capacity, geo-coordinates and the date of commissioning. The dataset is based on the official plant installation register of the German Transmission System Operators (TSO). We use this dataset to construct our variables of interest, i.e. the number and capacity of WTs in a certain zip code or municipality and within a radius of 1 km, 3 km, 5 km, 7 km, 10 km and 20 km from the centroid of the zip code or municipality. Figure 7 shows the spatial distribution of the stock of wind turbines in Germany for the year 2013. 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, our first-stage regressions below confirm that two decades of subsidization have shaped the distribution of wind turbines in space.

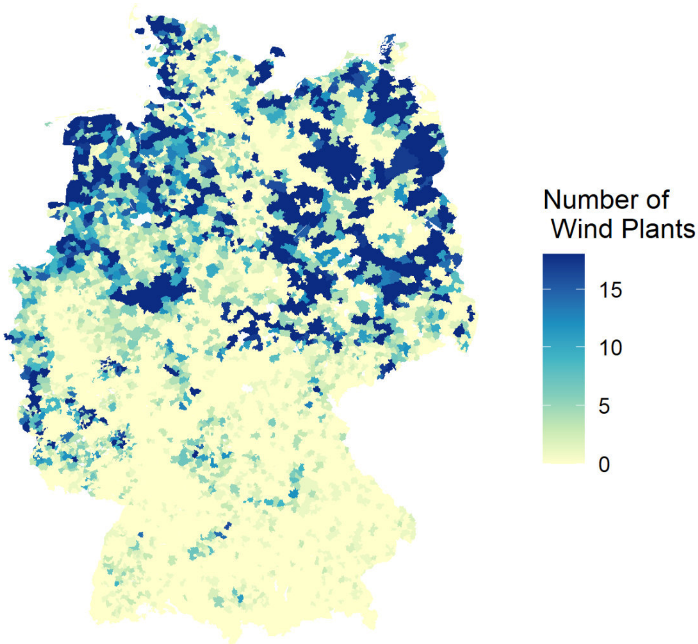
Feed-in tariffs and socio-economic data. We calculate the expected revenue of each wind turbine based on the reference yield model, using data on local wind potential from the German Meteorological Office (*Deutscher Wetterdienst - DWD*), as well as information on initial and base tariffs obtained from the German Transmission System Operators.[18] Expected revenue during the 20 years of subsidization is given by

$$ER_{it} = \left(FIT_{init,t} * n_{init,i} + FIT_{base,t} * n_{base,i}\right) * POTENTIAL_i, \tag{3}$$

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,

[18]See https://www.netztransparenz.de/EEG/Verguetungs-und-Umlagekategorien

Figure 7: Diffusion of wind turbines in 2013



with $n_{init,i} + n_{base,i} = 20$ years.[19] 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 variable $INELIGIBLE_{it} \times POTENTIAL_i$ is set to equal 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 and the German Federal Statistical Office for the municipality level. Data on commercial taxes of municipalities stem from the German Federal Statistical Office.

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

5.4 Spatial resolution

The spatial data resolution is at the German zip code level (8,039 zip codes) for the green electricity tariff queries and at the municipality level (10,003) for the election outcomes. For the green electricity tariff queries, we analyze the period 2011 to 2014. This period was chosen because earlier data were not available, and because the remuneration scheme for wind power was subject to a major change after 2014.[20] During this period, the installed net capacity from wind energy experienced a substantial expansion, rising from 26.9 GW in 2010 to 38.6 GW by the end of 2014 – a total increase of 43 percent in only four years. In our analysis of the election results of the Green Party, we use data from the *Bundestag* elections in 2009 and 2013. The installed net wind capacity increased from 22.8 GW in 2008 to 33.5 GW in 2013 – a total increase of 47 percent in only four years.

Descriptive statistics for both datasets are summarized in Tables 1 and 2 below.

Table 1: Summary statistics for the analysis of search queries for green electricity tariffs

	Mean	SD	Min	Max
Dependent variables				
Share of search queries for green tariffs in any query (%)	6.30	6.17	0.00	100.00
Variables of interest				
No. WT within zip code	2.03	5.96	0.00	102.00
Cap. WT within zip code	2.79	8.49	0.00	69.32
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 €/year)	43.49	7.51	21.03	110.34
Population (in thousands)	9.95	9.09	0.00	61.99
Young HH (%)	24.58	5.04	0.00	55.05
Obs.	32,252			

Notes: Descriptive statistics of zip-code level data. Annual data from 2011 until 2014.

[20] The 2014 amendment of the EEG law required large wind turbines that started operating after 2014 to sell their electricity competitively in the spot market. Instead of a feed-in tariffs, those plants only received an additional market premium for green electricity, which weakens our instrument.

Table 2: **Summary Statistics of the analysis of election results of the Green Party**

	Mean	SD	Min	Max
Dependent variables				
Share of votes for the Green party in federal elections (%)	7.38	3.78	0.00	45.83
Variables of interest				
No. WT within municipality	1.39	4.33	0.00	86.00
Cap. WT within municipality	1.83	5.92	0.00	49.60
Instrument and control variables				
Expected revenue of a WT (in thousand €/m^2 rotor surface)	1.11	0.24	0.43	2.37
Unemployment (%)	10.90	18.34	0.00	100.00
Population (in thousands)	6.61	28.85	0.00	1407.84
Young HH (%)	30.78	5.52	0.00	91.05
Obs.	22,102			

Notes: Descriptive statistics for municipality-level data. Annual data for 2009 and 2013.

6 Results

6.1 Main results

Green electricity tariffs. Table 3 shows results obtained when the outcome variable is the share of households searching for green electricity tariffs at any query during a search session. Our preferred estimate is reported in Column (1) and derives from 2SLS estimation of eq. (1). The IV coefficient implies that an additional wind turbine (WT) reduces the preference for green tariffs by approximately 37 percent.[21] This effect 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. This large discrepancy could be due in part 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.

Since the IV coefficient is our preferred estimated, we provide further results and statistics that support the validity of this approach. At the bottom of the table we report the first-stage F-statistic for the relevance of the instruments. As the Stock-Yogo

[21]Here and below, we use the exponential function to transform coefficients into percentage effects as follows: $e^{-0.458} - 1 = -0.367$.

10 percent critical value is 9.08, our instruments appear to be sufficiently strong to identify local wind power expansion. Also, correcting for endogeneity appears to be in order as the Durbin-Wu-Hausman test clearly rejects exogeneity of WT. Full first-stage results are reported in Appendix Table A3.

Columns (3) and (4) of Table 3 show the results from IV and OLS specifications where we use wind power capacity instead of the number of 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 17 percent. Since the average net capacity of a WT is 1.4 MW in our data, the qualitative findings are very similar, regardless of whether the number or the capacity of WTs is the regressor of interest.

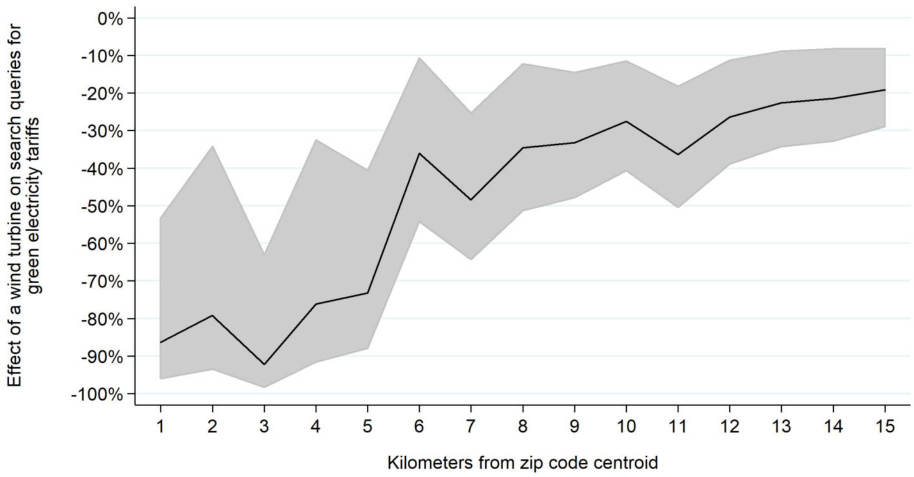
Table 3: Effect of wind power expansion on search queries for green electricity tariffs

Dependent variable is	*log(search queries for green tariffs)*			
	IV (1)	OLS (2)	IV (3)	OLS (4)
No. WT within zip code	-0.458***	-0.020***		
	(0.100)	(0.007)		
Cap. WT within zip code			-0.189***	-0.007***
			(0.043)	(0.003)
Population	0.026	0.055***	0.026	0.055***
	(0.018)	(0.014)	(0.018)	(0.014)
Young HH	-0.007	-0.003	-0.006	-0.003
	(0.009)	(0.008)	(0.009)	(0.008)
Purchasing power	-0.001	0.002	-0.002	0.002
	(0.007)	(0.006)	(0.007)	(0.006)
Year FE	Yes	Yes	Yes	Yes
Zip code FE	Yes	Yes	Yes	Yes
Durbin-Wu-Hausman test	0.00		0.00	
First stage F stat.	71.80		65.15	
Obs.	32,252	32,252	32,252	32,252

Notes: 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. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

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.[22] 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.[23] However, the fact that the 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.

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



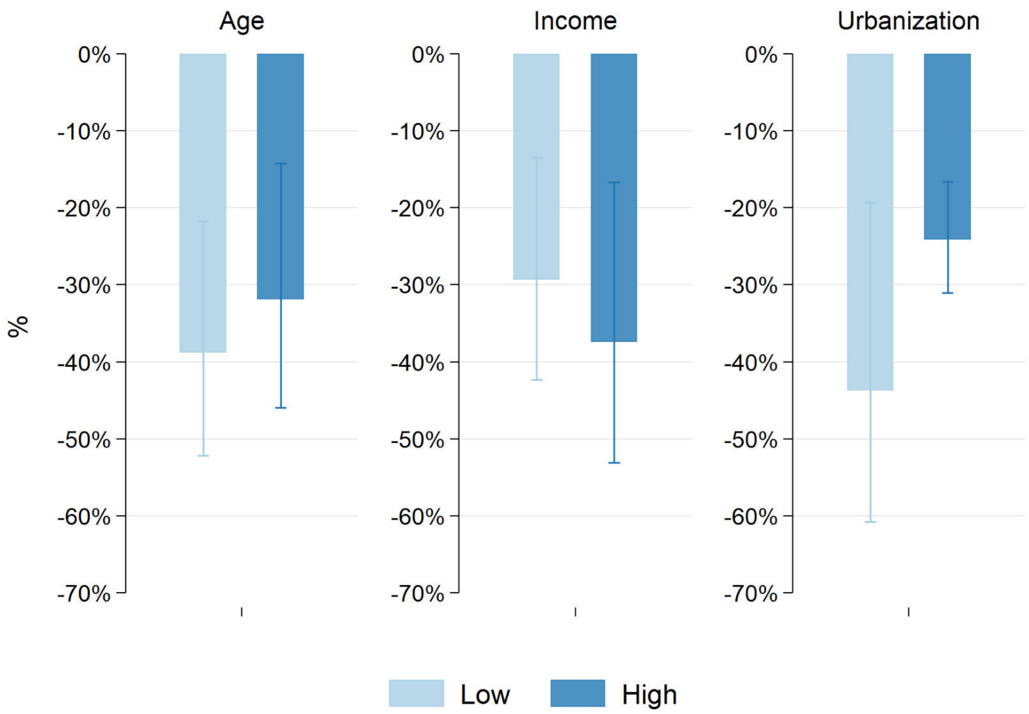
Notes: The figure plots the IV point estimates transformed into percentage effects $(e^{\beta} - 1) * 100$) and the corresponding 90 % confidence intervals of the effect of the number of wind turbines within a 1km-wide ring at distance $x$km from the zip-code centroid on green electricity tariff searches. Corresponding regression results are reported in Appendix Table A5.

[22] The average size of a zip code is 46 km^2 and can be approximated by a circle with radius 3.8 km.

[23] 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.

We further examine treatment heterogeneity across different sub-populations by estimating our model on sub-samples split according to the median values of (i) the share of young households, (ii) income levels (average purchasing power per household), or (iii) urbanization. The results are shown as percentage effects in Figure 9 and reveal negative treatment effects for all groups, without any statistically significant differences across them.

Figure 9: Effect of the number of wind turbines on search queries for green electricity tariffs – sample split



Notes: The figure plots the point estimates transformed into percentage effects $(e^{\beta} - 1) * 100$) and the corresponding 90 % confidence intervals of the effect of wind turbines on green electricity searches for different subpopulations. Estimates are based on specification (1) from Table 3. For full results, see Appendix Table A6.

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 municipal election results in German federal elections held in 2009 and 2013. The results are reported in Table 4. The IV estimate in column 1 implies that an additional WT in a municipality reduces election outcomes for the Green Party by 17 percent. As above, the OLS estimate is strongly biased towards zero. A slightly positive point estimate suggests that the reverse causality is even stronger over the 4-year intervals considered here compared to the regressions with yearly data above. The Durbin-Wu-Hausman test also corroborates our conjecture that wind turbine deployment is endogenous. The first-stage F-statistic of 42.7 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 9 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.

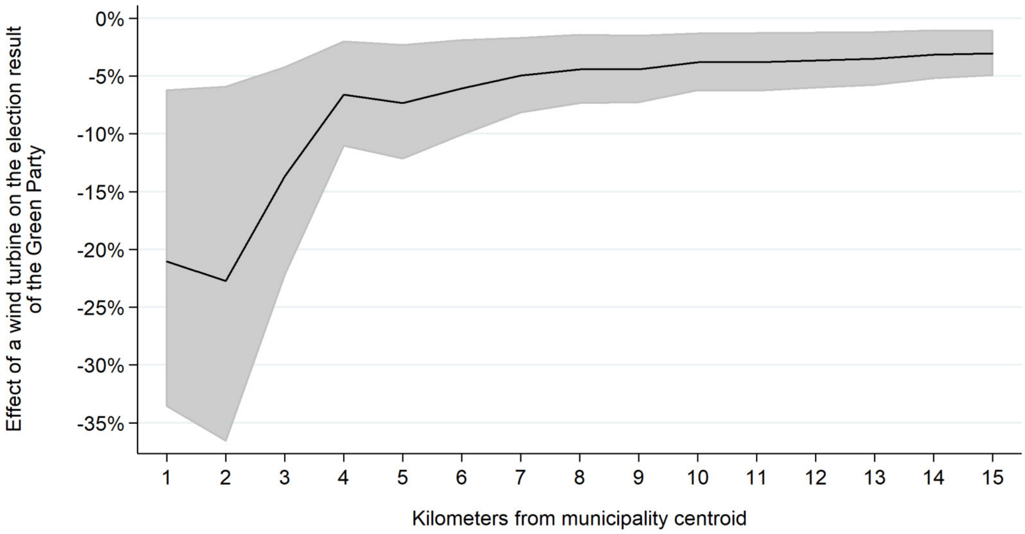
Table 4: Effect of wind power expansion on election results of the Green party

Dependent variable is	*log(vote share of the Green Party)*			
	IV (1)	OLS (2)	IV (3)	OLS (4)
No. WT within municipality	-0.187***	0.004		
	(0.052)	(0.003)		
Cap. WT within municipality			-0.090***	0.002
			(0.026)	(0.001)
Population	-0.005	-0.002	-0.006*	-0.002
	(0.003)	(0.002)	(0.004)	(0.002)
Young HH	-0.001	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Unemployment	-0.005**	-0.002	-0.005*	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Year FE	Yes	Yes	Yes	Yes
Zip code FE	Yes	Yes	Yes	Yes
Durbin-Wu-Hausman test	0.00		0.00	
First stage F stat.	42.69		41.96	
Obs.	20,158	20,158	20,158	20,158

Notes: 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. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

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 10, the treatment effect is as large as 21% for WT located within 1km from the municipality centroid, but it drops by more than half when this distance is increased to 4km and continues to decline beyond that.[24] Our analysis of WT penetration across different sub-populations yields the results that negative effects of wind turbines are pronounced in rural municipalities and those where unemployment is low, as depicted in Figure 11 .

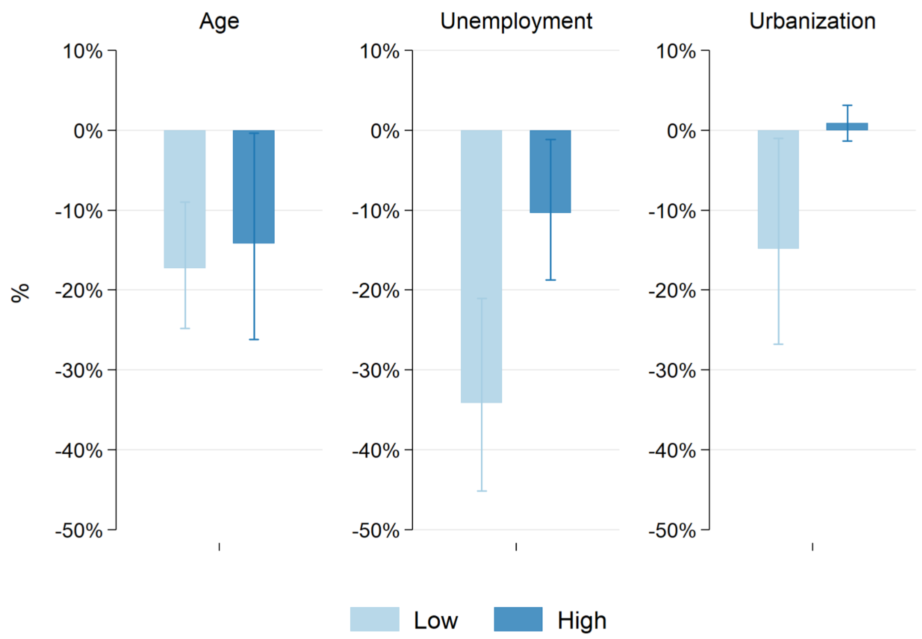
Figure 10: Effect of the number of wind turbines on election results of the Green Party – different distances



Notes: The figure plots the IV point estimates transformed into percentage effects $(e^{\beta} - 1) * 100)$ and the corresponding 90 % confidence intervals of the effect of the number of wind turbines within a 1km-wide ring at distance $x$km from the zip-code centroid on election results for the Green Party. Corresponding results are reported in Appendix Table A7.

[24]As explained in footnote 23, spatial correlation likely prevents the effect size from going all the way to zero.

Figure 11: Effect of the number of wind turbines on election results of the Green Party – sample split



Notes: The figure plots the point estimates transformed into percentage effects ($(e^{\beta} - 1) * 100$) and the corresponding 90 % confidence intervals of the effect of wind turbines on election results of the Green Party for different subpopulations. Estimates are based on specification (1) from Table 4. See Appendix Table A8 for detailed regression results.

6.2 Robustness

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

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. Appendix Tables A9 and A10 report results from regressions that address 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 y. In further regressions, we drop zero-valued observations from the estimation sample. Since green electricity searches take very high values in some zip codes, we also re-estimate the model after dropping observations where the outcome variable exceeds the 99th, 95th and 90th percentile. The results remain qualitatively robust to all these transformations.

To address the non-negative nature of the outcome variables more directly, we employ a Poisson Pseudo Maximum Likelihood (PPML) estimator where the first-stage residuals are included as a control function for endogeneity. The results, reported in Appendix Tables A11 and A12, are very similar to those from the linear 2SLS regressions.

Spatial correlation Spatial correlation in the error terms might lead to incorrect inference. We thus re-estimate the baseline model but with spatial standard errors using the estimator in Conley (1999). The Conley covariance matrix estimator has 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 A15 and A16 show that the treatment effect remains statistically significant when allowing the errors to be correlated within larger geographical areas.

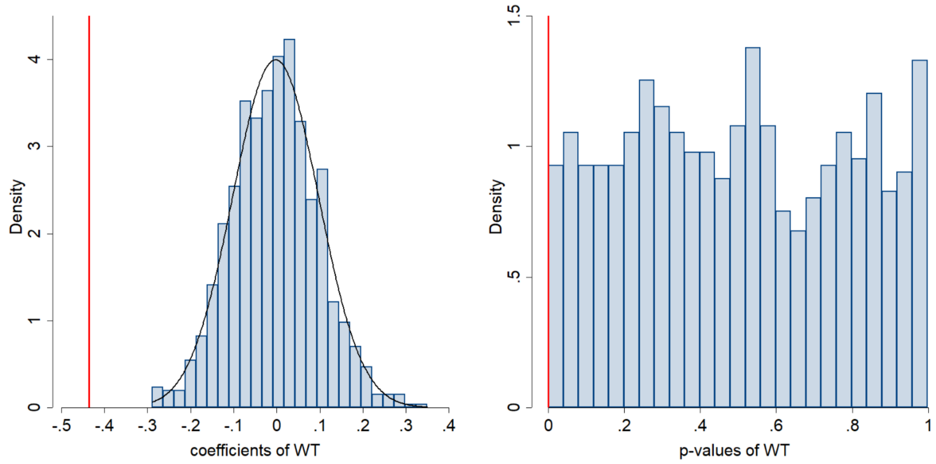
Pecuniary vs. non-pecuniary externalities Wind turbines exert downward pressure on land prices because of negative externalities for residents, or upward pressure because renewable energy subsidies are capitalized into land prices (Haan and Simmler, 2018). Such pecuniary externalities add to -or subtract 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 A13 and A14 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 In our main specification on the effect of WTs on searches for green electricity tariffs we use the share of households that searched at least once for a green electricity tariff during their search session. As a sensitivity test we check robustness of our findings to two alternative definitions of our "Green electricity searches" variable. In the first version, we compute the share of households that ticked the "show only green tariffs" box already in the first query of their search session (3.7 percent of the households). The advantage of this measure is that consumers who immediately search for green tariffs are likely to have a very strong preference for green tariffs. The number of search sessions where the "show only green tariffs" option is ticked in the last query is the second alternative measure (5.1 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 A4 reports the estimated effects of wind turbines on the *share of households searching for green electricity tariffs* for these two alternative definitions. The results are very similar to those from our main specification.

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.[25] Estimating the baseline specification (column 1 of Tables 3 and 4) on 1,000 placebo datasets yields the distributions of the WT coefficients and their

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

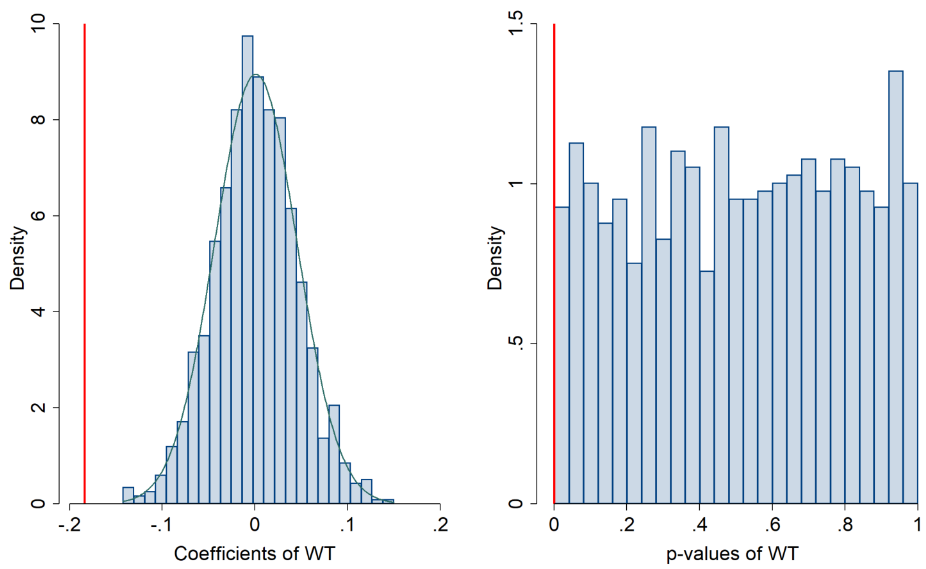
Figure 12: Placebo analysis of search queries for green electricity tariffs – distribution of treatment coefficients (a) and p-values (b)



(a) **(b)**

Notes: The red vertical lines indicate estimation results from Column (1) in Table A4, with a point estimate of -0.46 (p = 0.00). The black line presents a normal distribution. Durbin-Wu-Hausman's p = 0.49.

Figure 13: Placebo analysis of election outcomes of the Green Party – distribution of treatment coefficients (a) and p-values (b)



(a) **(b)**

Notes: The red vertical lines indicate estimation results from Column (1) in Table A4, with a point estimate of -0.19 (p = 0.00). The black line presents a normal distribution. Durbin-Wu-Hausman's p = 0.50.

p values plotted in Figure 12 (for electricity tariff searches) and Figure 13 (for election outcomes of the Green Party).

For both outcome variables, placebo regressions yield mean coefficient estimates of 0.00 and p-values of 0.5, which is in stark contrast with the negative and highly significant treatment effects obtained above. In line with the random assignment of wind turbines to outcomes in the placebo treatment, the p-values exceed 0.1 level in 90 percent of cases, and the Durbin-Wu-Hausmann tests no longer reject exogeneity. The result strongly suggest that the estimation results are not an artifact of random chance.The precise zero estimates for both outcome variables in the placebo regressions strengthen the confidence in our main findings.

6.3 Extensions

Effects of the first wind turbine. One may conjecture that the reaction to an additional WT critically depends on whether or not the population is already exposed to them. A negative reaction is likely higher 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.[26] Do new wind turbines have a stronger effect on citizens' support in those areas than overall?

To investigate this, we re-estimate the baseline specification after excluding all regions that already had at least one WT at the beginning of the observation period. The results, reported in Appendix Tables A17 and A18, show that the estimated effects are indeed substantially larger than in the full sample. First-time installation of a WT in a zip code reduces the share of green tariff queries by as much as 81 percent, suggesting that people in these areas then almost entirely dismiss renewable energy tariffs. Similarly, votes for the Green Party drop by 38 percent in municipalities that had no WTs in 2009 but at least one in 2013, as compared to municipalities that remained without any WT until at least 2013.

[26]Out of 10,003 municipalities, 8,075 had not a single WT installed by 2009, and 6,011 out of 8,039 zip codes had no wind turbine installed by 2011. At the end of the respective sample periods, 425 municipalities and 303 zip codes had seen the installation of the first WT on their territory.

Excluding locations that already had WTs at the beginning of the sample reduces variation in the data and hence the power of our instrument, as indicated by the rather low first-stage F-statistics of 13.28 for searches and 7.82 for vote shares. According to the critical values of Stock and Yogo (9.08 and 6.46, respectively), the estimates of the election results may suffer from a bias in the range of 10 percent to 20 percent. However, even in light of this consideration, the effect of the first WTs remains substantially larger than in the full sample.

Voter migration. We have seen that the share of votes for the Green Party decreases locally following the installation of WTs. Consequently, the election outcomes of other parties must increase. *Cui bono*? We examine this by estimating the effect of new WTs on the votes of the other main political parties. The results -reported in Appendix Table A19- suggest that election outcomes remain unchanged for all parties except for the Social Democratic Party (SPD) which improves its election outcome by 18%. This is in line with voter migration between the two parties traditionally being the highest in the German political spectrum (see, e.g., Tagesschau, 2013). An important conclusion from this is that the SPD, despite being the senior coalition partner in the "Red-Green" government that implemented the renewable energy support, did not pay a political price for the adverse impacts of this policy. This makes sense if voters attribute political responsibility for ecologically-minded policies to the Green Party, like we assume here, and otherwise regard the SPD as a close-enough substitute in terms of other policy domains.[27]

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

[27]Conversely, it is widely held that the political price for unpopular labor market reforms implemented by the Red-Green government was entirely paid by the SPD and not by the Green Party.

in 66 percent of German municipalities.[28] 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 A20. The coefficient estimates imply that an additional WT reduces the votes of the Green Party by 22 percent (compared to 17 percent in the *Bundestag* elections).

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 requirements on distances for the construction of new wind turbines to residential areas, which have

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

been introduced in German federal and state laws, could be effective at securing support for a continued wind power expansion. However, minimum distance requirements are controversial because they can dramatically limit the remaining set of suitable construction sites, thereby putting in jeopardy the successful transformation of the energy system. This is why there is great interest in alternative policy instruments that avoid such trade-offs. In the public debate, particular attention has been given to financial participation as a possible cure for NIMBYism. The idea is to compensate affected residents for the local externalities of renewable electricity generation. In this section, we explore whether our data and setting lend empirical support to the effectiveness of such a policy.

Transferring revenues from wind power plants to affected communities would be a direct form of financial participation and could be implemented within existing schemes of local taxation in Germany.[29] For example, profits of wind power plants are subject to the commercial tax (*Gewerbesteuer*) levied by municipal governments. Along with the property tax, this tax generates the bulk of municipal tax revenues and constitute an important share in municipalities' budget. However, if the company operating the WT is not headquartered in the same municipality as the WT, the tax base is divided between those municipalities. Until 2009, the division was based on the company's labor cost share in each municipality. Given that WTs – once operational – only incur minimal labour costs, municipalities with WTs did not have much tax revenue to gain. This changed in 2009 when new rules allocated 70 percent of commercial tax revenues from WTs based on the book value of tangible fixed assets, and only 30 percent according to labor cost shares.

The reform was intended to increase commercial tax revenues of municipalities that host wind turbines. We test whether this goal was achieved by regressing the commercial tax base on the lagged number of wind turbines in an annual panel of

[29] Furthermore, the most recent amendment of the renewable energy support act in 2021 includes a voluntary scheme to directly compensate municipalities in which a wind turbine is placed.

German municipalities from 2009 until 2015.[30] We estimate this relationship in first differences to control for municipality fixed effects, include year effects to control for aggregate shocks, and instrument for WT deployment as in our main specification. The coefficient estimates are positive and statistically significant at the 90 at the 90% level or better, as shown in Table A21. The installation of an additional WT increases the commercial tax base by about 11 to 15 percent in profits in the subsequent year. At the median, this is equivalent to an increase in the annual tax base by around 10 to 13 thousand Euros per additional wind turbine.

This is the right kind of variation in municipal tax revenues for learning about the effect of financial participation on local support for renewables. Moreover, the design of the tax reform allows us to disentangle the variation in the location of WTs from unobserved determinants of citizen support because it raised tax revenues only for those municipalities that hosted wind turbines but not for others that also hosted the operator's headquarters. To construct a measure of financial participation based exclusively on quasi-experimental variation in tax revenues, we regress the change in commercial tax revenues between 2008 and 2009 on lagged WT and socioeconomic controls as in the main specifications.[31] Regions with positive residuals in 2009 likely benefited from the new tax regime (we cannot assess this more directly since we do not observe the location of headquarters). We define an indicator variable for beneficiaries of the policy change which is one for regions with positive residuals *and* at least one wind turbine installed. We then augment the baseline regression eq. (1) by the interaction of the number of wind turbines with this indicator variable and report the 2SLS estimates in Table 5.

The point estimates on WT in regions that did not benefit from the tax change for wind turbines resemble those of our main results and are statistically significant

[30] We use the tax base instead of tax revenues to sidestep the issue of local governments endogenously changing commercial tax rates in response to wind power expansion (Langenmayr and Simmler, 2021). We lag WTs by one year because a new turbine contributes to commercial taxes only in the year following the installation.

[31] For the analyses of search requests on the zip code level, we use the commercial tax base of the municipality that is associated with the respective zip code whenever this is possible, or else exclude these observations from the analysis.

Table 5: Effect of wind turbines on citizens' support and the role of local commercial tax revenues

Dependent variable is	*log(search queries for green tariffs)*	*log(vote share of the Green Party)*
	(1)	(2)
No. WTs	-0.536***	-0.163***
	(0.123)	(0.052)
No. WTs x Tax benefit	0.225*	0.064**
	(0.138)	(0.027)
Population	0.034**	-0.005
	(0.017)	(0.003)
Young HH	-0.007	0.000
	(0.009)	(0.001)
Purchasing power	0.002	
	(0.007)	
Unemployment		-0.005*
		(0.003)
Durbin-Wu-Hausman test	0.00	0.01
First stage F stat.	36.10	19.59
Obs.	31,297	19,972

Notes: All estimations are done in first differences and include year fixed effects. Standard errors clustered at the municipality and zip code level in parenthesis, respectively. 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. The estimation period refers to 2011 to 2014 for green tariffs queries and 2009 and 2013 for election results of the Green Party, respectively. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

at conventional levels.[32] The coefficient estimates on the interaction of interest is positive and statistically significant, suggesting that the negative effect from wind turbines on both support measures is alleviated for those regions that were able to financially participate in wind power profits through taxes. Given the importance of local commercial tax revenues for municipalities' budgets, revenues from wind power could be used to either lower existing local taxes, such as the property tax, or increase the provision of local amenities.[33]

Overall, these results support the notion that more local participation in wind power profits could mitigate the negative impact of nearby installation of wind turbine on citizen's support for renewable energy.

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 35 percent when a wind turbine is installed in the zip code. Similarly, we have found that votes for the Green Party in German federal elections decrease by about 17 percent

[32]For renewable tariff queries, the point estimate is a bit larger than in the baseline specification, while the one for votes is in a similar range.

[33]Anecdotal evidence points to increases in municipal spending in some cases (e.g., https://www.spiegel.de/wirtschaft/soziales/energiewende-wie-windkraft-ein-113-seelen-dorf-reich-machte-a-1078759.html)

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.

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. 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 citizen's 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

Notes: 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

	2009				2013			
	CDU	FDP	Green	SPD	CDU	FDP	Green	SPD
Wind	3	3	11	2	7	1	36	5
Energy transition	0	0	2	1	11	10	74	33
Renewable energy	16	20	61	24	13	14	75	33
Climate	44	32	151	22	24	21	153	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 revenue of a WT	0.660***
	(0.130)
Ineligible	0.704***
	(0.061)
Ineligible × Wind potential	0.014
	(0.052)
Population	-0.046*
	(0.024)
Young HH	-0.006
	(0.005)
Purchasing power	-0.007*
	(0.004)
Year FE	Yes
Zip code FE	Yes
Obs.	32,252

Notes: Standard errors clustered at the zip code level in parenthesis. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A4: Effect of wind power expansion on search queries for green electricity tariffs – alternative measures

Dependent variable is	*log(searches for green tariffs in first query)*	*log(searches for green tariff in last query)*
	(1)	(2)
No. WT within zip code	-0.436***	-0.364***
	(0.108)	(0.103)
Population	0.040*	0.049***
	(0.021)	(0.019)
Young HH	-0.012	-0.013
	(0.010)	(0.009)
Purchasing power	0.012*	0.001
	(0.007)	(0.007)
Year FE	Yes	Yes
Zip code FE	Yes	Yes
Durbin-Wu-Hausman test	0.00	0.00
First stage F stat.	71.80	71.80
Obs.	32,252	32,252

Notes: In our main specifications we use 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 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. The period under investigation covers the years 2011 to 2014. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A5: Effect of wind power expansion on search queries for green electricity tariffs – different distances

	Dependen variable is *log(any query)*					
	(1)	(2)	(3)	(4)	(5)	(6)
Donut 1km distance	-1.991***					
	(0.478)					
Donut 2km distance		-1.572***				
		(0.448)				
Donut 3km distance			-2.556***			
			(0.606)			
Donut 5km distance				-1.317***		
				(0.309)		
Donut 10km distance					-0.322***	
					(0.078)	
Donut 15km distance						-0.213***
						(0.050)
Population	0.050***	0.021	0.054*	0.062***	0.069***	0.053***
	(0.019)	(0.025)	(0.031)	(0.019)	(0.015)	(0.015)
Young HH	0.002	-0.010	0.008	-0.021*	-0.011	-0.010
	(0.010)	(0.010)	(0.012)	(0.012)	(0.009)	(0.009)
Purchasing power	-0.009	-0.003	0.000	0.008	0.000	0.001
	(0.008)	(0.007)	(0.008)	(0.009)	(0.007)	(0.006)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip code FE	Yes	Yes	Yes	Yes	Yes	Yes
Durbin-Wu-Hausman test	0.00	0.00	0.00	0.00	0.00	0.00
First stage F stat.	20.15	17.06	13.17	23.86	47.57	60.22
Obs.	32,252	32,252	32,252	32,252	32,252	32,252

Notes: Standard errors clustered at the zip code level in parenthesis. Estimates are by 2SLS as in specification (1) in Table 3. The coefficients of interest measure the effect of an additional wind turbine deployed within a 1km-wide ring at distance $x$km from the zip-code centroid on the outcome variable. The period under investigation covers the years 2011 to 2014. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A6: Effect of wind power expansion on search queries for green electricity tariffs – sample split

Dependent variable is	*log(search queries for green tariffs)*					
	Age		Income		Urbanization	
	young (1)	old (2)	low (3)	high (4)	rural (5)	urban (6)
No. WT within zip code	-0.492***	-0.384***	-0.347***	-0.469***	-0.575***	-0.276***
	(0.150)	(0.140)	(0.124)	(0.175)	(0.219)	(0.058)
Population	0.048***	-0.013	0.034*	-0.038	0.066	0.085***
	(0.017)	(0.038)	(0.019)	(0.026)	(0.049)	(0.016)
Young HH	-0.006	-0.013	0.016	-0.017	-0.019	-0.001
	(0.010)	(0.016)	(0.012)	(0.014)	(0.015)	(0.006)
Purchasing power	-0.002	-0.001	0.001	-0.003	-0.008	0.014***
	(0.009)	(0.010)	(0.010)	(0.008)	(0.010)	(0.005)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip code FE	Yes	Yes	Yes	Yes	Yes	Yes
Durbin-Wu-Hausman test	0	0	0	0	0	0
First stage F stat.	31.12	40.09	40.41	28.11	29.56	45.97
Mean of *first query*	6.75	5.84	6.03	6.56	5.40	7.20
Obs.	16,127	16,125	16,128	16,124	16,128	16,124

Notes: The dependent variable is *log(search queries for green tariffs)*. Standard errors clustered at the zip code level in parenthesis. Estimates are based on specification (1) from Table 4. The local adoption rate of wind power is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield mode. The period under investigation covers the years 2011 to 2014. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A7: Effect of the number of wind turbines on election results of the Green Party – different distances

	Dependent variable is *log(election result of the Green Party)*					
Donut 1km distance	-0.236***					
	(0.067)					
Donut 2km distance		-0.258***				
		(0.076)				
Donut 3km distance			-0.147***			
			(0.040)			
Donut 5km distance				-0.076***		
				(0.021)		
Donut 10km distance					-0.039***	
					(0.010)	
Donut 15km distance						-0.031***
						(0.008)
Population	-0.002	-0.004	-0.003	-0.001	-0.002	-0.002
	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)
Young HH	-0.001	-0.002	-0.000	-0.001	-0.000	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Unemployment	-0.002	-0.003*	-0.004*	-0.002	-0.002	-0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Durbin-Wu-Hausman test	0.00	0.00	0.00	0.00	0.00	0.00
First stage F stat.	30.40	21.94	30.12	52.86	92.66	116.39
Obs.	20,158	20,158	20,158	20,158	20,158	20,158

Notes: Standard errors clustered at the municipality level in parenthesis. Estimation is by 2SLS as in specification (1) in Table 4. The coefficients of interest measure the effect of an additional wind turbine deployed within a 1km-wide ring at distance $x$km from the municipality centroid on the outcome variable. The period under investigation covers the elections 2009 and 2013. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A8: Effect of the number of wind turbines on election results of the Green Party – sample split

Dependent variable is	*log(vote share of the Green Party)*					
	Age		Unemployment		Urbanization	
	young (1)	old (2)	high (3)	low (4)	rural (5)	urban (6)
No. WT within municipality	-0.189***	-0.153*	-0.109*	-0.418***	-0.161*	0.009
	(0.058)	(0.091)	(0.059)	(0.111)	(0.092)	(0.014)
Population	-0.004	-0.023**	-0.003	-0.104***	-0.187	-0.002
	(0.003)	(0.010)	(0.002)	(0.039)	(0.151)	(0.001)
Young HH	0.003	-0.006	0.006*	-0.006	-0.003	0.005***
	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.001)
Unemployment	-0.002	-0.005*	-0.003	-0.009	-0.004	-0.000
	(0.003)	(0.003)	(0.002)	(0.009)	(0.003)	(0.001)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip code FE	Yes	Yes	Yes	Yes	Yes	Yes
Durbin-Wu-Hausman test	0.00	0.13	0.04	0.00	0.07	0.18
First stage F stat.	32.75	10.30	10.11	24.76	11.40	41.02
Mean of *voting share*	7.65	7.09	6.41	8.27	6.87	7.85
Obs.	10,692	9,466	9,262	10,896	9,418	10,740

Notes: The dependent variable is *log(vote share 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. The period under investigation covers the elections 2009 to 2013. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A9: Effect of the number of wind turbines on search queries for green electricity tariffs – alternative transformations

Dependent variable is	*log(search queries for green tariffs)*				
	IHS (1)	Zeros excluded (2)	>99% excluded (3)	>95% excluded (4)	>90% excluded (5)
No. WT within zip code	-0.312***	-0.269***	-0.456***	-0.437***	-0.353***
	(0.070)	(0.053)	(0.100)	(0.103)	(0.108)
Population	0.062***	0.115***	0.025	0.026	0.027
	(0.014)	(0.015)	(0.018)	(0.019)	(0.018)
Young HH	-0.017***	-0.026***	-0.008	-0.012	-0.015*
	(0.006)	(0.005)	(0.009)	(0.009)	(0.009)
Purchasing power	0.003	0.005	-0.001	0.003	0.003
	(0.004)	(0.004)	(0.007)	(0.006)	(0.006)
Year FE	Yes	Yes	Yes	Yes	Yes
Zip code FE	Yes	Yes	Yes	Yes	Yes
Durbin-Wu-Hausman test	0.00	0.00	0.00	0.00	0.00
First stage F stat.	71.80	68.66	69.58	64.27	51.75
Obs.	32,252	30,252	31,929	30,612	28,984

Notes: The dependent variable is the share of search queries for green electricity tariffs. In Column (1) we trandform 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. The period under investigation covers the years 2011 to 2014. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A10: Effect of the number of wind turbines on election results of the Green Party – alternative transformations

Dependent variable is	*log(vote share of the Green Party)*				
	IHS (1)	Zeros excluded (2)	>99% excluded (3)	>95% excluded (4)	>90% excluded (5)
No. WT within municipality	-0.156***	-0.124***	-0.149***	-0.127**	-0.130**
	(0.040)	(0.032)	(0.050)	(0.055)	(0.063)
Population	-0.004	-0.004	-0.005	-0.018***	-0.021***
	(0.003)	(0.002)	(0.003)	(0.005)	(0.006)
Young HH	-0.001	-0.000	0.002	0.003	0.003
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)
Unemployment	-0.004*	-0.001	-0.005**	-0.004*	-0.004
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Year FE	Yes	Yes	Yes	Yes	Yes
Zip code FE	Yes	Yes	Yes	Yes	Yes
Durbin-Wu-Hausman test	0.00	0.00	0.01	0.07	0.15
First stage F stat.	42.69	42.98	44.31	35.09	27.91
Obs.	20,158	19,988	19,822	18,428	16,752

Notes: 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. The period under investigation covers the elections 2009 to 2013. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A11: Effect of the number of wind turbines on search queries for green electricity tariffs – PPML estimation with control function

Dependent variable is	*Share of search queries for green electricity tariffs*
No. WT within zip code	-0.405***
	(0.059)
Population	0.092***
	(0.015)
Young HH	-0.008
	(0.006)
Purchasing power	-0.004
	(0.004)
Control function	0.391***
	(0.059)
Year FE	Yes
Zip code FE	Yes
Obs.	32,176

Notes: Standard errors clustered at the zip code level in parenthesis. The local adoption rate of wind power is considered endogenous. Estimation by PPML with control function inclusion for endogeneity. . $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A12: Effect of the number of wind turbines on election results of the Green Party – PPML estimation with control function

Dependent variable is	*Vote share of the Green Party*
No. WT within municipality	-0.141***
	(0.029)
Population	-0.002***
	(0.001)
Young HH	-0.002
	(0.002)
Unemployment	-0.002**
	(0.001)
Control function	0.144***
	(0.029)
Year FE	Yes
Municipality FE	Yes
Obs.	20,152

Notes: Standard errors clustered at the municipality level in parenthesis. The local adoption rate of wind power is considered endogenous. Estimation by PPML with control function inclusion for endogeneity. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A13: Effect of the number fo 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	-0.448***	(0.102)
Population	0.022	(0.019)
Young HH	-0.011	(0.009)
Purchasing power	-0.001	(0.007)
log(Land prices)	-0.034	(0.030)
Year FE	Yes	
Zip code FE	Yes	
Durbin-Wu-Hausman test	0.00	
First stage F stat.	69.89	
Obs.	31,065	

Notes: 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. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A14: Effect of the number of wind turbines on election outcomes of the Green Party – controlling for land prices

Dependent variable is	*log(vote share of the Green Party)*	
No. WT within municipality	-0.184***	(0.050)
Population	-0.005	(0.003)
Young HH	-0.001	(0.003)
Unemployment	-0.005**	(0.002)
log(Land prices)	-0.016	(0.012)
Year FE	Yes	
Municipality FE	Yes	
Durbin-Wu-Hausman test	0.00	
First stage F stat.	42.48	
Obs.	19,914	

Notes: 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. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A15: 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	-0.458***	-0.458***	-0.458***
	(0.087)	(0.095)	(0.089)
Population	0.026*	0.026	0.026
	(0.016)	(0.017)	(0.018)
Young HH	-0.007	-0.007	-0.007
	(0.008)	(0.008)	(0.009)
Purchasing power	-0.001	-0.001	-0.001
	(0.006)	(0.005)	(0.005)
Year FE	Yes	Yes	Yes
Zip code FE	Yes	Yes	Yes
Conley cluster distance	10km	25km	50km
First stage F stat.	45.77	27.76	20.66
Obs.	32,252	32,252	32,252

Notes: 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. The period under investigation covers the years 2011 to 2014. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A16: 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 of the Green Party)*		
	(1)	(2)	(3)
No. WT within municipality	-0.187***	-0.187***	-0.187***
	(0.051)	(0.061)	(0.067)
Population	-0.005**	-0.005*	-0.005
	(0.003)	(0.003)	(0.003)
Young HH	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.003)
Unemployment	-0.005**	-0.005**	-0.005**
	(0.002)	(0.002)	(0.002)
Constant	0.000	0.000	0.000
	(0.003)	(0.004)	(0.004)
Year FE	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Conley cluster distance	10km	25km	50km
First stage F stat.	30.85	70.65	28.99
Obs.	21,089	21,089	21,089

Notes: 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. The period under investigation covers the years 2011 to 2014. ***$p < 1\%$, **$p < 5\%$, *$p < 10\%$.

Table A17: Effect of the first wind turbine on search queries for green electricity tariffs – estimations on a sample excluding areas that already had WTs at the beginning of the observation period

Dependent variable is	*log(search queries for green tariffs)*
No. WT within zip code	-1.807***
	(0.576)
Population	-0.003
	(0.037)
Young HH	-0.002
	(0.012)
Purchasing power	-0.010
	(0.010)
Year FE	Yes
Zip code FE	Yes
Durbin-Wu-Hausman test	0.00
First stage F stat.	13.28
Obs.	24,195

Notes: 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. ***$p < 1\%$, **$p < 5\%$, *$p < 10\%$.

Table A18: Effect of the first wind turbine on election results of the Green Party – estimations on a sample excluding areas that already had WTs at the beginning of the observation period

Dependent variable is	*log(vote share of the Green Party)*
No. WT within municipality	-0.506**
	(0.209)
Population	-0.006
	(0.015)
Young HH	0.000
	(0.003)
Unemployment	-0.007
	(0.006)
Year FE	Yes
Municipality FE	Yes
Durbin-Wu-Hausman test	0.02
First stage F stat.	8.35
Obs.	16,236

Notes: 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. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A19: Effect of the number of wind turbines on election results of other political parties

Dependent variable is log(vote share) of	CDU	FDP	SPD	others
	(1)	(2)	(3)	(4)
No. WT within municipality	-0.002	-0.036	0.220***	-0.067*
	(0.012)	(0.045)	(0.036)	(0.037)
Population	0.001	-0.000	0.005*	0.002*
	(0.001)	(0.003)	(0.002)	(0.001)
Young HH	-0.002***	0.013***	0.011***	0.003***
	(0.000)	(0.002)	(0.002)	(0.001)
Unemployment	-0.002***	0.004**	0.008***	0.005***
	(0.000)	(0.002)	(0.002)	(0.002)
Year FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Durbin-Wu-Hausman test	0.37	0.00	0.00	0.00
First stage F stat.	42.69	42.69	42.69	42.69
Obs.	20,158	20,158	20,158	20,158

Notes: 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. The period under investigation covers the elections 2009 to 2013. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Table A20: Effect of the number of wind turbines on election results of the Green Party: Elections to the European Parliament

Dependent variable is	*log(vote share of the Green Party)*
No. WPS within municipality	-0.243***
	(0.048)
Population	0.002
	(0.002)
Young HH	-0.001
	(0.001)
Unemployment	-0.002
	(0.004)
Year FE	Yes
Municipality FE	Yes
Durbin-Wu-Hausman test	0.00
First stage F stat.	57.40
Obs.	20,076

Notes: 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. The period under investigation covers the elections 2009 to 2014. *others* in Column (4) contains the voting shares of all parties except the Green Party, CDU, FDP and SPD. ***$p < 1\%$, **$p < 5\%$, *$p < 10\%$.

Table A21: Local commercial tax base and wind power expansion

Dependent variable is	D.log(taxbase)	D.log(taxbase - top 5% removed)	D.log(taxbase - top and bottom 5% removed)
	(1)	(2)	(3)
LD.No. WTs within municipality	0.111*	0.140*	0.149**
	(0.067)	(0.078)	(0.071)
Durbin-Wu-Hausman test	0.04	0.04	0.02
First stage F stat.	29.53	26.86	27.41
Obs.	41419	38966	37633

Notes: Standard errors clustered at the municipality level in parenthesis. Estimation by 2SLS. The number of WTs is lagged by one year and is considered endogenous. Instruments based on expected revenues of a WT according to the reference yield model. Regression is estimated in first differences and includes year fixed effects. Commercial tax base is tax revenues divided by tax rate. To mitigate the effect of outliers, we trim the commercial tax base values at various thresholds. Point estimates are in a similar range when trimming at thresholds in between the displayed one. ***$p < 1\%$, **$p < 5\%$, *$p < 10\%$.

A.2 Additional figures

Figure A1: Screenshot of the price comparison website "Toptarif"

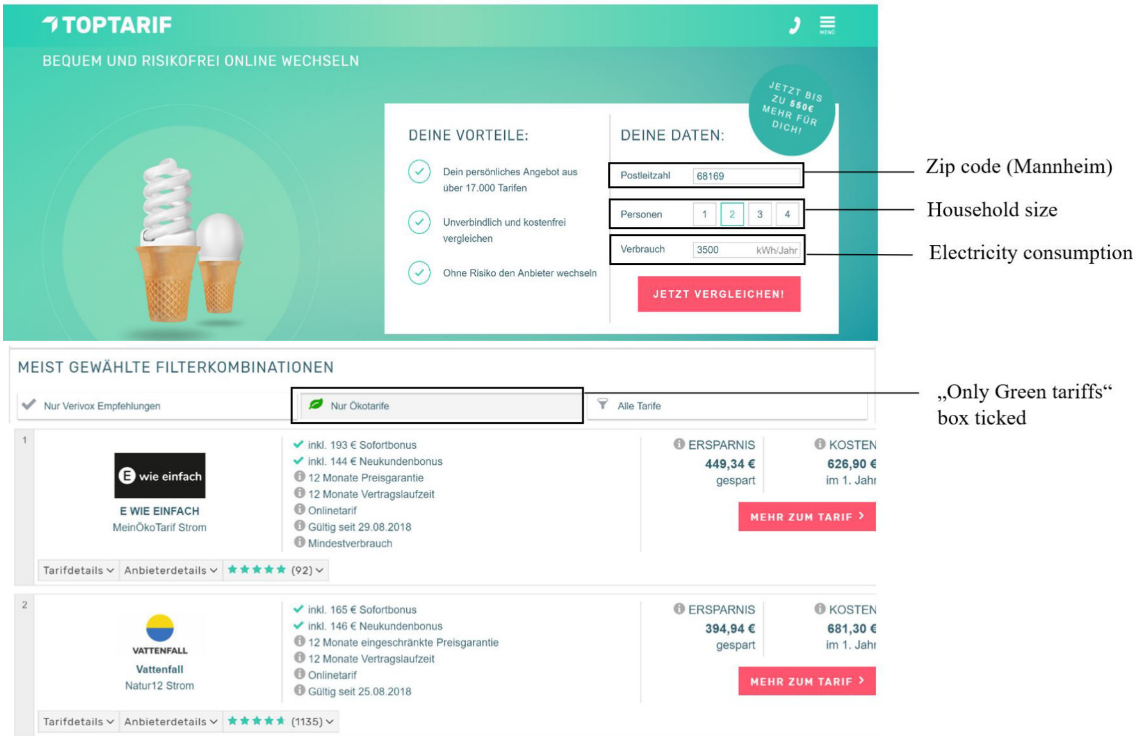
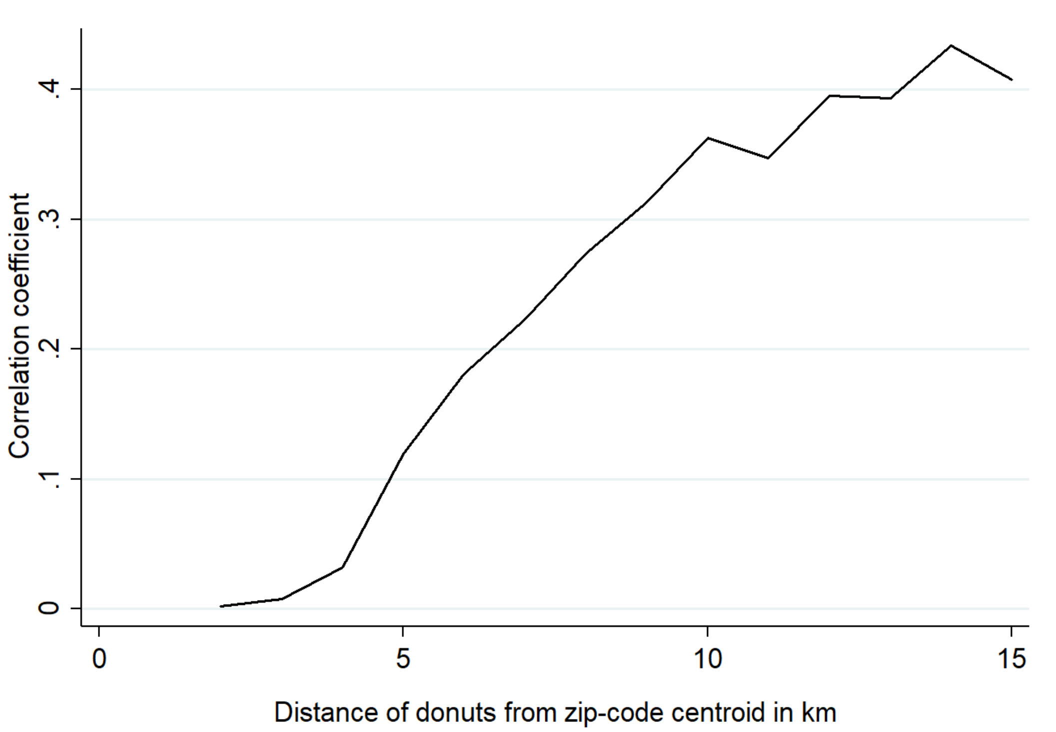


Figure A2: Spatial correlation in the number of WTs



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