Headwind in Sight? The Reaction of Local Residents to Visible Wind Turbines

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Abstract

Constructing new wind turbines is an important environmental policy goal in many countries, yet it arguably entails disamenities for local residents. The factors influencing residents' reaction and the underlying opinion formation process are not yet well understood. With new fine-grained location data, we use the visual exposure of German residential areas to wind turbines as an identification strategy. In a setting of revealed preferences, we measure whether a new visible turbine reduces residents' support for renewable energy, as measured by the vote share for the German Green Party. While we do not find a significant effect in earlier election periods (1998 to 2009), there is a sizable decrease in support by residents treated to visible wind turbines in later election periods (2013 to 2021). With data on wind turbine ownership and citizens' initiatives, we discuss the drivers of these developments, pointing to involvement in the decision making process and participation in improved municipal finances as policy implications for obtaining more support.

JEL Classification: Q40, O18, R14, D72

Keywords: Wind turbines, municipalities, renewable energy, geo-spatial data, revealed preferences

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1 Introduction

The expansion of renewable energy is a vital measure of environmental policy for countries around the world in order to achieve climate neutrality and to comply with the goals of the Paris Climate Change Agreement (Intergovernmental Panel on Climate Change, 2022). Along with solar and hydro power, wind energy is one of the main sources of renewable energy generation. The expansion of wind energy is receiving a substantial amount of funds as one of the pillars of the European Green Deal (European Commission, 2020) as well as the Inflation Reduction Act in the U.S. (The White House, 2023), considered the 'largest climate investment in U.S. history' (CNN, 2022). Yet, while many people support wind energy generation in general, there are arguably some disamenities for those living in the vicinity of wind turbines. Understanding voters' concerns and reactions is important for policymakers who decide on the construction of new wind turbines.

A backdrop to this situation is formed by the increasing political polarization as well as regional inequality that many industrialized countries have experienced in recent years. The term 'urban-rural political divide' captures the differences in attitudes and voting behavior between people in big cities and those in rural areas. It has been extensively analyzed, among others for the U.S. (e.g. McKee, 2008, Scala and Johnson, 2017), Britain (e.g. Jennings and Stoker, 2016), France (e.g. Agnew and Shin, 2020) and in the cross-country meta-study by Kenny and Luca (2020).[1] This phenomenon increases the relevance of the local effects of environmental policy. Douenne and Fabre (2022) argue that people outside of big urban centers often have to bear the brunt of the transition in energy and mobility, as evidenced by the *Gilets Jaunes* protests of car-dependent rural residents against a carbon tax in France in 2018/19. In a similar way, wind turbines are predominantly being built in rural areas and how they shape the attitudes of local residents is an important issue of the public debate.

A new wind turbine in people's vicinity might affect them through a number of different channels. These include a 'visual intrusion of the landscape' (Wolsink, 2000, p.51), noise pollution, and bird endangerment, but also potentially cheaper electricity prices, windfall taxes from wind turbine construction, and/or jobs for locals (Hoen et al., 2019, Liebe and Dobers, 2019, Diermann, 2023). The importance of these effects can further be influenced by factors such as the participation of residents in the location selection process (Jobert et al., 2007), the ownership structure of the turbine (Lienhoop,

[1] This matters for climate-change mitigation measures: In what McKann (2020) calls 'the geography of discontent', the right-wing populist voting share tends to be particularly high in formerly industrialized regions that are losing out to globalization, structural change and decreasing demand for energy based on fossil fuels (Rodríguez-Pose, 2018).

2018, Langer et al., 2017), as well as some vocal opponents trying to shift public opinion (Schwarz, 2020). The outcome in terms of people's reaction to the construction of a local wind turbine is consequently the result of a complex interplay. It is an empirical question whether exposure to a wind turbine may lead to a backlash of local attitudes towards the energy transition and under which circumstances. Despite a growing number of research papers dealing with wind energy, a comprehensive answer is still lacking.

One challenge relates to the measurement of people's attitudes, in particular their support for wind energy in general. A number of papers follow a qualitative approach via survey results among residents, eliciting stated preferences (e.g. Wolsink, 2000, van der Horst, 2007, Liebe and Dobers, 2019). By contrast, we intend to uncover revealed preferences by interpreting their voting behavior under particular conditions. Another issue plaguing numerous empirical studies is the correct treatment identification. The straightforward approach in the literature is to consider a municipality as treated if at least one wind turbine has been constructed within its administrative boundaries (e.g. Larsen et al., 2021, Germeshausen et al., 2021). However, a wind turbine might be located far from the actual settlement and hardly be visible for its residents, or, conversely people might be affected by a turbine constructed just across the border in a different municipality. Differences in terms of windfall gains from improved municipal finances from which residents potentially benefit might also confound the identification.

In this paper, we provide new insights by addressing these issues in a comprehensive study on the effects of visible wind turbine construction on local residents of German municipalities from 1998 to 2021. Our contribution is threefold:

(i) Combining municipal-level data on voting behavior over two decades with the precise location of each wind turbine in Germany, we have much more fine-grained data at our disposal than previous studies. We can thus go much deeper in the analysis and, inter alia, differentiate between turbines in residents' municipalities and neighboring ones, discuss turbine ownership, migration as well as the presence of citizens' initiatives.

(ii) We employ robust econometric methods. We address concerns that plague the traditional two-way fixed effects estimations in settings with multiple periods and treatment timings (Abraham and Sun, 2018) by estimating the effect for each group of municipalities treated at the same time separately (staggered difference-in-difference methods). Moreover, we account for the anticipation effect that matters in wind turbine construction.

(iii) Crucially, our identification strategy rests on the visibility of a wind turbine from a settlement area rather than its mere presence. While survey respondents often mention visual intrusion of the landscape as their main reason for opposition (Lehmann et al., 2023, Wolsink, 2000), we are the first study to empirically elucidate this important channel. Moreover, our focus on the visibility allows us to contour the endogeneity issue by looking at visually-exposed residents from neighboring municipalities rather than those where the turbine is located.

We work with German data for a number of reasons: Germany is the most populous country in Europe and an industrial powerhouse with coal and gas as traditional energy sources, but the *Energiewende* (energy transition) has driven the expansion of renewables. In 2021 - even before the invasion of Ukraine by Russia -, 42.4% of electricity in Germany came from renewable sources, half of which was generated by wind energy (Destatis, 2022). According to survey data, 70% of respondents supported the energy transition (Holzmann and Wolf, 2023). This expansion of wind energy across Germany occurred gradually over the last decades, with sizeable variation across both time and space. With the geo-locations of wind turbines and their building date at our disposal, we can exploit this variation in our econometric analysis.

Yet, Germany brings another advantage for our approach of revealed preferences: It allows us to use the vote share of the Green party as a proxy for attitudes towards renewable energy more broadly. The German Green party has run on a strongly pro-environmental platform since its foundations in the 1980s, campaigning against nuclear energy and in favor of renewable energy sources (Bukow, 2016). The party is thus strongly associated with the climate topic in public opinion (Wagner and Meyer, 2014), arguably much more so than other, more comprehensive progressive parties, such as the Democrats in the U.S.

If the vote share for the Green party decreases after exposure to a visible wind turbine - compared to the control municipalities -, we see this as evidence for a change in attitudes. In a theoretical framework on the opinion formation process with individual heterogeneity, we motivate our approach of revealed preferences. While some people might always be in favor of renewable energy and others might always oppose it, the most relevant group for policymakers are those who change their attitude after they can observe a wind turbine in their vicinity for the first time. In the literature, NYMBYists ('Not in my backyard') see the necessity of wind energy as a public good but want to free-ride by not having turbines in their own vicinity. By contrast, NIABYists ('Not in any backyard') oppose that kind of energy generation in general (Wolsink, 2000, van der Horst, 2007). Despite the overall large public support of wind energy projects (Aldy et al., 2012), both groups have been shown to be empirically relevant (Liebe and Dobers, 2019, Wolsink, 2000).

We relate to and build on various strands of the literature, ranging from the local effects of environmental policy to public amenities and disamenities, as well as the

decision formation process.
In particular, we build on the insights gained by the number of studies trying to capture residents' attitudes to wind turbines with survey data (Liebe and Dobers, 2019, van der Horst, 2007). The survey respondents point to turbines' "perceived impact on scenery, visual intrusion of the landscape" (Wolsink, 2000, p.51) as a reason for their opposition. These results form the conceptual basis for us to work with turbine visibility from settlements. Yet, the stated preference approach in this strand of the literature relies on reported data by the residents that participate in the survey. Our approach is to measure their attitude change proxied by their actual voting behavior.

Another strand of the literature looks at the effects of wind turbine construction on house prices rather than attitudes, thereby trying to uncover revealed preferences. A number of studies have failed to find statistically significant effects of turbines on nearby houses, e.g. Hoen et al. (2011) in the U.S. and Sims et al. (2008) in the UK. Yet, (Gibbons, 2015) highlights the small sample sizes of house sales directly after wind turbine construction as well as the measurement issues plaguing some of these studies. With data from England and Wales, he tries to measure the visibility of wind turbines from sold houses and finds a negative impact. We follow in his steps in considering visibility as a vital feature.

Finally, there is a number of studies that has analyzed the voting outcome of wind turbine construction, often with a view towards punishment of local politicians. The empirical results are heterogenous and vary a lot with the political systems and parties (that might be single-issue or broad parties), time periods (when climate change was a more or less dominant topic compared to other issues), and units of observations (at which the presence of a wind turbine might yield different effects). For example, studies from Canada (Stokes, 2016) and Denmark (Larsen et al., 2021) report a punishment of politicians by voters after the construction of wind turbine, while Urpelainen and Zhang (2022) finds that more wind power capacity in U.S. Congressional districts has lead to a 0.03 percentage point increase in vote shares for the Democratic party. Germeshausen et al. (2021) and Otteni and Weisskircher (2021) find contradictory results for Germany in the 2010s.[2] Our study differs from most of these studies in various ways. Apart from our longer time horizon and different econometric method, our identification strategy is the visibility of a wind turbine rather than its mere presence

[2]Germeshausen et al. (2021) look at the federal elections of 2009 and 2013 to find a sizable 17% decrease in vote share of the Green party resulting from a wind turbine in a municipality. On the other hand, Otteni and Weisskircher (2021) analyze German federal and regional elections between 2013 and 2019. They find a small positive rather than negative effect of wind turbine construction on the vote shares of both the Greens and the far-right, anti-renewable AfD party, suggesting an increase in voters' polarization.

within administrative boundaries. In fact, we specifically consider wind turbines located in a different municipality but still visible to residents across the municipal border. As we will show, this helps us to contour endogeneity concerns. Moreover, we do not aim to capture a punishment effect for local politicians, which might be driven by idiosyncracies of candidates. Instead, we use the vote of the Green party (rather than individual candidates) as a proxy for attitudes towards pro-renewable energy more broadly.

As we will explain in more detail in the following, we compute the viewshed of each wind turbine to see if visibility leads to a decrease in our attitude proxy, the vote-share of the Green party. Focusing on the visibility allows us to isolate one crucial channel of sensory perception.[3] Attitudes towards wind turbines are shaped by many issues, including, for example, concern for birds, but those that oppose wind energy for wildlife conservation reasons, would arguably do so irrespective of whether the wind turbine is visible to them or not. Our visibility analysis builds upon the qualitative insights of the literature and is therefore our identification strategy. Such an implementation of a viewshed, in combination relation to an attitude proxy based on voting behavior, is novel to the literature.

!!! UPDATE!!! Our results suggest no sizable local blacklash against pro-renewable at the ballot box most of the time. Constructing a wind turbine that is visible from a nearby settlement is not followed by a decrease in the Green party's local vote share in most earlier election periods from 1998 to 2013. Since then, the pattern has changed and statistically negative effects emerged in 2013, 2017 and 2021, with the magnitude increasing over time. Municipalities first treated before the 2021 election saw a decrease in Green party vote share by 1.0 to 1.3 percentage point compared to the control group. We discuss these recent developments and point to various factors, including a more polarized political debate and the expansion of wind turbines to less supportive areas. These results entail insights for policymakers that implement the energy transition and have to make sure that voters are on board.
Policy recommendations based on our findings would be for politicians to ensure citizen involvement and financial participation. This can either be done by citizen ownership

[3] Visibility and audibility are the main physical sensory perceptions related to wind turbines. Some voters might perceive the presence of wind turbines as annoyance or disruptive to the landscape. In addition, there is a risk of shadow flicker, which can be caused by the shadows cast by rotating rotor blades, although this effect is very small with modern generations of turbines (Freiberg et al., 2019). Others may have concerns about noise generated by wind turbines, which is strongly correlated with visibility, as physical obstructions block both light rays and (in part) sound waves and the exposure decreases with increasing distance. Actual noise exposure also depends on various factors such as aerodynamic processes, and the audible radius is much smaller than the visible one (Bakker et al., 2012). While there is no visibility regulation, a plant can only be built in Germany with a noise protection permit, which is granted if the surrounding area is not affected by sound to a certain degree (4th BImSchV), so arguably, most of the sensory perception of turbines that is relevant in this natural experiment is visual.

of turbines or by an increased provision of the public goods thanks to better municipal finances. Ensuring people beyond the municipal border benefits is crucial, as well as addressing citizens' concerns so that a small minority does not dominate public opinion.

The remainder of this paper is organized as follows: Section 2 lays out the theoretical framework of our approach. Section 3 explains the construction of our data set, in particular our calculation of wind turbine visibility from settlements. Section 4 contains a discussion of the econometric methods employed. In Section 5, we present and interpret our main results, whose implications we discuss in Section 6. Section 7 concludes.

2 Theoretical framework

We motivate our empirical analysis with a theoretical framework to formalize how various channels can shape people's perception of the wind turbine expansion. To do so, we consider a country with multiple regions $r = r(1, ..., R)$ (e.g., counties), each consisting of municipalities $m = m(1, ..., M)$, our units of observation. The country has a level of wind turbines $w = \sum_{r=1}^{R} w_r$. A certain share of these regional turbines are visible to the residential areas of a municipality $\phi_{mr} \cdot w_r$, with $\phi_{mr} \in \{0, 1\}$ representing the fraction of turbines in r that is visible from m.

To capture the various impacts of a wind turbine expansion on the perception of an individual, we define utility maximizing individuals $i = i(1, ..., I)$ that live in a municipality m in region r. They spend their income y_{imr} entirely on a composite consumption good x_i. Among other things, this income is a function both of the total level of local wind turbines w_r and as the visible share $\phi_{mr} \cdot w_r$, as we argue below. Individuals derive utility not only from the consumption good x_i, but also from the perceived environmental good or ecosystem services e_{imr} (i.e., the natural surrounding of i's home) and the expected or anticipated environmental good of the future f_{imr}:

$$\begin{aligned} \max_{x_i} U_{imr} &= U\Big(x_i, e_{imr}(w_r, \phi_{mr}), f_{imr}\Big(\sum_{r=1}^{R} w_r\Big)\Big) \\ \text{s.t. } & y_{imr}(w_r, \phi_{mr}) = x_i \end{aligned} \tag{1}$$

An individual's utility function is assumed to be twice differentiable, continuous, and concave. We aggregate the inputs of the utility maximization problem to these components, as they are sufficient to illustrate the different influences of wind turbines.

Our analysis is based on four assumptions that we motivate from the literature:

$$\frac{\partial y_{imr}}{\partial w_r} \geq 0 \quad \text{(Assumption 1)} \qquad \frac{\partial y_{imr}}{\partial(\phi_{mr} \cdot w_r)} \leq 0 \quad \text{(Assumption 2)}$$

$$\frac{\partial e_{imr}}{\partial(\phi_{mr} \cdot w_r)} \leq 0 \quad \text{(Assumption 3)} \qquad \frac{\partial f_{imr}}{\partial w} \geq 0 \quad \text{(Assumption 4)}$$

First, the positive relation between regional wind turbines and the income of residents (Assumption 1) is based on numerous studies reporting beneficial local labor market effects after wind turbine construction. In particular, decreasing local unemployment (Fabra et al., 2023), an increase in the number of local jobs (Brown et al., 2012) and rising wages (Mauritzen, 2020) have been found. In addition to labor markets, Brunner and Schwegman (2022) show a positive influence of a wind turbine expansion on local GDP and median household income, and Brunner et al. (2022) estimate an uplift in local government tax revenues, leading to a reduction in the property tax burden for the local population.[4]

Assumption 2 is supported by the evidence that *visible* wind turbines can have a negative impact on the economy. For example, Broekel and Alfken (2015) report a decrease in tourism demand due to local wind turbines and argue that the visible impact on the landscape is a driving factor. Hence, while local wind turbines can have a positive impact on income (Assumption 1), their visible component can have negative income effects (Assumption 2).

Assumption 3 refers to the impact of visible wind turbines on the non-market environmental ecosystem good e_{imr}. It has been shown that wind turbines can be perceived by local residents as an impairment of the landscape panorama (Lehmann et al., 2023, Wolsink, 2000). We capture this by a decreasing impact on the utility of individuals in the exposed municipality.

Finally, it is the scientific consensus that the global wind energy expansion has the potential to mitigate climate change (Barthelmie and Pryor, 2014), thereby leading to an improvement of the future environmental good f_{imr}.[5] Assumption 4 states that individuals are aware of that. So, the continuum of all installed turbines ($w = \sum_{r=1}^{R} w_r$), not only the regional ones, can have a beneficial effect on the expected environmental good.

Given these assumptions, the utility maximization problem of the household living in m which is part of r can be represented as eq. (1). In this stylized framework,

[4] This channel is particularly important in Germany, as 70 percent of the trade tax generated by a turbine goes to the municipality in which it is located (further discussion in Section 4.4).

[5] We keep the model static as it aims to represent how different factors influence the decision process. We therefore assume that f_{imr} is the environmental good in a time period that is outside the time window we observe.

individuals only choose their optimal consumption given an exogenous level of turbines and visibility. We address potential self-selection issues in Section Section 4.4 by exploiting the exogenous variation of turbine visibility. In addition, we assume that households are not moving, which we discuss in Section 4.5.

Taking the total differential of eq. (1) with respect to w yields:

$$\frac{dU_{imr}}{dw} = \frac{\partial U_{imr}}{\partial x_i}\left(\frac{dy_{imr}}{dw_r} + \frac{dy_{imr}}{d(\phi_{mr} \cdot w_r)}\right) + \frac{\partial U_{imr}}{\partial e_{imr}} \frac{de_{imr}}{d(\phi_{mr} \cdot w_r)} + \frac{\partial U_{imr}}{\partial f_{imr}} \frac{df_{imr}}{d(w)} > 0 \quad (2)$$

eq. (2) simply states that individuals gain utility if the benefits of the turbine expansion is higher than its costs. The idea is to show the multidimensional implications of wind turbine expansion on individual utility, with negative factors associated with visibility. Combining market goods with non- market goods that are difficult to quantify[6] can be problematic in finding solutions of the household problem, but it is reasonable to show the cost-benefit trade-off for each household internally valuing those factors.

Obviously, individuals' preferences and opportunities regarding wind energy vary, not only in terms of economic possibilities but also how they perceive the current and future environmental good and the influence of wind turbines on it. Given the data and the focus of this paper, we are not attempting to differentiate between the various factors that can shape the perception but to isolate the impact of visual exposure. For some individuals, economic benefits of regional turbines can outweigh a negative impact of visual exposure on the current environmental good. Others might not benefit economically at all but value the positive impact on the future environmental good higher than potential costs for the environmental good of today.

We therefore define three different agents:

1. For "Always Supporter" (s), the benefits from the turbine expansion are always higher than the costs, independent of potential visual exposure.

2. For "Always Opposer" (o), the costs from the turbine expansion are always higher than the benefits, independent of potential visual exposure.

3. For the "Switcher" (c), visual exposure determines whether the benefits or the costs are higher. As long as ϕ_{mr} is zero, benefits for c are higher, while the visual exposure increases $c's$ costs so they outweigh the benefits.

Hence, it is the "switchers" who react to the installation of visible wind turbines with a change in their attitude towards wind energy, and we want to estimate how large their voting share is and how it has evolved over time. We assume that support for wind

[6]The monetary value of the environmental good can be estimated using indirect methods such as hedonic house price functions or travel cost analysis.

energy can be gauged by a political vote (in our case, for the German Green party, see the discussion in Section 3.3). It is then captured by μ_m in eq. (3), i.e., the sum of supporter share in m:

$$\mu_m = \frac{1}{n_m} \sum_{i=1}^{n_m} \mathbf{1}\{\frac{dU_{imr}}{dw} > 0\} \tag{3}$$

The main objective of this paper is to recover the impact of $\phi_{mr} \cdot w_r$ on μ_m by comparing changes in vote shares of first visually exposed municipalities with those located within the same region and having similar characteristics but are not visually exposed.

3 Data Set Construction and Descriptives

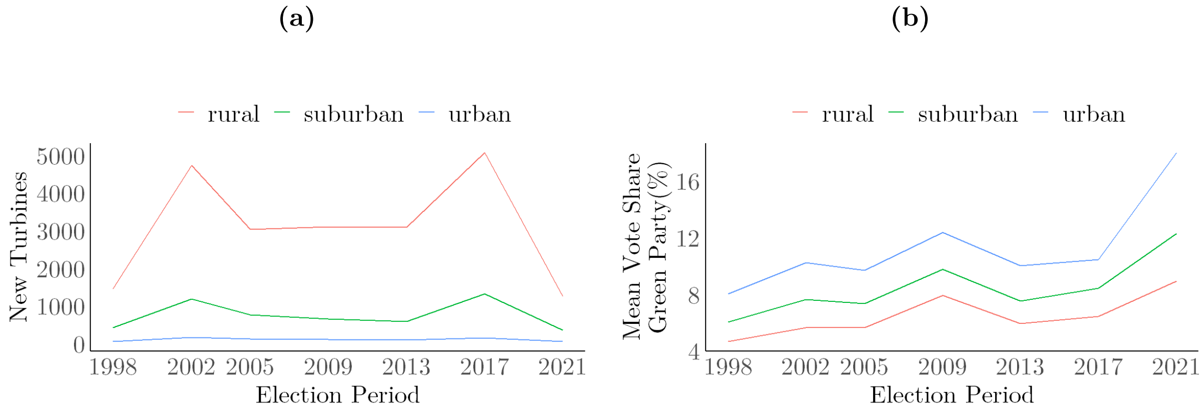
Let us now set the scene for the application of our theoretical framework and briefly review the situation of the German wind power extension. We describe the data at our disposal for the construction of the turbine viewshed, as well supplementary data on energy cooperatives and citizen initiatives. Furthermore, we discuss the Green Party vote share data and its link to public support for the renewable energy transition.

3.1 The German Wind Turbine Expansion

As of 2021, there were about 28,156 wind turbines in Germany. Whereas the expansion of wind energy in Germany already began in the late 1980s, it accelerated rapidly during the time the Green Party was part of the government from 1998 to 2005 (Figure 1). In 2000, the Renewable Energy Sources Act (EEG) was passed, introducing feed-in tariffs (i.e., a fixed price per unit of energy generated) and a feed-in priority for wind energy. Although between 2008 and 2011 the expansion was low, a second surge began in 2012, commonly explained by reforms to the EEG and a refocus on renewable energy generation following the Fukushima accident in 2011 and the subsequent phase-out of nuclear power (Fuchs, 2021).

While many municipalities in the north had their first turbine in the earlier expansion periods, many in the south had their first turbine in more recent election periods or had no turbine until 2021. In addition to worse topographical characteristics (Blankenhorn and Resch, 2014), protests by local residents, particularly in Southern parts of the country are often used as an explanation of these differences. Furthermore, expansion has occurred almost exclusively in rural areas due to inexpensive and available land, but support for the Green Party is significantly lower there than in more urbanized areas (Figure 1). This underlines the political relevance and brings up the question if the political divide might increase further if more even wind turbines are being constructed.

Figure 1 – Number of turbines installed (a) and the vote share for the Green Party (b) per election period in areas with different types of urbanization



3.2 Wind Turbine Visibility

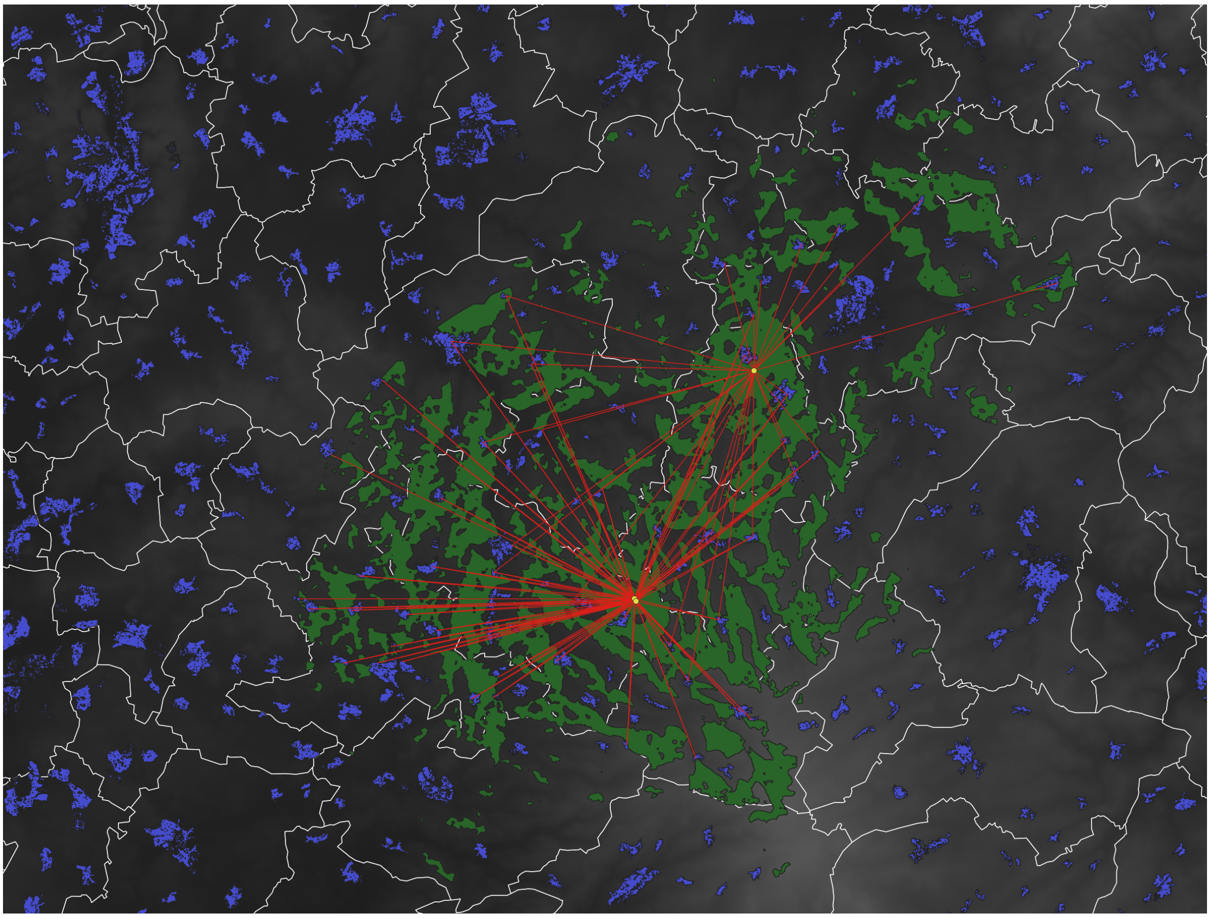
For our spatial analysis, we use fine-grained data on the position of wind turbines in Germany based on the federal network agencies data base adjusted by Eichhorn et al. (2019). We combine the geo-coded turbine data including their hub heights and construction dates with the digital surface model EU-DEM, a representation of the elevation including the height of ground features such as trees and non-natural structures in Europe (First-Surface Model). To assess how many potential voters can see how many turbines from a given distance in a given election period, we calculate the viewshed of all installed turbines, i.e., the area around the turbine from which a person with an eye height of 1.6 m can see the hub, accounting for earth curvature and atmospheric refraction. Figure 2 visualizes the intervisibility network (i.e., the distance between each settlement and the visible turbines) for turbines constructed within the 2013 election period (2010-2013) in the state of Hesse.

Each cell of the resulting viewshed grid represents the sum of visible turbines within a certain distance. Second, we superimpose the EU's Global Human Settlement Layer (GHSL), which represents the global settlement area based on satellite imagery, and the viewshed grid to calculate which settlement area is visually exposed to what extent in each election period. We merge this with the municipal boundary map as of 2020.

3.3 Green Party Vote as Proxy for Pro-Renewable Attitudes

In our analysis we use the Green party vote share as a proxy for pro-renewable support of residents, given the party's strong pro-climate profile (Wagner and Meyer, 2014). Our goal is not to investigate a possible punishment of local politicians, who voters might personally hold responsible for wind turbines, but to gauge pro-renewable support more

Figure 2 – Intervisibility network of turbines constructed in 2013 (yellow points) and residential areas (blue polygons) in the state of Hesse. The green area represents the viewshed of the turbines and the red lines the distances between the settlements and all visible turbines. The lighter the background, the higher the elevation



broadly.[7] The official data on federal election results from 1998 to 2021 come from the Federal Returning Officer. Socioeconomic covariate data (Section XXX) is provided by the Federal Statistical Office, the Federal Employment Agency and the INKAR data set from the Federal Office for Building and Regional Planning (BBSR, 2020). Our unit of analysis is the municipal level (NUTS-4). Since 1998, there have been several municipal area reforms in Germany. Many municipalities, especially in eastern Germany, were merged or parts of one municipality were assigned to another. In 1998, Germany had over 14,000 municipalities, whereas by 2023, the figure had reduced to 10,773. To make the municipalities comparable, we adjusted the data to the 2020 territorial status based on the transfer key of the Federal Office for Building and Regional Planning and exclude the municipalities with missing data. Furthermore, we restrict the data to municipalities with at least 50 valid votes in a federal election, as this is the minimum number for

[7]Note that the approval process of wind turbines is complex and involves many different political entities at the federal level, state level as well as county and municipal level. The details also vary across German states. We therefore abstract from the 'punishment' and 'accountability' arguments by focusing on the party vote in federal elections.

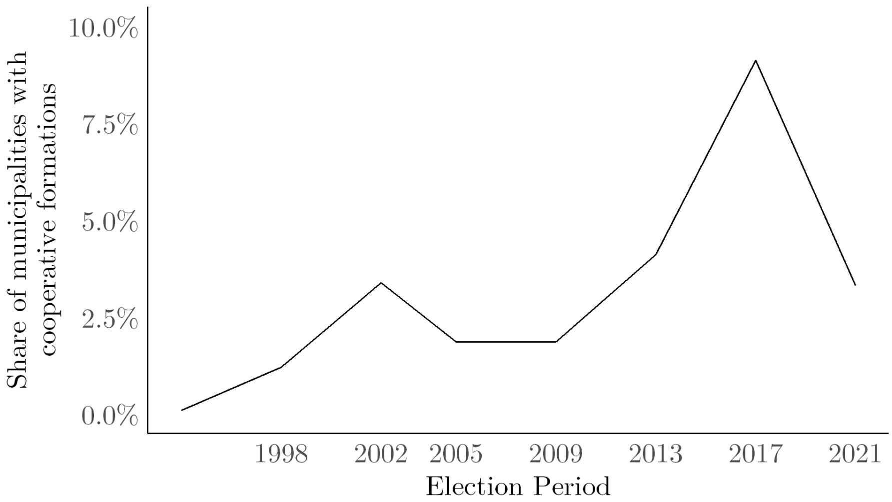
publication by the Federal Returning Officer since the election of 2021.[8] We do also not include the so-called city states of Bremen, Hamburg, and Berlin, as they have a special administrative structure and consist of only one municipality, which is difficult to compare with others. In addition, we must exclude the state Saarland for the 2021 election period as the Green Party was excluded from the election due to a violation of electoral law. The final panel consists of 10,268 municipalities in 2021 and 10,441 in the election periods.

3.4 Wind Turbine Ownership

Our theoretical framework in Section 2 suggests that financial benefits play a role in whether people always support, always oppose or switch their attitude towards wind energy. In the extension in Section B.3 we consider the case of financially participating from local wind turbines via energy cooperatives. We take this concept to the data in a supplementary analysis. Energy cooperatives are a collective approach to renewable energy production allowing locals to participate financially in the revenues from the sale of electricity. The first energy cooperatives were founded in Denmark in the 1970s, while in Germany many cooperatives were formed in the early 2000s, followed by the liberalization of the energy market under the EEG Act in 2000 (Mautz et al., 2008). Although these projects vary widely in terms of ownership structures and participation opportunities, the cooperative members are usually individuals living near the turbines and benefiting financially (Holstenkamp, 2013). Thus, some individuals earn additional income from the share of regional turbines installed by energy cooperatives, but participation opportunities may vary between individuals within that region. Data on cooperative installations are provided by !Holstenkamp et. al. who categorize the installations into types of participation options. Across election periods, the share of municipalities in which energy cooperatives have formed within a six-kilometer radius of their residential area is below five percent, with the exception of the 2017 election period, in which the share jumps to almost ten percent (Figure 3). In 2017, a shift to a tendering system in the installation process was introduced, which arguably made it more difficult to found an energy cooperatives (Fell, 2019), possibly explaining a sharp increase before the law came into force and a decrease afterwards. As noted by the authors, the information on energy cooperatives is incomplete, so we only include it in a supplementary analysis. In order to better isolate the effects of visual exposure, we estimate the effects on a subset of the main data with municipalities for which we could not identify an energy cooperative near their settlements.

[8] The votes in the 2021 election for municipalities with less than 50 votes were added to a larger municipalities count. Hence, we need to exclude the receiving municipalities for this election period.

Figure 3 – Share of municipalities in which an energy cooperative was established within a 6 km radius of their residential areas, per election period



3.5 Citizens' Initiatives

Several studies have shown that while wind farms are generally supported by a majority, political engagement by local citizens' initiatives can in turn have a negative impact on support for expansion. Anti-wind energy initiatives propagate new (subjective) information to the local population that can influence their perception of the expansion and its impact on the environment (Hobman et al., 2012, Horbaty et al., 2012, Gardt et al., 2021). In Section B.2, we incorporate this perception updating mechanism on the negative impact of visual exposure into the theoretical framework. In addition to an amplification of negative perceptions, citizens' initiatives can have an influence on the siting decisions of turbines. Azau (2011) estimates that 30 percent of unfinished wind farm projects in Europe are stopped due to litigation and public opposition. Thus, an endogeneity problem may arise due to strong local opposition politically, as this can be described as selection into non-treatment, which we need to account for. Similar to Gardt et al. (2021), we use data from Germany's largest anti-wind protest platform to identify the location of each citizen initiative and in which municipality a group was active.[9] Overall, anti-wind initiatives have formed over time in 25 percent of all municipalities in Germany without wind turbines, while it is 30 percent across municipalities with wind turbines. In addition to the issue of selection into non-treatment, there is also a potential bias from selection into treatment, which is discussed and accounted for in Section 4.4.

[9]The data is taken from the platform "windwahn.de" and includes the link to the website of the initiative as well as the geo-coordinates, but the information cannot be validated externally. This is why we only use if for the supplementary analysis.

4 Econometric Methods

Our empirical model is based on Difference-in-Difference (DiD), as it internally controls for nationwide trends in the support for the Green party as well as time invariant differences between groups. As wind turbines are constructed gradually over time, municipalities are visually exposed at different points in time. From now on, we are referring to all municipalities first visually exposed in the same election period as a timing group or cohort g.[10] Since the data covers seven election periods, during each of which turbines were built, we have seven timing groups, for six of which we can estimate the immediate effect on the results of the subsequent election[11] ($t = g$), resembling a group-time average treatment effect proposed by Callaway and Sant'Anna (2021). The main argument is that analysing each timing group individually can reveal how voting responses might vary for different election periods. Furthermore, Goodman-Bacon (2021), Callaway and Sant'Anna (2021) and Abraham and Sun (2018) show that any Two-Way Fixed Effects model with multiple treatment timings yields biased results if the effects vary over time or are heterogeneous between municipalities treated at different points in time (i.e., between timing groups), these comparisons will bias the results. Given the long observation period (23 years), it is highly plausible that impacts change over time or between timing groups, since, for example, the first visible wind turbine in a municipality built in the early 2000s might be perceived differently than it was in late the 2010s due to changing policy debates about renewable energy and climate change mitigation. In addition, turbines have evolved over the years, e.g., they have become larger (McKenna et al. (2016)), but also quieter (Hansen and Hansen (2020)). By comparing only the change in support (S) between one pre-visible election period and one post-visible election period for each timing group separately, we avoid these potential problems of Two-Way Fixed Effects models, since each estimate is a simple 2x2 DiD setup with equal treatment time windows (one election period prior the installation versus one election period after) and a comparison only between treated and untreated units.

The main results are estimated with three different methods. With the first (UC), we purely relay on the matching procedure (Section 4.2) to construct control groups that unconditionally on covariates resemble comparisons for each timing group. Assuming parallel trends, no anticipation and that the Green Party election outcomes is a valid proxy for the support of the wind energy expansion ($\mu_m = S_m$), eq. (4) targets the average effect of visual exposure for each group of municipalities seeing a turbine for the first time ($g = 2002, ..., 2021$).[12]:

[10] For example, municipality m is first visually exposed in 2007, which falls in the 2009 election period (the year the next federal election is held), so m belongs to the timing group $g = 2009$.

[11] For the first timing group ($g = 1998$), we cannot estimate the effect as we do not have a pre-treatment period in the panel.

[12] The 2005 election period is only three years long as the election was brought forward, hence the pre treatment election for $g = 2005$ is in $g - 3$.

$$ATT_{UC}(g) = \mathbb{E}[S_g - S_{g-4}|G_g = 1, D_g = 1] - \mathbb{E}[S_g - S_{g-4}|G_g = 0, D_g = 0] \tag{4}$$

G_g indicates if the municipality belongs to timing group g and D_g is an dummy indicator if a municipality is already treated at $t = g$. UC has the advantage of a non-parametric estimation, i.e. we do not have to make functional form assumptions. With the second and third method, we condition on socioeconomic covariates $X_{m_g t}$ to control for the municipal population density, the share of the population with an age under 35, the share of female population, the municipal unemployment rate and the share of workers with a university degree at the county level.[13] The second estimation (OLS) is done with linear regression (eq. (5)) with municipal fixed effects (η_{m_g}), time fixed effects (α_t) and a treatment dummy ($V_{m_g,t}$) at $t \in \{g-4, g\}$.

$$ATT_{OLS}(g) = \beta \quad \text{from} \qquad S_{m_g,t} = \eta_{m_g} + \alpha_t + \beta V_{m_g,t} + X'_{m_g,t}\gamma + \epsilon_{m_g,t} \tag{5}$$

Including covariates in a linear way is most common in applied work but comes at the cost of making strong assumptions about their relationships. With the third method, we estimate the effect semi-parametrically with the Doubly Robust estimator (DR) proposed by Sant'Anna and Zhao (2020), based on kernel outcome regression (Heckman et al., 1997) and inverse probability weighting (Abadie, 2005). It has been a widely used method in staggered DiD estimations (e.g., Alexander and Karger (2023), Brynjolfsson et al. (2023)), as it is generally more robust against model misspecifications but only allows to control for pre treatment covariate levels. Given the propensity score $p_g(X_{g-4})$, i.e., the probability of being first treated at $t = g$, conditional on covariates at $t = g - 4$, and the population outcome regression for the control group of cohort g denoted as $a_g = \mathbb{E}[S_g - S_{g-4}|X_{g-4}, D_g = 0, G_g = 0]$, the DR estimator is represented in eq. (6):

$$ATT_{DR}(g) = \mathbb{E}\left[\left(\frac{G_g}{\mathbb{E}[G_g]} - \frac{\frac{p_g(X_{g-4})(1-D_g)(1-G_g)}{1-p_g(X_{g-4})}}{\mathbb{E}\left[\frac{p_g(X_{g-4})(1-D_g)(1-G_g)}{1-p_g(X_{g-4})}\right]}\right)(S_g - S_{g-4} - a_g))\right] \tag{6}$$

With all methods, we treat visibility as binary, i.e., turbines are visible from residential areas or not. Brunner et al. (2022) has used installed capacity per student within a school district as a continuous treatment variable to estimate the impact on district revenues through taxes generated by the turbines. Whereas it is plausible that this relationship is linear, as taxes increase with each kw/h installed, it is less clear for visual exposure.

[13]These socio-economic variables have been shown in the political economics literature to be strongly associated with voting behavior (Chrysanthou and Guilló, 2010, Kosse and Piketty, 2021) Given our use of the Green party vote share as a proxy for renewable energy attitudes, we control for these factors.

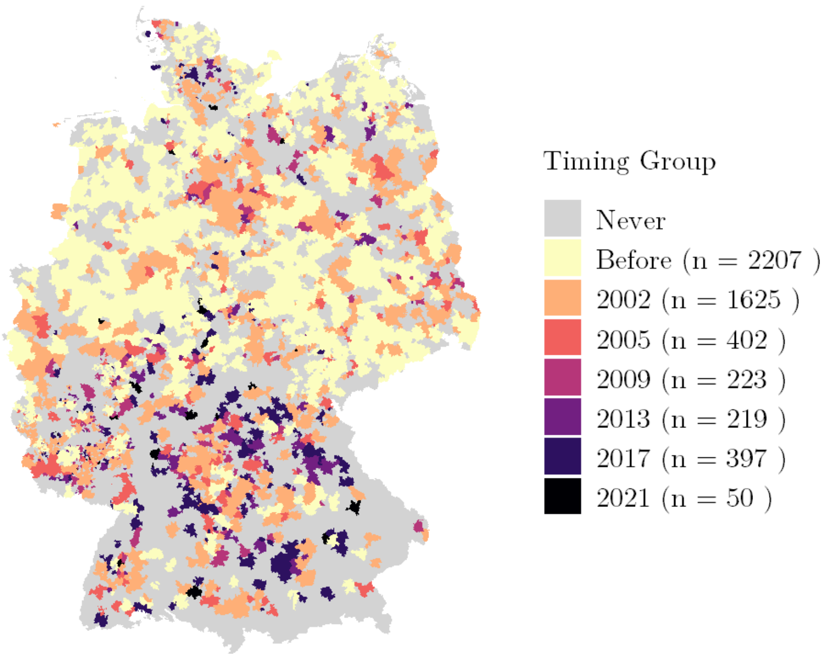
First, multiple turbines of different sizes are often only partially visible to a portion of each residential area from various distances. For specific positions in space, one could calculate the visual angle (i.e., the size of the turbine image on the retina) and use the share of the visual panorama covered by the turbines as a treatment variable but for that one must assume that the effects are linear in all these dimensions (e.g. the impact of a few nearby wind turbines is comparable to the effect of more turbines further away but covering the same part of the observer's panorama). It seems reasonable to assume that the effects of visual exposure diminish the higher the exposure is, or at least that they are not linear. Moreover, using a measure such as coverage ratio is not practical for our analysis because we observe the vote share of an entire municipality, so the viewing angle is different at each point within the area. Finally, Callaway et al. (2024) show that when estimating a slope effect of a continuous treatment variable with difference-in-difference, one must make the strong assumption that compared units with different treatment intensities would have responded the same way if they had experienced the same intensity, i.e., assuming parallel trends of potential untreated outcomes is not sufficient.

4.1 Treatment Groups

With an unobstructed ray of light, there is theoretically no limit to the visibility of an object, but the visual angle decreases with increasing distance (e.g. Rock and McDermott (1964)). Buchan (2002) finds that details of wind turbines are diminished at a distance of eight kilometers, while Breuner (2001) suggests a smaller distance at which a wind turbine is perceived as disruptive. Thus, a threshold for visual intrusion is not clearly defined and may depend on the subjective perception of the observer. In light of this, we narrow the treatment group of each election period (timing group) to municipalities whose residential area is visually exposed up to six kilometers in the post-treatment period ($t = g$) and not visually exposed up to eight kilometers in the pre-treatment period ($t = g-4$), imposing a buffer zone of two kilometers to address the ambiguity about the extent to which turbine visibility might have an effect. In , we alter the treatment distance for robustness.

As most of the installed turbines are only partially visible from residential areas, we limit the treatment group to municipalities where at least one turbine is visible for the first time from the residential areas. All timing groups are comparable in terms of visual exposure, with a similar mean distance of settlements to the nearest visible facility (Figure A-3) and a similar proportion of settlements visually exposed (Figure A-4), but there are also some differences between timing groups. First, the proportion of municipalities first visually exposed in the 1990s is larger in the east and west/north than in the south, while the proportion of southern municipalities is higher from the 2000s onward (Figure A-1). Finally, the number of municipalities in each time group decreases over time, indicating that most turbines installed in later election periods are visible from settlement areas already visually exposed to turbines installed earlier (Figure A-2).

Figure 4 – Spatial distribution of Timing Groups



4.2 Control Groups

Similar municipalities that are geographically close to the treated municipalities but have no turbines in sight are used as a control group, up to a buffer distance of eight kilometers, again to prevent treatment spillovers from turbines further away than the treatment threshold of six kilometers. The key identifying assumption is parallel trends, i.e., the change in vote share of the control group equals the counterfactual change in vote share of the treated group. Thus, it is essential for a comparison with untreated units to find municipalities that are similar to those of the treated group with the exception of turbine visibility. In the theoretical framework, this is true when two assumptions hold. First, the distribution of regions for each timing group g and its control group must be the same (i.e., $r^0, r^1 \perp G_g$). This ensures that the level of regional turbines (w_r) is similar across both groups and they only differ in visibility. Second, the composition of people living there should be comparable, so that individuals react similar to wind turbines. We attempt to minimize differences other than visual exposure with an iterative optimal matching procedure by pairing each visually exposed municipality to a control municipality that is geographically close to the treated one within the smallest administrative level possible as those might share cultural, political and socioeconomic similarities (Tobler, 1970).

For each municipality in timing group g, we find a municipality in the same county that is not or not yet visually affected by wind turbines by matching municipality pairs such that the overall Euclidean distance between the centroids of treatment and control group is minimized. We restrict the matching to pairs with the same urbanization status according to the DEGURBA classification since people in urban and rural areas could have systematically different preferences regradless of geographic proximity. To reduce the likelihood that previously planned wind power projects in these municipalities failed due to local opposition, we restrict the control group to municipalities where we cannot detect a citizen initiative in any election period, as these municipalities cannot be considered untreated. For those municipalities in each timing group where we could not find a control municipality in the same county (NUTS-3) and with the same urbanization status as the treatment municipality, we repeat this linear programming step for the closest municipality in the same federal state (NUTS-1). If, again, there is no control municipality in the same state, we continue to search in the same part of Germany (east or west). The goal of this iterative matching process is to find matches that are geographically close, but also have as many administrative similarities as possible.[14]

So given $v_g = 1, ..., V_g$ treated municipalities of timing group g and their possible control municipalities $c_g = 1, ..., C_g$, we solve the assignment problem eq. (7) with distance d_{v_g,c_g} of treated municipality v_g to control municipality c_g. x_{v_g,c_g} equals one if $v is assigned to c and zero if not$.

$$\begin{aligned}
&\min_{d_{v_g c_g}} Z = \sum_{v_g=1}^{V_g} \sum_{c_g=1}^{C_g} d_{v_g c_g} x_{v_g c_g} \\
&\qquad\qquad \text{s.t.} \\
&\qquad\qquad \sum_{v_g=1}^{V_g} x_{v_g c_g} \leq 1, \quad c_g = 1, 2, \ldots, C_g, \\
&\qquad\qquad \sum_{c_g=1}^{C_g} x_{v_g c_g} = 1, \quad v_g = 1, 2, \ldots, V_g, \\
&\qquad\qquad \text{and } x_{v_g c_g} \in \{0, 1\}, \quad \text{for all } v_g \text{ and } c_g
\end{aligned} \tag{7}$$

We conduct this matching procedure without replacement, hence, each treated municipality in each timing group g is matched to a unique control municipality. The treatment group of each timing group therefore has the same number of observation as its control group. In Section C.5, we conduct a robustness check in which we match with replacement and increase the number of matches for each treated municipality.

[14]This is especially crucial at the county level, since these are mostly identical to German electoral constituencies, in each of which the same candidate for the Bundestag is running and can be elected with the first vote. We analyze the second vote (which is for the party rather than the politician), but the voting decision might still be partially influenced by the local candidate.

4.3 Baseline Model: Seen versus Unseen

In the Baseline Model, each timing group consists of all municipalities visually exposed for the first time, independent of the location of the visible turbines. The binary treatment variable takes the value of one if turbines are seen from the residential areas of municipality m for the first time in election period $t = g$. This model serves primarily as a benchmark for comparison against other specifications, since it does not address potential concerns related to endogeneity, unobserved heterogeneity, or anticipatory behaviors.

4.4 External Exposure Model: Inter-Municipal Visibility

The baseline specification is straightforward, yet one might be concerned about selection bias and unobserved heterogeneity for a number of reasons. First, turbine construction may be more likely in municipalities where Green Party support is high, increasing the likelihood of visual exposure (i.e., ϕ_{mr} would be endogenous). While the spatial planning process for wind turbines is primarily decided at the state or regional planning level, in some cases the municipal administration and its residents have the opportunity to influence the siting decision in their land use plans (Meier et al., 2023). [15]

In addition, there could be systematic heterogeneity in the effect due to differences in agreements with turbine operators, the municipal administration, and local residents. Municipal governments and community groups can involve residents in public hearings, consultations, and other participatory processes to solicit their opinions and ensure that the project meets their needs and preferences (Zoellner et al., 2008). Jobert et al. (2007), Lienhoop (2018) and Schwarz (2020) suggest that participation plays a key role in how the local population perceives these projects.

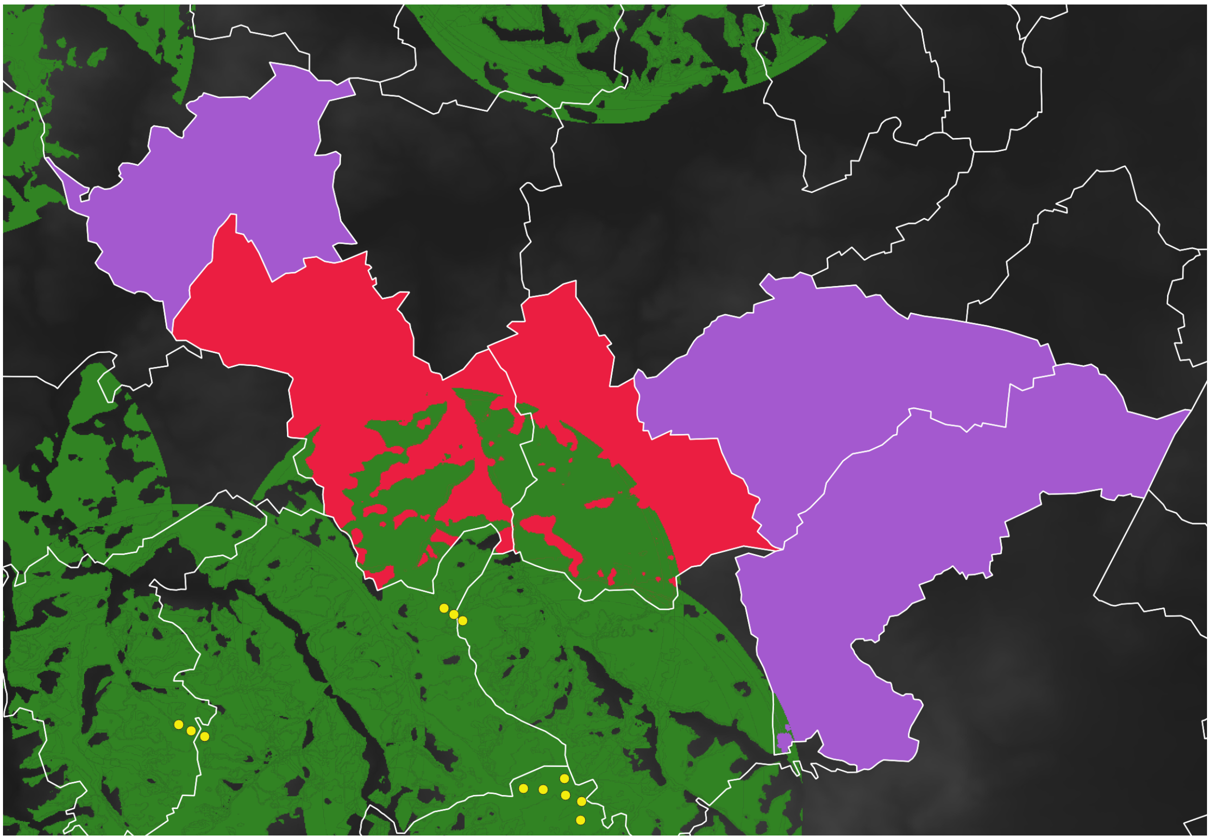
Beyond participating in siting decisions, the municipal administration and its citizens can also participate financially. [16] Tax reductions due to higher municipal tax revenues, lower energy costs and financial participation can increase the disposable income of the residents of the municipality in which the facility is located. Also, higher tax revenues can contribute to improved provision of public goods. These municipality-specific effects of turbines may vary between the treatment group and the control group

[15]Under the Regional Planning Act, the regional plans of the German states designate priority areas for the construction of wind turbines. Although municipalities are fundamentally bound by the regional plans, they still have some influence over siting decisions by designating areas for the construction of wind turbines in their land-use plans in accordance with the regional plan, to which they in turn contribute.

[16]First, 70 percent of the trade tax revenue generated remains in the municipality where the wind turbine is located, which enhances the municipal budget. Municipalities can also become involved as energy providers by establishing municipal energy companies (Mez and Schneider, 2007), thereby lowering local energy costs. In some cases, citizens can also participate financially by renting land to turbine operators, paying reduced electricity tariffs, or joining community energy cooperatives to participate in energy production (Radtke et al., 2022). While financial participation is usually associated with an increase in acceptance, some opposers may perceive such payments as a form of bribery (Cass et al., 2010, Knauf, 2022).

and are independent of visual exposure, thus potentially biasing the results of the baseline model upwards. In Online Appendix B, we extend the theoretical framework to include municipal-specific dynamics to express this problem more formally.

Figure 5 – Municipalities of the 2021 timing group (red) and the control group (purple) of the External Exposure Model with nearby turbines (yellow points) and their viewshed (green) in the state of Hesse.



In summary, the placement of wind turbines in municipalities might not be random and go in line with varying agreements and/or benefits at the municipal level that shape residents' attitudes. To address these issues, we utilize the variation in visibility of wind turbines. Most turbines are observable not just in the municipalities where they are situated, but also from neighboring areas. As the first paper in the literature, we therefore consider people's reaction to visible turbines in adjacent municipalities rather than in their own. This more restrictive External Exposure Model, limits both the treatment and control groups to municipalities with no turbines within their boundaries in the pre- and post-treatment election periods. Similar to the baseline model, residents in both groups are not visually exposed in the pre-treatment period, but those in the treatment group are exposed in the post-treatment period (Figure 5). Given that inhabitants of adjacent municipalities lack decision-making authority in the administrative processes of the hosting municipality, the External Exposure Model enables an estimation of the exogenous variation of visibility on attitudes. Moreover, since a considerable part of the unobserved heterogeneity can be attributed to agreements within the municipality the turbines are located in, it is expected that neighboring municipalities would be less involved unrelated to visibility. Although residents of adjacent municipalities may still have some opportunities to participate in the form of agreements with the operator, energy cooperatives (see Section 3.4) or the administration of the hosting municipality, their influence is plausibly smaller. Consequently, the External Exposure Model is better suited to isolated the exogenous impact of visual exposure.

4.5 Balance and Validity Tests

In this section, we evaluate the performance of the matching process and conduct a series of tests to assess the assumptions underpinning the theoretical framework and empirical approach of both models. After matching, 73 percent and 79 percent of the treated municipalities across the timing groups are located in the same county (NUTS-3) as their matched control municipality for the Baseline and External Exposure Models, respectively. Looking at the rest, 22 percent and 19 percent are in the same federal state (NUTS-1), and 5 percent and 1 percent are only in the same East/West region of Germany. For the Baseline Model, the median distance between matched pairs' centroids is 12 km, with the 90th percentile at a distance of 43 km. For the External Exposure Model, this median distance is 10.5 km and has the 90th percentile at 32 km. Figure 6 shows that the distance distributions and the administrative unit overlap between the treatment and control groups are similar across the timing groups. In addition, the standardized mean differences (SMD) of the covariates between the treatment and control groups across the timing groups ranges from -0.05 to 0.06, supporting the comparability of the treatment and control groups.

Figure A-5 plots the vote share for each timing group and its corresponding control group over time. While common pre-treatment outcomes are not necessary nor sufficient to provide evidence for post parallel trends, they increase the assumption's plausibility. Moreover, we conduct two placebo tests: First, by shifting the treatment timing for each timing group to all possible pre-treatment election periods (Section C.2), and second, by constructing placebo treatment groups (Section C.3). This is done by pairing each control group with municipalities located within the same counties such that the overall Euclidean geographic distance is minimized, analogous to the main matching procedure. When treatment is incorrectly assigned, whether temporally or spatially, the estimates are insignificant across all specifications. While we can already see a negative trend one period prior visual exposure for the 2021 cohort, this could be related to anticipation, which we discuss and account for in Section C.7.

In the theoretical framework (Section 2) we assume that changes in support is not driven by migration, i.e., people with higher costs than benefits move away from the visual

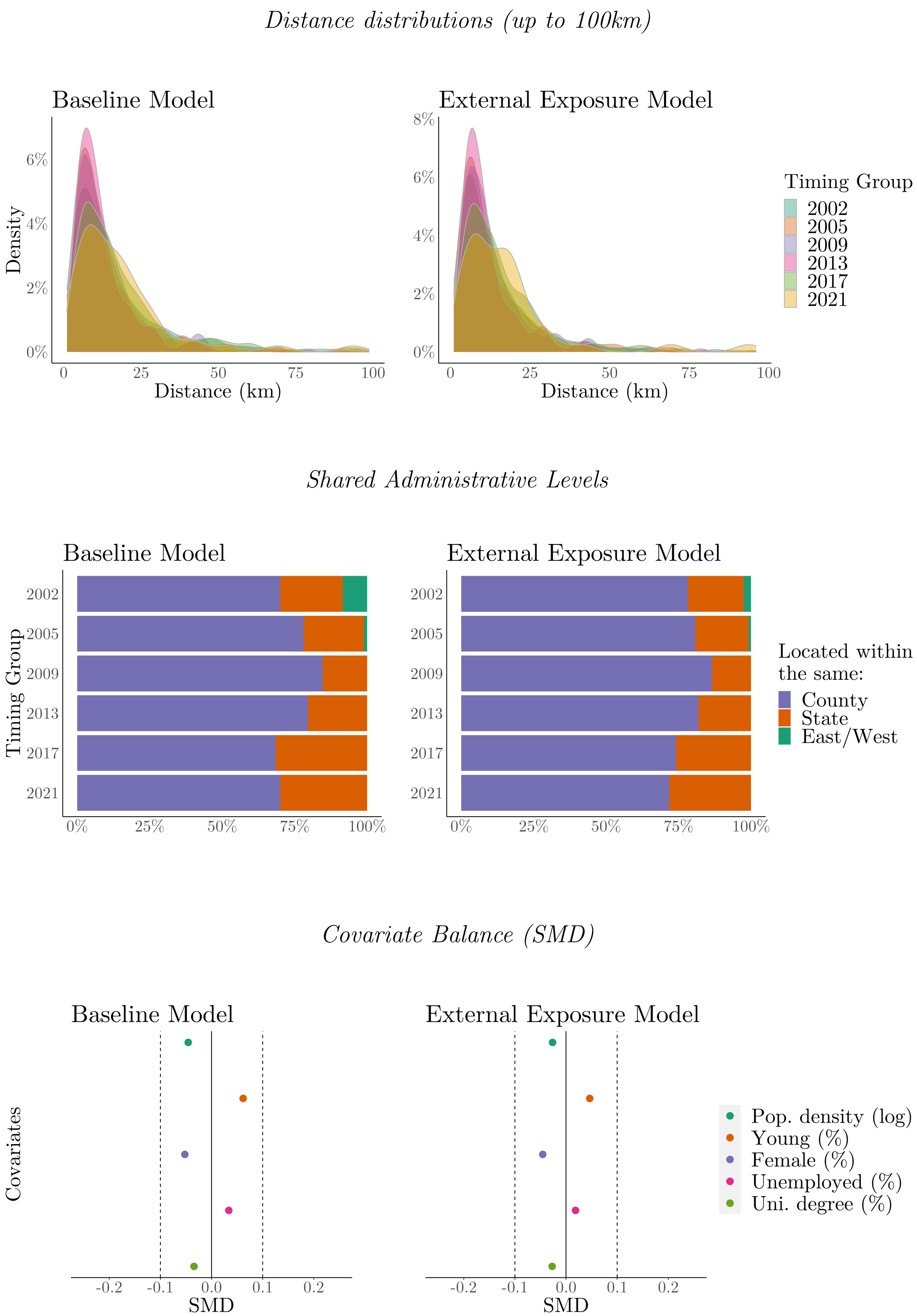
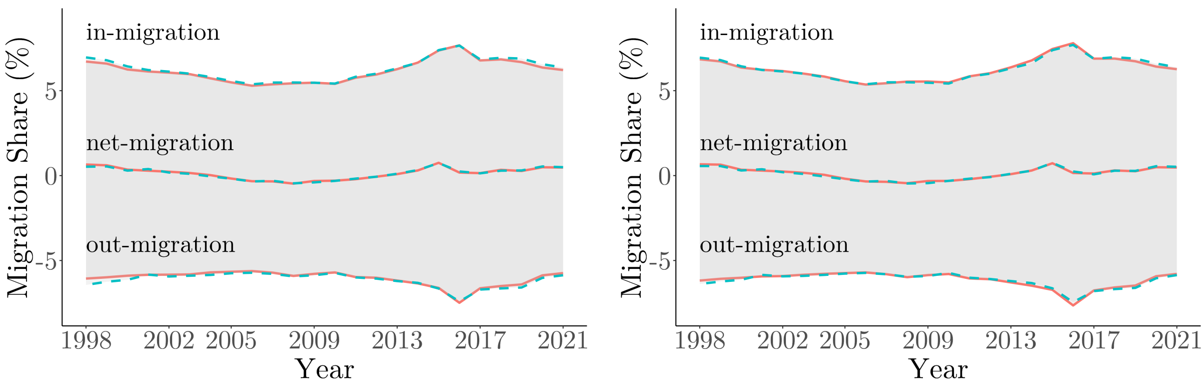


Figure 6 – Comparisons of treatment and control groups with the Euclidean distance distribution between pairs, the share of administrative similarities, and covariate standardized mean differences.

exposed municipality (or vice versa). Reference to Figure 6?

Figure 7 – In-, out- and net-migration share of population.
Red: Treatment Group, Blue: Control Group

(a) Baseline Model **(b)** External Exposure Model

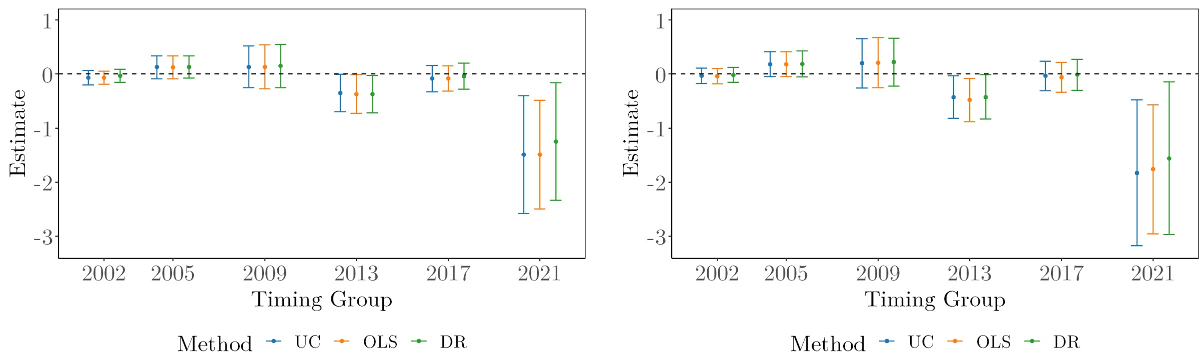


5 Results

Figure 8 illustrate the estimates at a distance of six kilometer for the six timing groups (2002 to 2021). The estimated ATT's suggest that visual exposure is associated with a statistically significant decrease in Green Party vote share for two out of the three last cohorts.

Figure 8 – Estimates for each timing group, 95 percent CI

(a) Baseline **(b)** External Exposure



For earlier timing groups (2002, 2005, 2009), the Baseline Model's estimates are both minor and statistically insignificant. However, the coefficients become negative for municipalities that were first visually exposed afterwards (Section C.1). For the 2013 cohort, the effect is significant at the five percent level across all methods with a decrease in vote share by 0.35 to 0.37 percentage points (a 4.5 to 4.7 percent decrease, evaluated at the sample mean). For the 2021 timing group, the estimated impact on the Green party vote share is markedly stronger, ranging from -1.3 to -1.5 percentage points (14 to 16.8 percent). The results for the External Exposure Model are similar (Section C.1), but the magnitude of the negative effects are larger, with a decrease in Green Party vote share associated with the visual exposure of 0.43 to 0.48 percentage points (5.6 to 6.2 percent) for the 2013 group and 1.5 to 1.8 percentage points (16.8 to 20.8 percent) for the 2021 group. The results are consistent with our theoretical framework and can be interpreted in line with the literature: Residents visually exposed to wind turbines in neighboring municipalities can be expected to be less involved in the turbine siting process or to receive financial windfall gains that matter for acceptance (Jobert et al., 2007, Lienhoop, 2018, Schwarz, 2020). Thus, as outlined in Section 4.4, the upward bias due to potential endogeneity or other effects apart from visual exposure may be smaller, resulting in a slightly stronger negative estimate.

Interestingly, the negative effects for the 2017 cohort are minimal and not significant in both models. As shown in Section 3.4, the share of municipalities with new energy cooperatives is much higher in this election period than in others, suggesting that a potential positive effect of participation could counteract a negative effect of visual exposure, biasing the estimates upwards. To address these issues, we repeat the estimation with a restriction to municipalities with residential areas outside a six-kilometer radius of an identified energy cooperative (Section C.4). While for most cohorts point estimates are similar but with a lower level of statistical significance, the negative effect for the 2017 cohort increases to -0.15 to -0.21 percentage points, with the OLS method being significant on a ten percent level.

In the Online Appendix, we subject our estimations to various further robustness checks. In particular, we (i) change the matching procedure (Section C.5), (ii) shift the distance of visual exposure (Section C.6), and (iii) account for anticipation effects (Section C.7). Our insights remain unaltered, so we now proceed to a more in-depth analysis of the underlying mechanisms.

6 Discussion of Results and Mechanisms

Our results imply that visible wind turbines did not have a negative effect on residents' attitudes towards renewable energy in earlier periods (up to 2009), but the pattern has changed in recent years. While individuals visually exposed in the 2017 election period barley respond, the reaction of the 2013 and especially the 2021 cohort is less favorable to the construction of wind turbines in their visible surroundings. In terms of our theoretical framework, this would correspond to a significant number of individuals becoming "switchers". These results call for a supplementary analysis into the mechanisms and explanations. Obviously, several factors play a role.

A first point that comes to mind is that comes to mind is the change over the years in the public debate on climate action. In the years up to the 2021 election, the 'Fridays for Future' movement of young activists have put the issue on the political agenda and raised awareness, but also polarization (Fabel et al., 2022). The Green party itself played a key role in the polarized political debate, fielding a candidate for chancellor for the first time.[17] It is conceivable that the strong media coverage and the polarized public climate debate have intensified the reaction of some voters to the construction turbines in the vicinity.

In addition, our results should be viewed against the backdrop that wind turbines had already been built for many years in those regions that were geographically appropriate and where arguably local politicians as well as residents might have been more supportive. Figure XX shows that many earlier wind turbines were built in flat, windy Northern Germany. Once these low-hanging fruits have been grasped, locations have been chosen that might have been less inclined. These inherent differences between early wind turbine adopters and laggards might explain the varying effects over time. In fact, they might be interpreted in the vein of Allcott (2015)'s findings about energy conservation programs in the U.S., namely that results from first adopters overstate the overall efficiency because of their concentration in the most environmentalist-friendly areas, which changes as the measure expands to the rest of the country. Similarly, wind turbines can now be thought to be expanding to some less supportive areas.

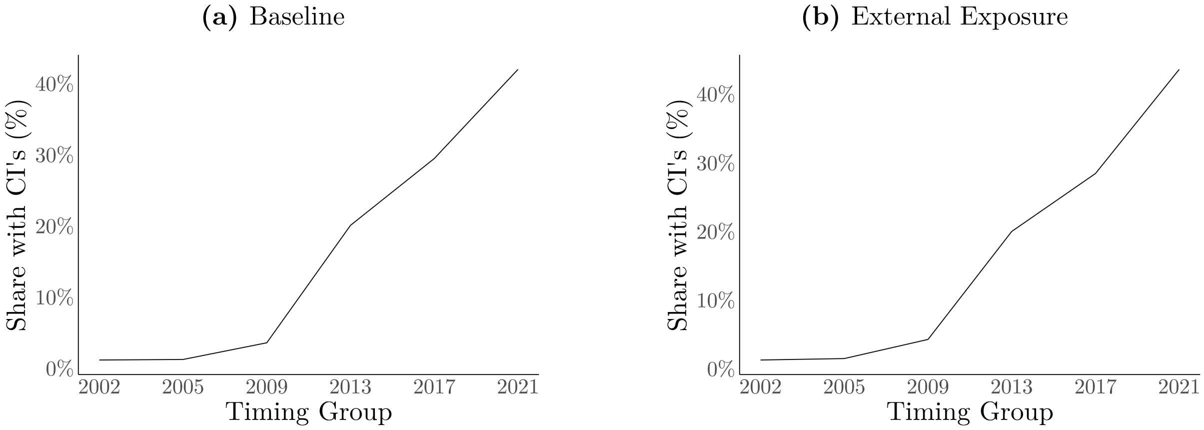
This point is elucidated by looking at the data on citizens' initiatives opposing wind turbines. Up to the 2009 timing group, the share of municipalities with reported citizens' initiatives is less than five percent, after which it increases with each election, with over 40 percent of all municipalities having an initiative within their municipal boundaries in the 2021 cohort (Figure 9). These initiatives may have delayed the installation of turbines until recent election periods by swaying public opinion to a negative side, which could subsequently be reflected in the Green Party vote share once turbines were installed.[18]

Related to this, We observe a marked increase in the average installation periods in Figure XX. It is conceivable that to strong local opposition might have played a role in delaying the installation of turbines by legal action, creating a self-reinforcing cycle of opposition. The extended timelines provide opponents with more opportunities to

[17] In May 2021, the Green party briefly topped the polls with close to 30%. They ended up with 14.8% in the elections in September. Among others, it has been argued that the strong pro-climate proposals (from more wind energy to speed limits on motorways) have their proponents and sceptics, with both groups very outspoken (Hille, 2021).

[18] Evidence on how protests and vocal opposition can sway public opinion is, among others, provided by Douenne and Fabre (2022) on the Gilets Jaunes protests in France: Their survey data that the protests shifted the public perception of the proposed carbon tax as regressive and environmentally ineffective.

Figure 9 – Share of municipalities with a citizens' initiative per timing group



organize, mobilize and amplify their concerns, cultivating a broader sentiment against wind turbines in the municipality. This escalation of opposition may have contributed to a further decline in local support for the projects, causing a feedback loop that made the initial perception of the local population more negative.

At the same time, a financial participation can mitigate opposition and thus works into the other direction as the factors discussed before. The varying number of energy cooperative turbines is a further mechanims that explains our results. In particular, in 2017, the high number of energy cooperatives might have played a role in counteracting the influence of citizen initiatives. By contrast, in 2021 ... (write out that both go in the same direction)

The even stronger effect in municipalities where turbines are visible from their residential areas, but do not have turbines on their municipal territory themselves, is a further indication that participation opportunities may indeed be a vital channel, as argued by Jobert et al. (2007), Lienhoop (2018), Schwarz (2020).

One obvious caveat of our study is that it by design only captures the reaction of potential Green voters, hence people who might consider voting for the Green party at all and whose voting decision would be affected by a visible wind turbine. Voters who would never even consider voting for the Greens might react to wind turbines in ways which we cannot capture in our study because there would be too many other confounding factors. In the terminology of our framework, we cannot say anything about the size of the supporter or opposer groups, which are without doubt politically relevant for policymakers.

On the other hand, our focus on the "switchers" brings with it the advantage of a identification of revealed preferences. From the perspective of policymakers, these individuals are particularly important because their attitudes change and policymakers need to understand why in order to keep them on board of the wind energy expansion. This will be particularly important in the coming years, if more turbines will be built in less-inclined and late-adopter areas. The results from our paper suggest that a combination of early-on information and involvement, financial participation, and quick approval processes can play a role to ensure local acceptance.

7 Conclusion

We study the reactions of voters after the construction of a wind turbine in their visible surroundings. Exploiting fine-grained data from Germany from 1998 to 2021 and robust econometric methods based on difference-in-difference, we are able to reconcile some of the ambiguous empirical results to date. Yet, the prime contribution of this paper is based on our calculation of the wind turbines' viewshed, allowing us the determine to what extent each wind turbine in Germany is visible from nearby settlement areas. The 'visible intrusion of the landscape' (Wolsink, 2000, p.51) is one of the most cited arguments by local opponents of this form of energy generation, yet has never been analyzed in that way. Focusing on the visibility of turbines allows us also to elucidate possible NIMBYism, because people who oppose wind energy in general (e.g. because of bird endangerment) should do so whether or not the wind turbine is visible to them. Our analysis therefore leads to new insights on what drives the acceptance of wind turbines and whether the expansion of wind energy poses a risk to the vote share of pro-renewable parties in rural areas, further deepening the urban-rural divide.

Summarizing, our preliminary results show a marked pattern. Constructing a wind turbine that is visible from a nearby settlement is not followed by a decrease in the Green party's local vote share in the first half of our sample period (1998-2009), but the trend towards a backlash is discernable afterwards (2013-2021). The magnitude and statistical significance has grown over time and in 2021 reached a vote share decrease of X percentage point compared to the control group without visible wind turbines. The results echo the widely cited growing tensions over where development should occur, with expansion to areas with lower levels of support, which is also reflected in an increase in the formation of local citizens' groups against these projects. Furthermore, the significant decline in vote share over the last election period is even more pronounced in municipalities only visually exposed but without turbines themselves, suggesting that lower participation is negatively related to support for renewable energy expansion. This is consistent with the results of qualitative work on this topic. While more research is needed on the channels to obtain public support, our study illustrates the importance of careful consideration of the local effects of global environmental policy.

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A Appendix: Descriptive Statistics

A.1 Timing Groups Statistics

Figure A-1 – Geographic distribution of the timing groups

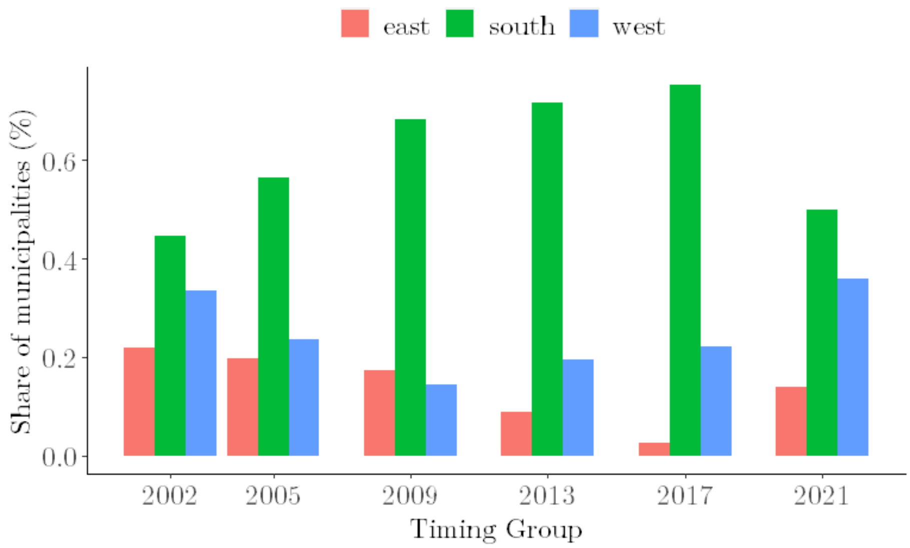


Figure A-2 – Number of municipalities per timing group first visually exposed up to a 6km

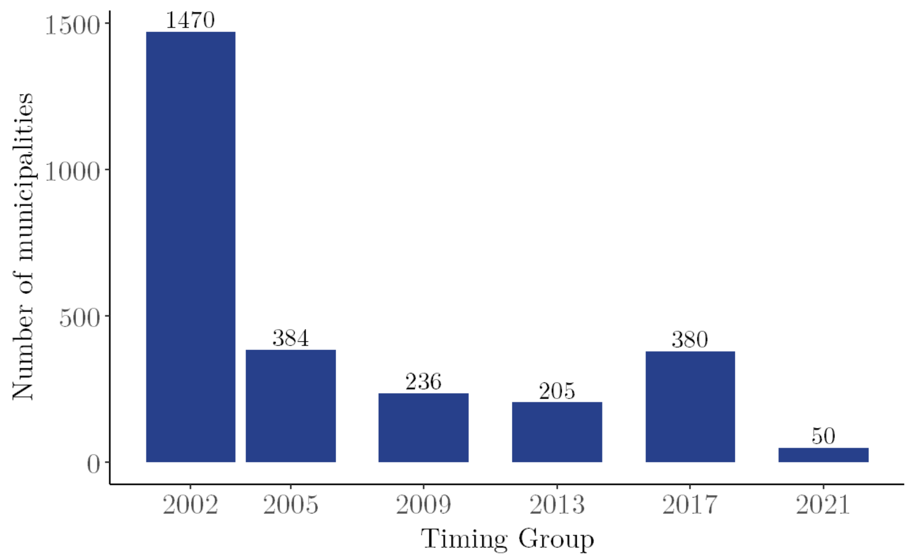


Figure A-3 – Mean distance to the closest visible turbine for each timing group

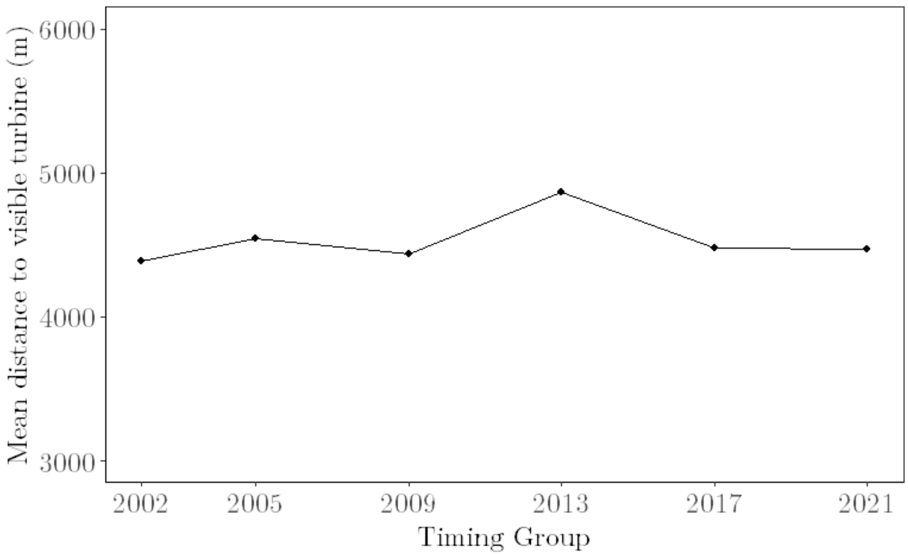
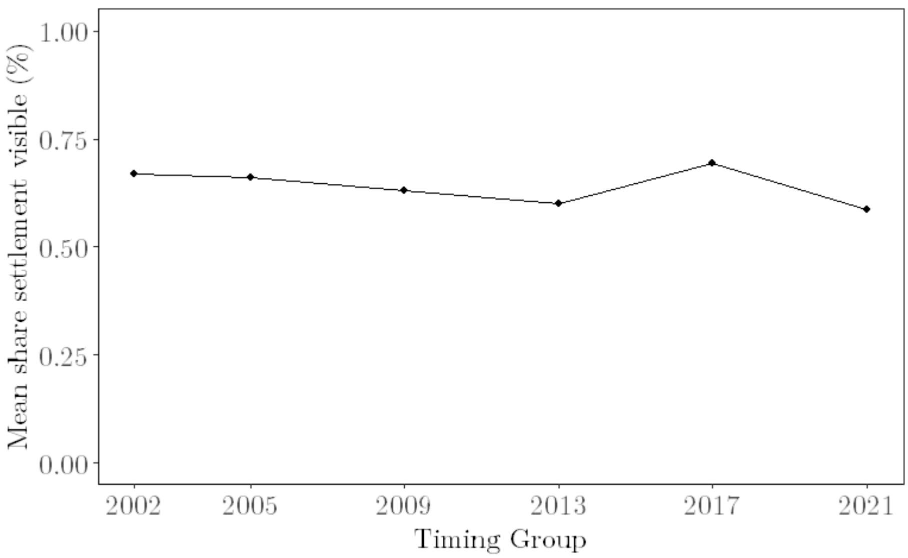


Figure A-4 – Mean share of the settlement area visually exposed for each timing group

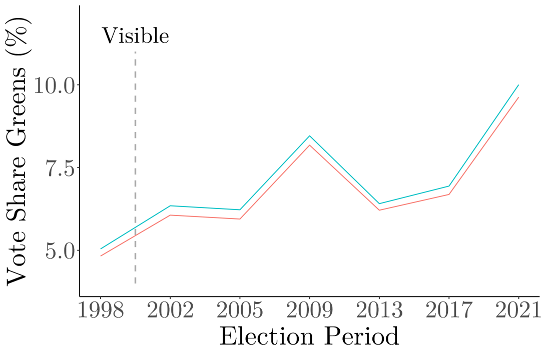


A.2 Parallel trends

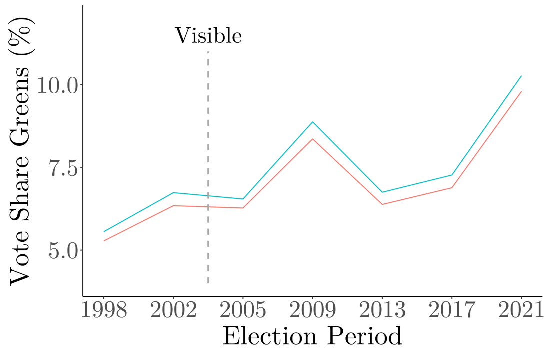
Figure A-5 shows the vote share of the Green Party for each timing group and their control group for the Baseline Model. Figure A-6 is the same for the External Exposure Model. We see that...

Figure A-5 – Baseline Model: Green Party vote share per timing group.
Blue: Treatment Group, Red: Control Group

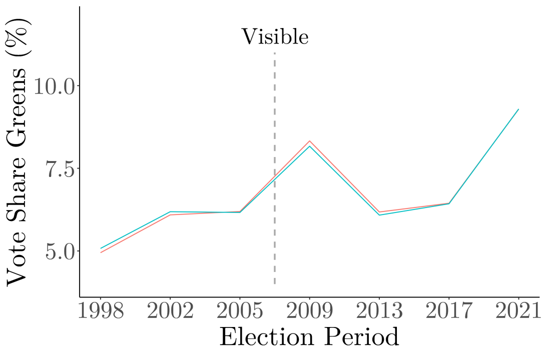
(a) 2002



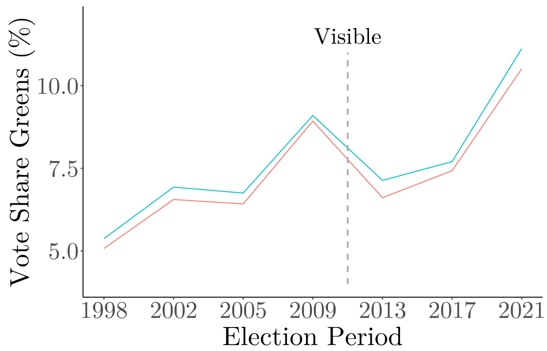
(b) 2005



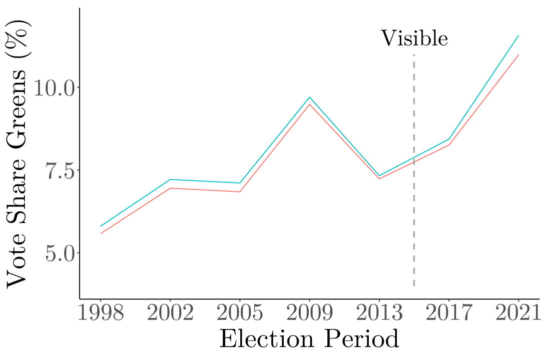
(c) 2009



(d) 2013



(e) 2017



(f) 2021

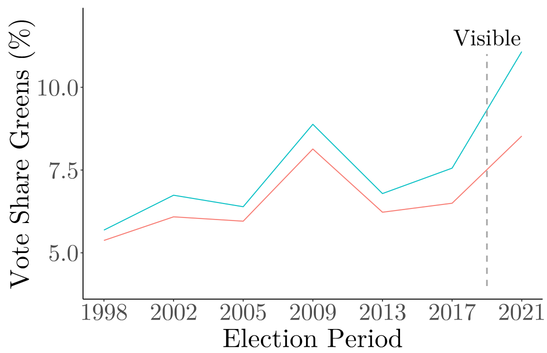
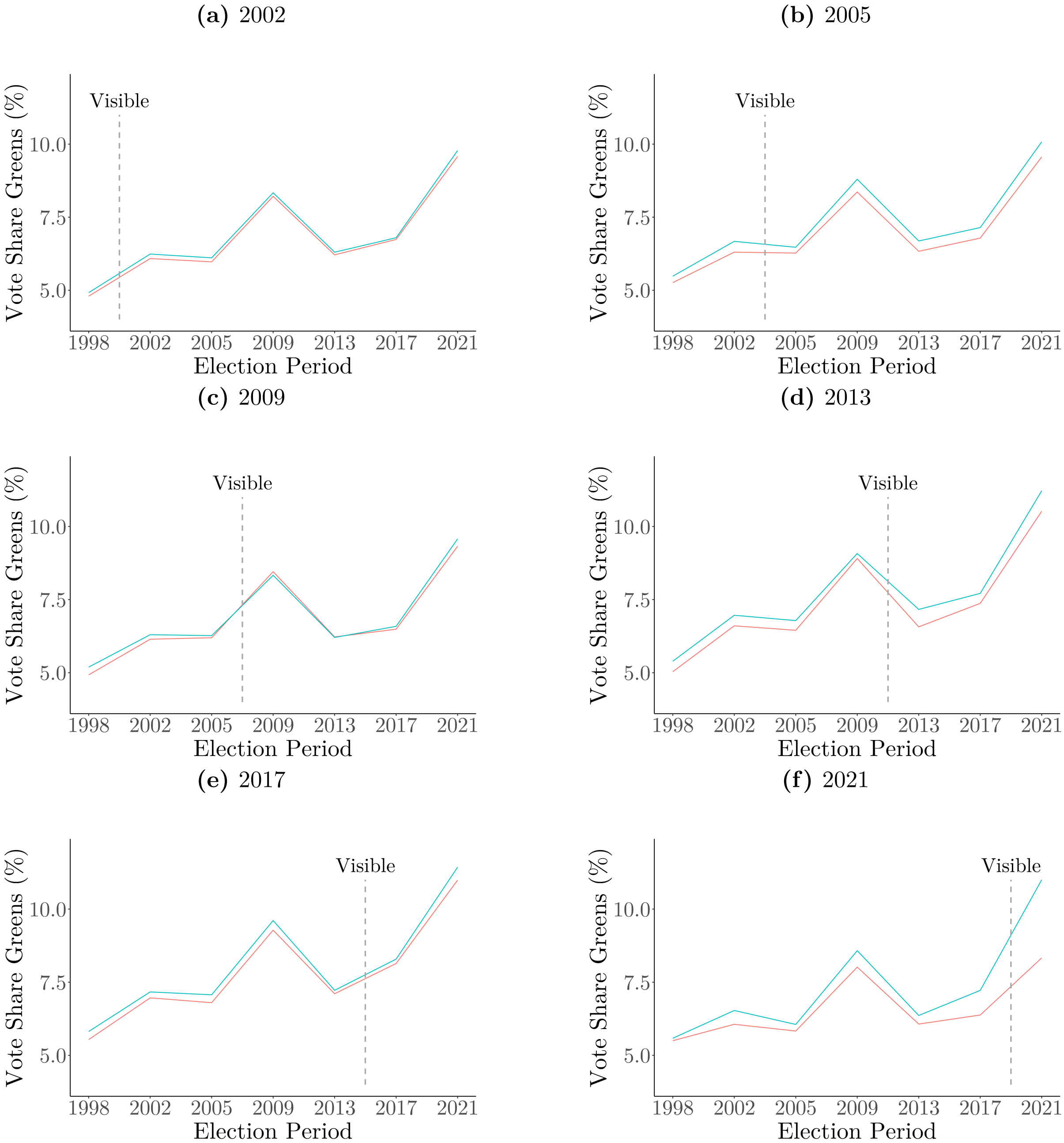


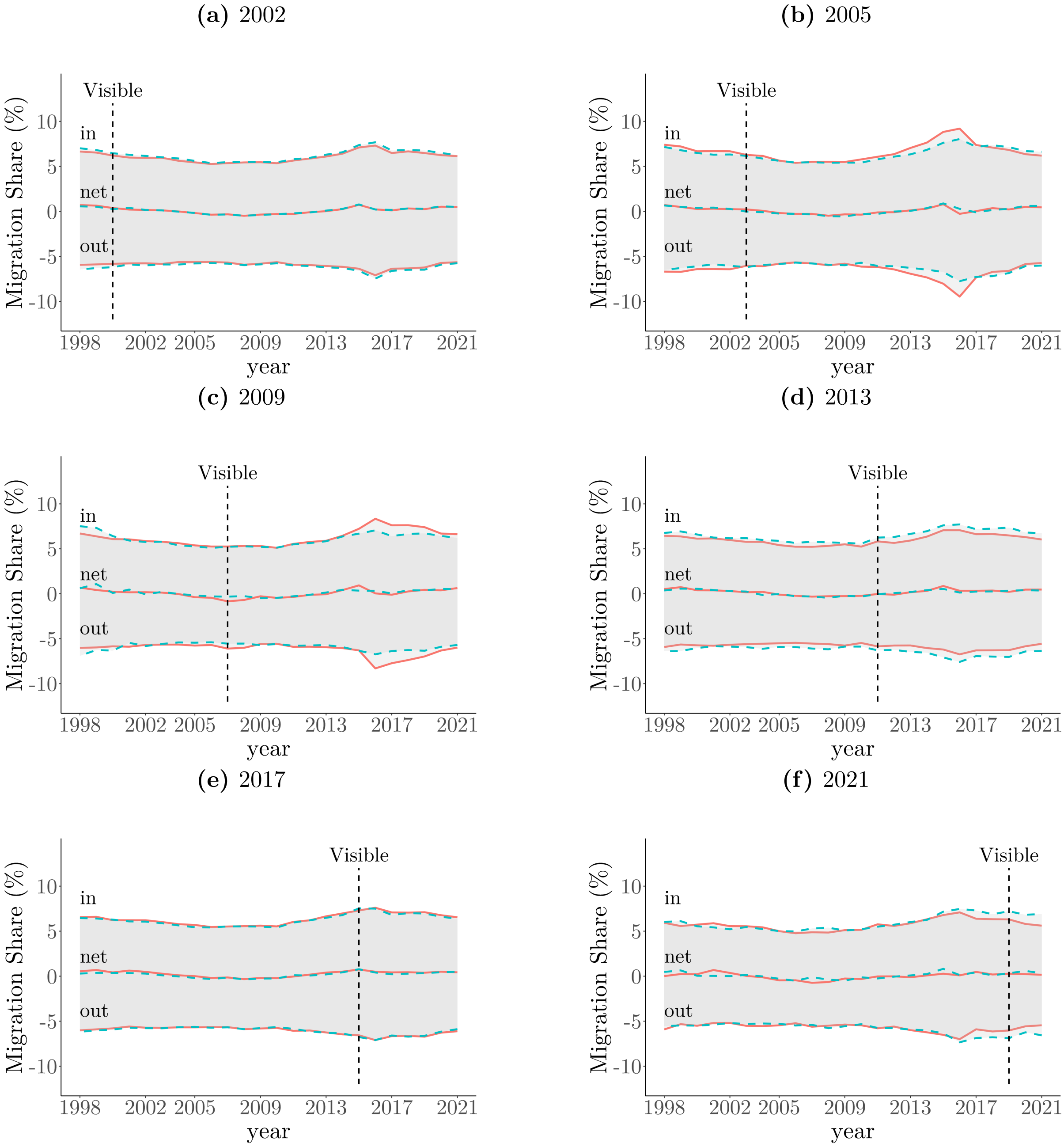
Figure A-6 – External Exposure Model: Green Party vote share per timing group. Blue: Treatment Group, Red: Control Group



A.3 Migration

Figure A-5 shows the vote share of the Green Party for each timing group and their control group for the Baseline Model. Figure A-6 is the same for the External Exposure Model.

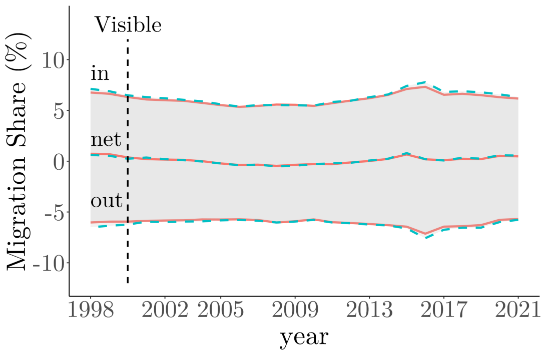
Figure B-7 – Baseline Model: In-, out- and net-migration share of population.
Red: Treatment Group, Blue: Control Group



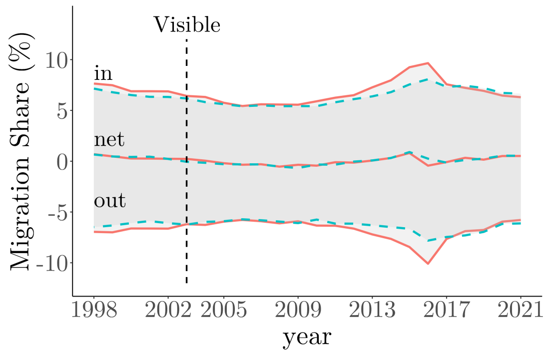
(a) 2002 **(b)** 2005 **(c)** 2009 **(d)** 2013 **(e)** 2017 **(f)** 2021

Figure B-8 – External Exposure Model: In-, out- and net-migration share of population. Red: Treatment Group, Blue: Control Group

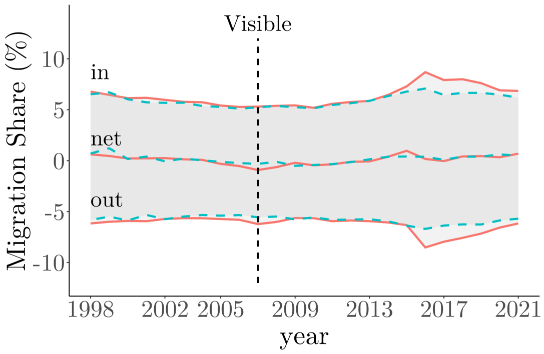
(a) 2002



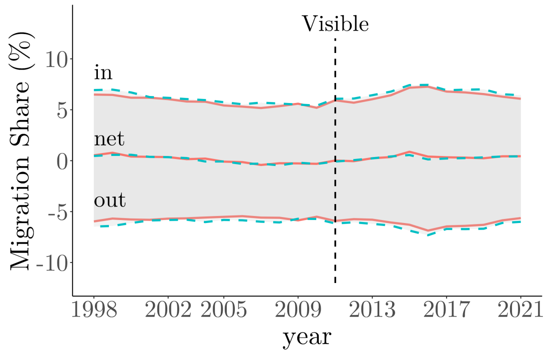
(b) 2005



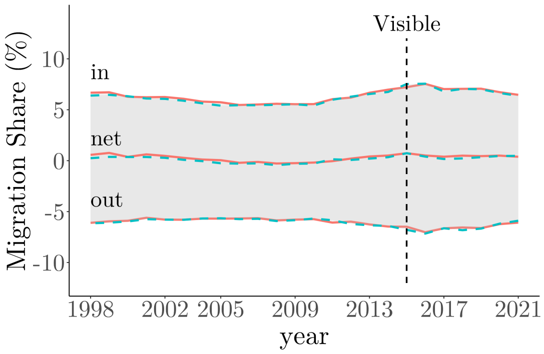
(c) 2009



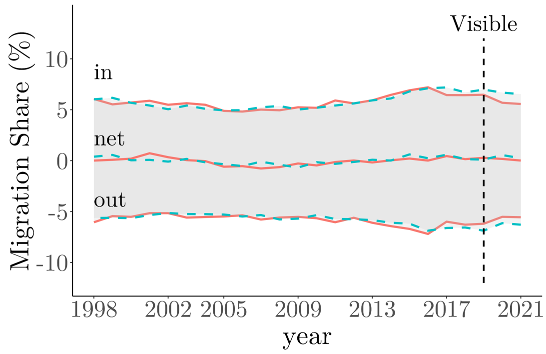
(d) 2013



(e) 2017



(f) 2021



B Appendix: Extensions of the Theoretical Framework

B.1 Turbine Ownership Structure

Let $\zeta_{ir} \in [0,1]$ be the share of regional wind turbines w_r in which individual i can participate financially. The budget constraint of i can therefore be extended to: $y_{imr}(w_r, \phi_{mr}w_r, \zeta_{ir}w_r) = x_i$. Thus, an additional positive income opportunity exists for i through participation in a cooperative investment ($\partial y_{imr}/\partial \zeta_i w_r \geq 0$). Since participation opportunities can vary between individuals within the same region ($\zeta_{ir} \neq \zeta_{jr}$), it might explain differences in support between individuals independent of visual exposure. In Section Section C.4, we run the estimation with a subset of the main data that excludes municipalities where we have identified an energy cooperative within 6 km of their residential area, the same threshold used for visual exposure.

B.2 Perception Updating

Let $v_i(k_i)$ be the perception of individual i on the impact of $\phi_{mr}w_r$ on $e_{imr}(\phi_{mr}w_r, v_i(k_i))$ which depends on $i's$ information set k_i. The larger perception $v_i(k_i)$ is, the less disturbing individuals find the sight of wind turbines in their immediate surroundings. A citizens' initiative against regional wind turbine installations can provide new (subjective) information that decreases $i's$ perception ($\delta v_i/\delta k_i < 0$). Given that the negative impact of $\phi_{mr}w_r$ on e_{imr} increases with decreasing perception, the new information provided amplifies the negative change of regional wind turbines on the environmental good and therefore utility. In the extension of the theoretical framework with this perception updating mechanism, eq. (B-1) represents the change of information k_i on individuals utility:

$$\frac{dU_{imr}}{dk_i} = \frac{\delta^2 e_{imr}}{\delta(\phi_{mr}w_r)\delta v_i}\frac{dv_i}{dk_i} \tag{B-1}$$

B.3 Municipal Specific Effects

We extend the individuals utility function by $\psi_{mr} \in [0,1]$, the share of w_r that is located in m, a public good g_{mr} provided by the municipality and financed by lump sum tax t_{mr} (eq. (B-2)). Given Chapter 5, the share of regional turbines in m can lower the residents tax burden (t_{imr} ($\partial t_{mr}/\partial(\psi_{mr}w_r) \leq 0$), raising $m's$ public good provision g_{mr} ($\partial g_{mr}/\partial(\psi_{mr}w_r) \geq 0$) and further increases the available income through other financial benefits ($\partial y_{imr}/\partial(\psi_{mr}w_r) \geq 0$).

$$\max_{x_i} U_{imr} = U\Big(x_i, e_{imr}(\phi_{mr} w_r), g_{mr}(\psi_{mr} w_r) f_{imr}\Big(\sum_{r=1}^{R} w_r\Big)\Big) \tag{B-2}$$
$$\text{s.t. } y_{imr}(w_r, \phi_{mr}, \psi_{mr}) = x_i - t_{mr}(\phi_{mr} w_r)$$

In the External Exposure Model (Section 4.4), we exclude municipalities in the treatment and control groups where turbines are located within their boundaries, i.e. $\psi_{mr} = 0$.

C Appendix: Additional Results

Here we provide supplementary information on the empirical results and the results of the validity and robustness tests.

C.1 Main estimation results

Table B-1 reports the estimation results of the three estimation methods with the main specification of six kilometer treatment zone and two kilometers of buffer for the Baseline and External Exposure Model. We see that

	Dependent Variable: vote share Green Party (percent)					
Timing Group	Baseline			External Exposure		
	UC	OLS	DR	UC	OLS	DR
2002	-0.07 (0.06)	-0.07 (0.06)	-0.03 (0.07)	-0.03 (0.07)	-0.04 (0.07)	-0.02 (0.07)
2005	0.13 (0.11)	0.12 (0.11)	0.13 (0.11)	0.18 (0.11)	0.18 (0.12)	0.19 (0.12)
2009	0.13 (0.21)	0.13 (0.21)	0.15 (0.21)	0.2 (0.24)	0.21 (0.24)	0.22 (0.24)
2013	-0.35** (0.18)	-0.37** (0.18)	-0.37** (0.17)	-0.43** (0.2)	-0.48** (0.2)	-0.43** (0.21)
2017	-0.08 (0.13)	-0.08 (0.12)	-0.04 (0.12)	-0.03 (0.14)	-0.06 (0.14)	-0.01 (0.15)
2021	-1.49*** (0.56)	-1.49*** (0.51)	-1.25** (0.59)	-1.83** (0.72)	-1.76*** (0.6)	-1.56** (0.71)

[a] UC: Estimation unconditional of covariates
[b] OLS: Linear regression with covariates
[c] DR: Doubly Robust estimation with covariates (Sant'Anna and Zhao, 2020)
[d] Signif. Codes: ***: 0.01, **: 0.05, *: 0.1
[e] Clustered standard-errors in parentheses

Table B-1 – Main estimation results of all three estimation methods

C.2 Validity Check: False Treatment Timings

We shift the treatment timing to all possible pre-treatment election periods ($t < g$) with the number of periods before treatment denoted as e. This approach entails that, at an event time of $e = -5$, solely the the 2021 timing group is incorporated. Moreover, we cannot shift the treatment timing for the 2002 timing group, as we do not have two pre-treatment election period for any $e < 0$. Table B-2 and Table B-3 reports the results for the Baseline and External Exposure Model, respectively. All coefficients for the false treatment timings are insignificant, supporting the main estimation. The estimates for the 2021 cohort in the election period before visual exposure ($e = -1$) are already negative, possibly related to anticipation effects, discussed in more detail in Section C.7.

	Dependent Variable: vote share Green Party (percent)														
	e = -1			e = -2			e = -3			e = -4			e = -5		
Timing Group	UC	OLS	DR	UC	OLS	DR	UC	OLS	DR	UC	OLS	DR	UC	OLS	DR
2005	-0.11 (0.12)	-0.09 (0.12)	-0.07 (0.11)												
2009	0.13 (0.15)	0.14 (0.15)	0.11 (0.14)	0.03 (0.15)	0.04 (0.15)	0.05 (0.14)									
2013	0.16 (0.19)	0.23 (0.18)	0.2 (0.18)	0.03 (0.13)	0.03 (0.12)	0.03 (0.13)	-0.06 (0.15)	-0.06 (0.15)	-0.01 (0.15)						
2017	0.12 (0.12)	0.1 (0.12)	0.07 (0.12)	0.05 (0.12)	0.04 (0.12)	0.05 (0.13)	0 (0.09)	-0.03 (0.09)	-0.03 (0.1)	-0.04 (0.11)	-0.05 (0.11)	0.07 (0.11)			
2021	-0.5 (0.39)	-0.34 (0.37)	-0.39 (0.38)	0.18 (0.29)	0.15 (0.27)	0.09 (0.31)	-0.31 (0.34)	-0.28 (0.31)	-0.28 (0.36)	0.22 (0.27)	0.17 (0.26)	0.22 (0.3)	-0.34 (0.36)	-0.27 (0.36)	-0.06 (0.37)

[a] UC: Estimation unconditional of covariates
[b] OLS: Linear regression with covariates
[c] DR: Doubly Robust estimation with covariates (Sant'Anna and Zhao, 2020)
[d] Signif. Codes: ***: 0.01, **: 0.05, *: 0.1
[e] Clustered standard-errors in parentheses
[f] e: Election period before treatment

Table B-2 – Baseline Model Estimation with false treatment timings

	Dependent Variable: vote share Green Party (percent)														
	e = -1			e = -2			e = -3			e = -4			e = -5		
Timing Group	UC	OLS	DR	UC	OLS	DR	UC	OLS	DR	UC	OLS	DR	UC	OLS	DR
2005	-0.15 (0.14)	-0.13 (0.13)	-0.1 (0.13)												
2009	0.08 (0.16)	0.11 (0.16)	0.06 (0.16)	0.11 (0.17)	0.13 (0.16)	0.14 (0.16)									
2013	0.16 (0.21)	0.24 (0.2)	0.21 (0.2)	0.01 (0.14)	0.01 (0.13)	0 (0.14)	0.01 (0.17)	0.02 (0.17)	0.09 (0.15)						
2017	0.21 (0.13)	0.2 (0.13)	0.18 (0.13)	-0.06 (0.14)	-0.08 (0.14)	-0.06 (0.14)	-0.07 (0.11)	-0.08 (0.1)	-0.08 (0.11)	0.07 (0.14)	0.04 (0.14)	0.12 (0.13)			
2021	-0.55 (0.44)	-0.45 (0.41)	-0.51 (0.42)	0.27 (0.34)	0.22 (0.33)	0.2 (0.36)	-0.34 (0.4)	-0.25 (0.36)	-0.3 (0.41)	0.25 (0.33)	0.22 (0.31)	0.26 (0.32)	-0.39 (0.42)	-0.29 (0.44)	-0.09 (0.45)

[a] UC: Estimation unconditional of covariates
[b] OLS: Linear regression with covariates
[c] DR: Doubly Robust estimation with covariates (Sant'Anna and Zhao, 2020)
[d] Signif. Codes: ***: 0.01, **: 0.05, *: 0.1
[e] Clustered standard-errors in parentheses
[f] e: Election period before treatment

Table B-3 – External Exposure Model Estimation with false treatment timings

C.3 Validity Check: Placebo Treatment Groups

As an additional falsification test, we construct placebo treatment groups for each timing group's control group, again by minimizing the overall distance between them. We restrict each placebo treatment group to municipalities located within the same counties as their control counterparts to ensure that the placebo group is as similar as possible to the control group, thereby reducing the chance that any estimated placebo effect is confounded by broader geographical disparities. Given the limited number of municipalities with the same urbanisation status and located within the control group's counties, the covariate balance between the placebo treatment groups and the original control groups are worse than in the main analysis, possibly explaining fairly large point estimates in some specifications (Table B-4). However, these results seem random and lack statistical significance on any level, which further substantiates the reliability of the estimation models.

	Dependent Variable: vote share Green Party (percent)					
Placebo Timing Group	Baseline			External Exposure		
	UC	OLS	DR	UC	OLS	DR
2002	-0.01 (0.11)	0 (0.11)	-0.02 (0.1)	-0.12 (0.15)	-0.15 (0.15)	-0.1 (0.12)
2005	0.28 (0.19)	0.24 (0.18)	0.21 (0.16)	-0.12 (0.19)	-0.11 (0.19)	-0.08 (0.17)
2009	0.1 (0.25)	0.07 (0.24)	0.07 (0.23)	0.22 (0.3)	0.35 (0.31)	0.11 (0.29)
2013	0.25 (0.27)	0.34 (0.25)	0.09 (0.25)	-0.47 (0.31)	-0.41 (0.3)	-0.29 (0.3)
2017	-0.02 (0.2)	-0.13 (0.19)	-0.05 (0.17)	-0.03 (0.23)	-0.08 (0.23)	-0.07 (0.23)
2021	0.54 (0.85)	0.93 (0.74)	0.71 (0.69)	-0.48 (0.99)	-0.55 (0.88)	-0.6 (0.79)

[a] UC: Estimation unconditional of covariates
[b] OLS: Linear regression with covariates
[c] DR: Doubly Robust estimation with covariates (Sant'Anna and Zhao, 2020)
[d] Signif. Codes: ***: 0.01, **: 0.05, *: 0.1
[e] Clustered standard-errors in parentheses

Table B-4 – Estimation results with a placebo treatment group

C.4 Robustness Check: Estimation with the Exclusion of Energy Cooperatives

Taking the data from !Holsenkamp et al., we re-estimate the effect with municipalities where we could not identify a energy cooperative within the 6 km treatment zone. Despite the fragmented data coverage, an exclusion should at least lower the proportion of municipalities where their inhabitants participate in those project. Significance lowered overall, with most of the estimates of the 2013 cohort being only significant on a ten percent level while for two specification not at all and for the 2021 cohort a five percent significance with the UC and OLS methods and ten percent with DR, potentially due to the reduced sample size. The negative effect for the 2017 cohort is indeed stronger across specifications, with a result of the OLS of the Baseline Model being significant on a ten percent level.

	Dependent Variable: vote share Green Party (percent)					
Timing Group	Baseline			External Exposure		
	UC	OLS	DR	UC	OLS	DR
2002	-0.09 (0.07)	-0.08 (0.06)	-0.06 (0.06)	-0.06 (0.08)	-0.05 (0.07)	-0.04 (0.07)
2005	0.1 (0.11)	0.09 (0.11)	0.1 (0.11)	0.15 (0.12)	0.15 (0.12)	0.16 (0.12)
2009	0.06 (0.21)	0.06 (0.21)	0.09 (0.21)	0.12 (0.23)	0.12 (0.24)	0.15 (0.25)
2013	-0.33 (0.23)	-0.39* (0.22)	-0.39* (0.21)	-0.39* (0.24)	-0.51** (0.25)	-0.44 (0.26)
2017	-0.2 (0.13)	-0.21* (0.12)	-0.18 (0.13)	-0.16 (0.14)	-0.19 (0.14)	-0.15 (0.15)
2021	-1.17** (0.54)	-1.22** (0.49)	-1.01* (0.63)	-1.52** (0.65)	-1.43** (0.59)	-1.35* (0.74)

[a] UC: Estimation unconditional of covariates
[b] OLS: Linear regression with covariates
[c] DR: Doubly Robust estimation with covariates (Sant'Anna and Zhao, 2020)
[d] Signif. Codes: ***: 0.01, **: 0.05, *: 0.1
[e] Clustered standard-errors in parentheses

Table B-5 – Estimation results with the exclusion of municipalities with nearby energy cooperatives

C.5 Robustness Check: Alternative Matching Procedures

To test whether the results in Section 5 are robust to changes in the matching procedure, we match a control group for each cohort with replacement. For each visually exposed municipality, we find the geographically closest control municipality that is not visually exposed at that time, has the same urbanization status, and has no identified citizen initiatives. Now, several treatment municipalities can be matched to the same control municipality, which we weight according to the frequency of assignment. The results are similar to the ones in the main specification, with larger point estimates (Table B-6), providing evidence that the results are not driven by the matching procedure.

	Dependent Variable: vote share Green Party (percent)					
Timing Group	Baseline			External Exposure		
	UC	OLS	DR	UC	OLS	DR
2002	-0.1 (0.1)	0.03 (0.11)	-0.06 (0.09)	-0.09 (0.11)	-0.1 (0.12)	-0.07 (0.1)
2005	0.2 (0.14)	0.1 (0.15)	0.18 (0.12)	0.24 (0.16)	0.23 (0.16)	0.23 (0.15)
2009	0.25 (0.26)	0.19 (0.24)	0.32 (0.27)	0.28 (0.26)	0.19 (0.27)	0.34 (0.27)
2013	-0.53** (0.24)	-0.51** (0.21)	-0.52** (0.21)	-0.52** (0.24)	-0.52* (0.27)	-0.46** (0.2)
2017	0.01 (0.22)	0.14 (0.17)	0.05 (0.19)	0.09 (0.23)	-0.19 (0.23)	0.13 (0.23)
2021	-1.92*** (0.72)	-1.56** (0.62)	-1.81*** (0.68)	-2*** (0.81)	-2.1*** (0.74)	-2*** (0.73)

[a] UC: Estimation unconditional of covariates
[b] OLS: Linear regression with covariates
[c] DR: Doubly Robust estimation with covariates (Sant'Anna and Zhao, 2020)
[d] Signif. Codes: ***: 0.01, **: 0.05, *: 0.1
[e] Clustered standard-errors in parentheses

Table B-6 – Estimation results with matching with replacement (1:1)

In addition, we increase the number of matches for each treated municipality to three, allowing additional variation in the control group. Again, the trend is comparable to the main specification, but the point estimates are lower, especially for the 2021 cohort, with only 10 percent significance for the *DR* method (Table B-7).

Timing Group	Dependent Variable: vote share Green Party (percent)					
	Baseline			External Exposure		
	UC	OLS	DR	UC	OLS	DR
2002	0.08 (0.34)	-0.04 (0.08)	0.1 (0.3)	-0.09 (0.1)	0.02 (0.08)	-0.06 (0.1)
2005	0.16 (0.12)	0.09 (0.11)	0.15 (0.11)	0.18 (0.12)	0.11 (0.12)	0.18 (0.11)
2009	0.05 (0.21)	0.09 (0.2)	0.08 (0.2)	0.12 (0.21)	0.06 (0.22)	0.16 (0.21)
2013	-0.38** (0.17)	-0.37** (0.16)	-0.4** (0.17)	-0.43** (0.19)	-0.38** (0.19)	-0.44** (0.18)
2017	-0.09 (0.12)	-0.02 (0.12)	-0.06 (0.12)	-0.02 (0.14)	0.03 (0.13)	0.01 (0.12)
2021	-0.99** (0.43)	-0.94** (0.38)	-0.73* (0.36)	-1.05** (0.5)	-1.28*** (0.44)	-0.82* (0.43)

[a] UC: Estimation unconditional of covariates
[b] OLS: Linear regression with covariates
[c] DR: Doubly Robust estimation with covariates (Sant'Anna and Zhao, 2020)
[d] Signif. Codes: ***: 0.01, **: 0.05, *: 0.1
[e] Clustered standard-errors in parentheses

Table B-7 – Estimation results with matching with replacement (1:3)

C.6 Robustness Check: 8 km Treatment Zone

As discussed in Section 4.1, the distance from which a turbine is perceived as intrusive is unclear and varies among observers. To test the sensitivity of the main results to changes in the treatment zone cut-off, we increase the maximum distance of turbine visibility. In the alternative specification, we also include municipalities only visually exposed in the buffer zone, i.e., we increase the treatment zone to eight kilometer. The point estimates are smaller and only significant for the 2021 timing group, suggesting a decreasing effect with increasing distance (Table B-8).

Timing Group	Dependent Variable: vote share Green Party (percent)					
	Baseline			External Exposure		
	UC	OLS	DR	UC	OLS	DR
2002	-0.01 (0.06)	-0.02 (0.05)	0.02 (0.06)	0 (0.06)	-0.02 (0.06)	0.02 (0.06)
2005	0.1 (0.09)	0.1 (0.09)	0.1 (0.09)	0.1 (0.1)	0.11 (0.1)	0.1 (0.1)
2009	0.12 (0.18)	0.13 (0.17)	0.17 (0.16)	0.16 (0.19)	0.17 (0.19)	0.22 (0.18)
2013	-0.12 (0.14)	-0.11 (0.14)	-0.12 (0.14)	-0.13 (0.16)	-0.13 (0.16)	-0.12 (0.17)
2017	-0.02 (0.11)	0 (0.11)	0.06 (0.11)	0.03 (0.12)	0.02 (0.12)	0.07 (0.12)
2021	-1.07*** (0.37)	-0.96*** (0.34)	-0.78** (0.35)	-1.18*** (0.4)	-1.03*** (0.38)	-0.85** (0.43)

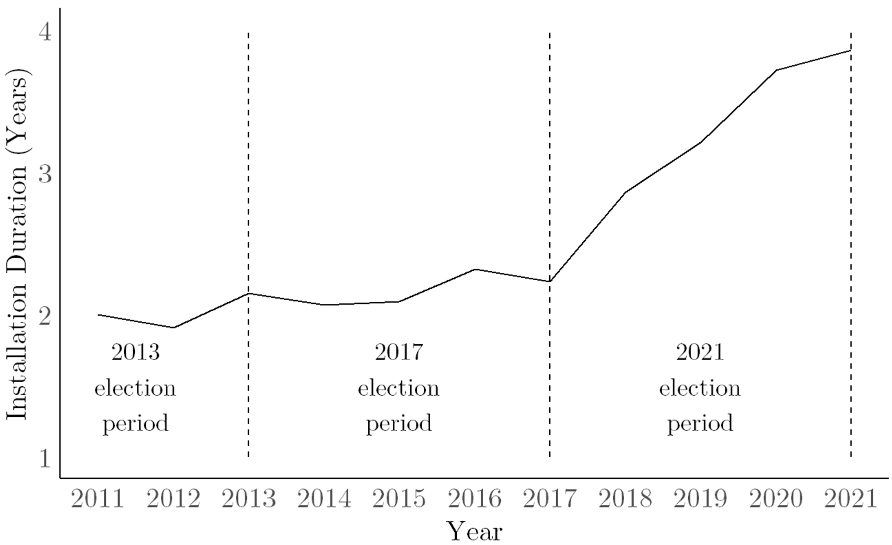
[a] UC: Estimation unconditional of covariates
[b] OLS: Linear regression with covariates
[c] DR: Doubly Robust estimation with covariates (Sant'Anna and Zhao, 2020)
[d] Signif. Codes: ***: 0.01, **: 0.05, *: 0.1
[e] Clustered standard-errors in parentheses

Table B-8 – Estimation results with an 8 km treatment zone

C.7 Robustness Check: Accounting for Anticipation

? found that the average planning, approval and construction duration of wind turbines in Germany was fairly constant at around two years until 2017 and has since increased to 3.9 years in 2021 (Figure B-9). As these projects are publicly announced in the planning phase, people in the 2021 cohort could already anticipate visual exposure in the pre treatment period period.

Figure B-9 – Mean planning, approval and construction duration of wind turbines (**?**)



Indications of this can be found in the pre-trends in Figure A-5 and the falsification test in Section C.2, with a negative estimate one election period before the visual exposure. To account for this, we shift the pre-treatment period for the group with the 2021 schedule to $t = g - 8$, i.e. two periods before the visual exposure (eq. (B-3)). Accounting for anticipation implies the assumption that parallel trends must persist over a longer time frame, but mitigates potential biases due to voter reactions prior to treatment.

$$\begin{aligned} ATT_{UC}^{Anti}(g = 2021) = &\mathbb{E}[S_g - S_{g-8}|G_g = 1, D_{g+4} = 1] \\ &- \mathbb{E}[S_g - S_{g-8}|G_g = 0, D_{g+4} = 0] \end{aligned} \tag{B-3}$$

The results are a further indication that individuals in the 2021 cohort may have already adjusted their perceptions in the previous election period due to the anticipation of visual exposure, as the point estimates increases to -1.36 for the Baseline Model with the DR estimator and -2.38 for the External Exposure Model with the UC estimation (Table B-9).

Timing Group	Dependent Variable: vote share Green Party (percent)					
	Baseline			External Exposure		
	UC	OLS	DR	UC	OLS	DR
2021	-1.99*** (0.62)	-1.83*** (0.53)	-1.36*** (0.5)	-2.38*** (0.7)	-2.17*** (0.62)	-1.85*** (0.69)

[a] UC: Estimation unconditional of covariates
[b] OLS: Linear regression with covariates
[c] DR: Doubly Robust estimation with covariates (Sant'Anna and Zhao, 2020)
[d] Signif. Codes: ***: 0.01, **: 0.05, *: 0.1
[e] Clustered standard-errors in parentheses

Table B-9 – Estimation results for the 2021 timing group, accounting for anticipation