Headwind at the Ballot Box? - The Effect of Visible Wind Turbines on Green Party Support

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Abstract

Whether pro-renewable political parties win or lose at the ballot box when wind turbines are built near voters' homes is still not well understood, particularly with regard to voter motivation and channels of influence. We contribute by using new fine-grained data on the location of wind turbines in Germany to determine the visual exposure of residential areas to wind turbines. This allows us to estimate the change in the vote share for the German Green Party after voters see a wind turbine from their neighborhood for the first time. In most election periods from 1998 to 2009, we find no significant effect of visible wind turbines on the Green Party vote share, suggesting that voters did not change their support for pro-renewable policies. Yet, for municipalities first visually exposed in the 2013, 2017 and especially the 2021 election period, we find a negative effect. In these municipalities, a growing number of citizens' initiatives have emerged prior to construction, indicating that wind energy generation is expanding to less supportive areas with strong opposition. When examining those only visually exposed but without turbines in their municipal area, the negative effect increases, providing further evidence that lower participation leads to lower support for wind energy expansion.

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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. 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 that 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. It is well documented that people in urban centers tend to vote differently from rural areas (see e.g. Kenny and Luca, 2020, Scala and Johnson, 2017, MacLeod and Jones, 2018, Rodríguez-Pose, 2018). This phenomenon increases the relevance of the local effects of environmental policy. Douenne and Fabre (2022) argue that in several instances, people outside of big urban centers have to bear the brunt of the transition in energy and mobility, as evidenced by the *Gilets Jaunes* protests against a carbon tax in France in 2018/19. In a similar way, wind turbines are typically built in rural areas.

This paper deals with voters' reaction to the construction of a visible wind turbine in their proximity. In particular, we study whether a change in the general support for renewables is reflected in the pro-renewable Green party at the federal election after voters being visually exposed. In theory, wind turbines in people's vicinity might affect them through various negative or positive channels that include noise pollution, bird endangerment, visual intrusion of the landscape, but also active contribution towards a cleaner energy supply with potentially cheaper prices, windfall taxes from wind turbine construction, and/or jobs for locals (Wolsink, 2000, Liebe and Dobers, 2019, Diermann, 2023). It is thus an empirical questions, whether pro-renewable parties will lose local votes after the construction of a wind turbine. Previous papers from various settings around the world have yielded ambiguous results (see for example Urpelainen and Zhang, 2022, Stokes, 2016, Germeshausen et al., 2021, Otteni and Weisskircher, 2021).

Here, we provide new insight on this topic by estimating the effects of visible wind turbine construction on Green party voting behavior from 1998 to 2021. The new contribution of this paper is threefold:
(i) Combining municipal-level data on voting behavior over two decades with the precise location of each wind turbine, we have much more fine-grained data at our disposal than

previous studies.
(ii) We employ robust econometric methods. We address concerns that plague fixed effects estimations by working with difference-in-difference methods with different combinations of treatment and Control Groups, also accounting for the anticipation effect.
(iii) Crucially, we focus on visibility of a wind turbine from a settlement area rather than its mere presence. We are the first study to do so and can thus empirically elucidate an important channel through which wind turbines might affect residents' attitudes.

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). 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 in terms of analyzing the local political effects of building wind turbines: It has a Green party that has run on a strongly pro-environmental platform since its foundations in the 1980s, arguing 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. This mitigates concerns that the voting behavior might be dominated by other issues. Moreover, it allows us to use the vote share for the Green party as a proxy of support for renewable energy more broadly.

Our preliminary 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.

The remainder of this paper is organized as follows: In Section 2, we anchor our contribution in the literature. Section 3 provides an overview of the German wind power expansion and its geographical and temporal distribution. Section 4 gives insights in the construction of our data set, in the particular our calculation of wind turbine visibility from settlements. Section 5 contains a discussion of the econometric methods employed. In Section 6, we present and interpret our main results, whose implications we discuss in Section 8. Section 9 concludes.

2 Relation to the existing literature

Just as climate change and its mitigation measures have become increasingly important topics of the political debate in countries around the world, the environmental economics literature on people's support and attitudes has expanded. Understanding who supports and who opposes renewable energy projects under which circumstances is vital for policymakers designing such measures.

Recent research has examined the impact of climate-change mitigation measures in light of the broader background of political polarization and regional inequality in many industrialized countries. It is well-documented that people in big cities tend to vote differently from those in rural areas and that this so-call 'urban-rural political divide' has deepened in recent years, in particular since the Great Recession of 2008. In the U.S., the political divide between Democrat-leaning urban centers and Republican strongholds in the countryside has been analyzed extensively (e.g. McKee, 2008, Scala and Johnson, 2017). Strong geographical differences in voting behavior have also been studied in many European countries, including Britain (e.g. Jennings and Stoker, 2016, MacLeod and Jones, 2018), France (e.g. Ivaldi and Gombin, 2015, Agnew and Shin, 2020) and the meta-study by Kenny and Luca (2020). 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 as well as the shift towards greener energy (Rodríguez-Pose, 2018).

At the same time, Douenne and Fabre (2022) suggest that people outside of big urban centers may have to bear the brunt of the transition in energy and mobility. They point to the Gilets Jaunes protests that erupted in France in 2018/19 and were sparked by a carbon tax that threatened the purchasing power of people in rural areas, who are dependent on cars as means of transport. This concern for purchasing power went in line with an anti-elite sentiment, and Douenne and Fabre (2022) show that the protests shifted the public perception of the carbon tax as regressive and environmentally ineffective.

Wind energy generation also constitutes a vital feature of the transition to a carbon-free economy, but, just like carbon taxes, the construction of wind turbines does not affect every citizen equally. It is concentrated in rural areas. While it is important for politicians to obtain public support, the literature has so far yielded ambiguous and contradictory results about the impact of new wind turbines on election outcomes.

Theoretically, the reaction to the construction of wind turbines is not clear-cut and residents tend to be aware of advantages and disadvantages. Among the opponents, two groups are typically distinguished: 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, while 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 are empirically relevant (Liebe and Dobers, 2019, Wolsink, 2000). Often-cited negative effects include noise pollution and interference with natural areas (such as bird endangerment). Yet survey respondents' attitudes towards wind projects are most strongly shaped by their "perceived impact on scenery, visual intrusion of the landscape" (Wolsink, 2000, p.51). In line with these arguments, visibility of a wind turbine from urban settlements plays a key role in our analysis. On the positive side, wind turbines actively contribute towards a cleaner and more sustainable energy supply, potentially going in line with cheaper electricity, more tax revenue at the local level and new jobs. To what extent these benefits accrue not only at the global, but also at the local level, might depend on the circumstances. Diermann (2023) analyzes cheaper electricity prices offered by suppliers to local residents of German wind parks. Participation opportunities for citizens have also been found to matter for acceptance (Langer et al., 2017). Whenever longer time horizons are considered, self-selection as well as habituation may play a role: Hoen et al. (2019) find that Americans that live closer to wind turbines have more positive attitudes towards them, in contrast to the negative impacts of noise and visual dominance that increase with proximity.

Which effect dominates empirically and whether or not voters close to wind turbines change people's attitudes toward wind energy reflected in pro-climate parties vote share, is far from clear. The literature has found very heterogenous results so far.
On the positive end of results, Urpelainen and Zhang (2022) finds that one more megawatt of wind power capacity within U.S. Congressional districts in 2003 to 2012

has lead to a 0.03 percentage point increase in vote shares for the Democratic party. They suggest that policies might endogenously create their political support. Yet, U.S. Congressional districts are comparatively large and it is also conceivable that overall economic benefits at the aggregate might mask discontent of those living closest to the turbine. In fact, Stokes (2016) finds that proximity to turbines plays a crucial role in determining voting outcomes. She works with municipal-level data from Ontario, Canada, between 2006 and 2013, to show that voters tend to punish incumbents after the construction of a wind turbine with a decrease in vote share by 4-10%. A negative effect of incumbents' vote share at the local level is also found for Denmark from 2000 to 2019 by Larsen et al. (2021). The vote share decreases by 3.5% on average after a construction of a wind turbine, with the effects on local incumbents much larger than on national politicians.

For Germany, 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.

This wide heterogeneity of estimated effects might be due a number of factors, including different countries with different political systems and parties (that might be single-issue or broad parties), different time horizons (when climate change was a more or less dominant topic compared to other issues), different units of observations (at which the presence of a wind turbine might yield different effects), as well as the precise data and measurement. It is conceivable that the first wind turbine in a municipality has a different impact from adding one more to a large exiting wind park. Moreover, some studies focus on local elections in which voters might punish individual local politicians they hold accountable for the wind turbine construction, while voting for or against pro-climate parties at a higher political level might represent pro-renewable attitudes more broadly. Another contributing factor to the widely varying results might be different econometric methods. Two-way fixed effects is the typical panel data estimator (Otteni and Weisskircher, 2021); however, some studies employ instrumental variable techniques to contour the potential endogeneity of turbine location. These instruments can be wind speeds (Stokes, 2016) or expected revenues (Germeshausen et al., 2021).

In this paper, we seek to advance the literature in various respects. With a comprehensive approach, we aim to gain new insights as well as to reconcile previous results.

Focusing on Germany and its pro-renewable Green party, we work with fine-grained municipal-level data for local variation, but use a larger time span of elections reaching back several decades. Looking at federal election results, we abstract from political accountability at the local level, so that we can use the Green vote share as a proxy for pro-renewable support. From a NIMBY perspective, we can elucidate if people who voted for the Greens before - and thus conceivably supported renewable energy- , stop doing so after a wind turbine is constructed in their proximity.

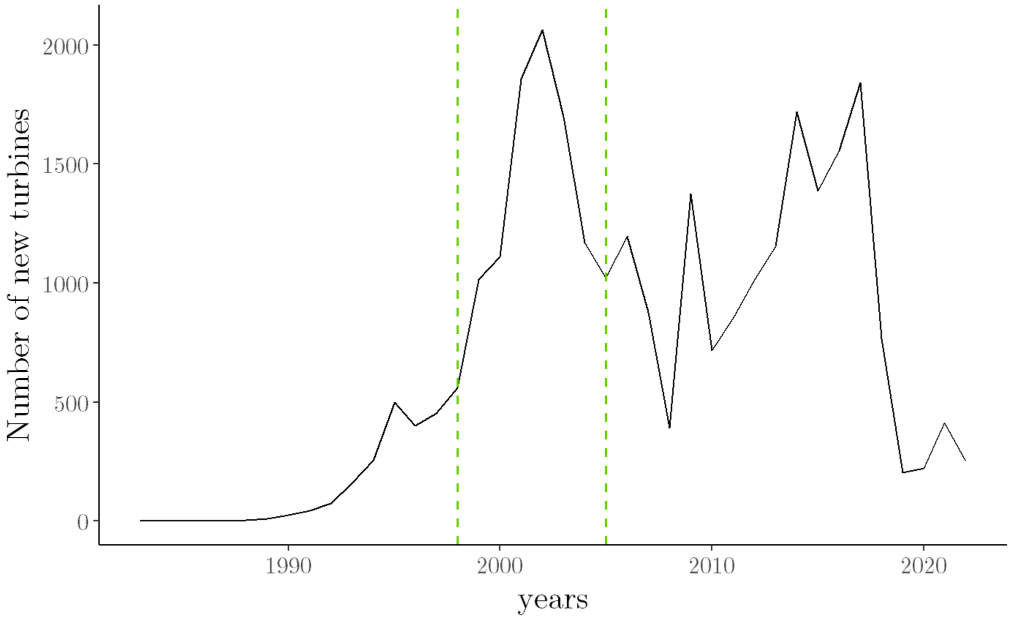
On the econometric side, we avoid the issues associated with the two-way fixed effects estimator in settings with multiple periods and treatment timings (Abraham and Sun, 2018) by estimating the effect for each group of municipalities treated at the same time separately. We also account for anticipation and inherent differences in municipalities by using as controls those units that get treated later on.

Finally and crucially, we exploit the precise location of wind turbines as well as settlements. Rather than taking the mere presence of a wind turbine in a municipality, we build on the survey literature that has highlighted both the proximity and the visibility of a turbine from the settlement as vital characteristics for shaping attitudes (Wolsink, 2000). 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 the vote-share of the Green party. Focusing on the visibility allows us to isolate one crucial channel of sensory perception.[1] 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 argument by Wolsink (2000) about respondents considering turbines as a 'visible intrusion into the landscape'. Studying to what extent people who voted for the Green party before stopped doing so after the construction of a visible wind turbine also allows us to study NIMBY effects. An analysis of the visibility feature on election outcome is, to the best of our knowledge, novel to the empirical literature.

[1]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.

3 The German wind turbine expansion

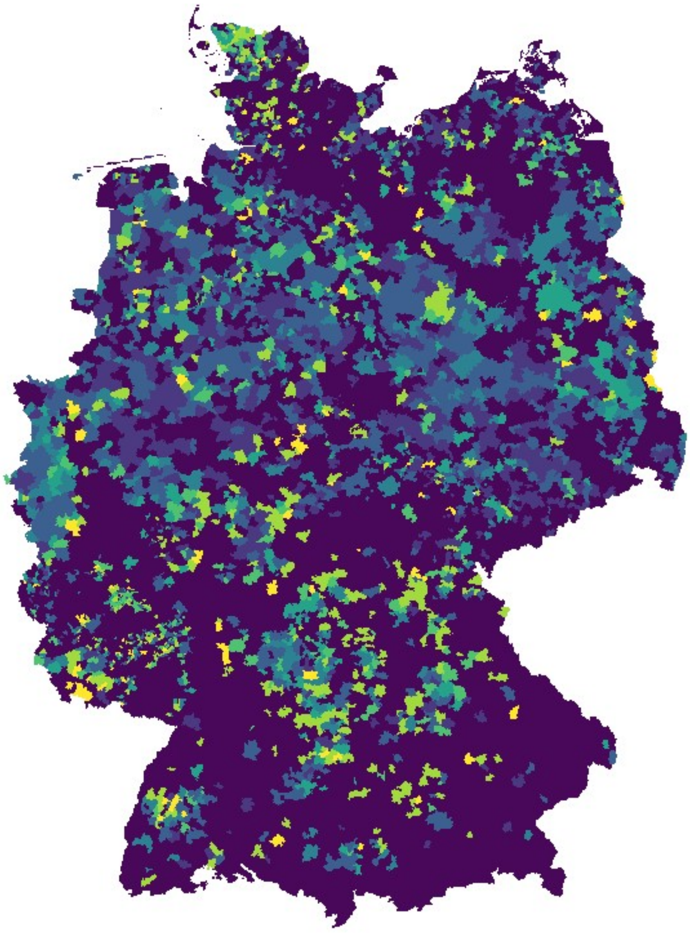
Figure 1 – Number of turbines installed over the years. The time frame marked by the green lines indicates the period during which the Green Party was involved in government



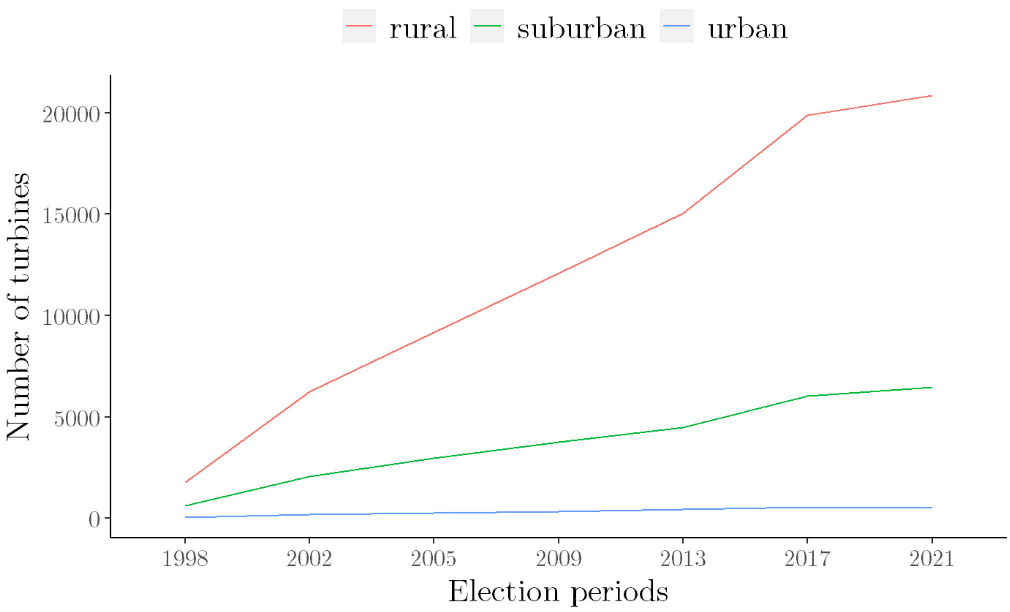
Whereas the expansion of wind energy in Germany already began in the late 1980s, it accelerated rapidly during the time the Green Party was part of the government from 1998 to 2005 (Figure 1). In 2000, the Renewable Energy Sources Act (EEG) was passed, introducing feed-in tariffs (i.e., a fixed price 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).

The map in Figure 2 visualizes in which election period the first wind turbine in each municipality was built. 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.

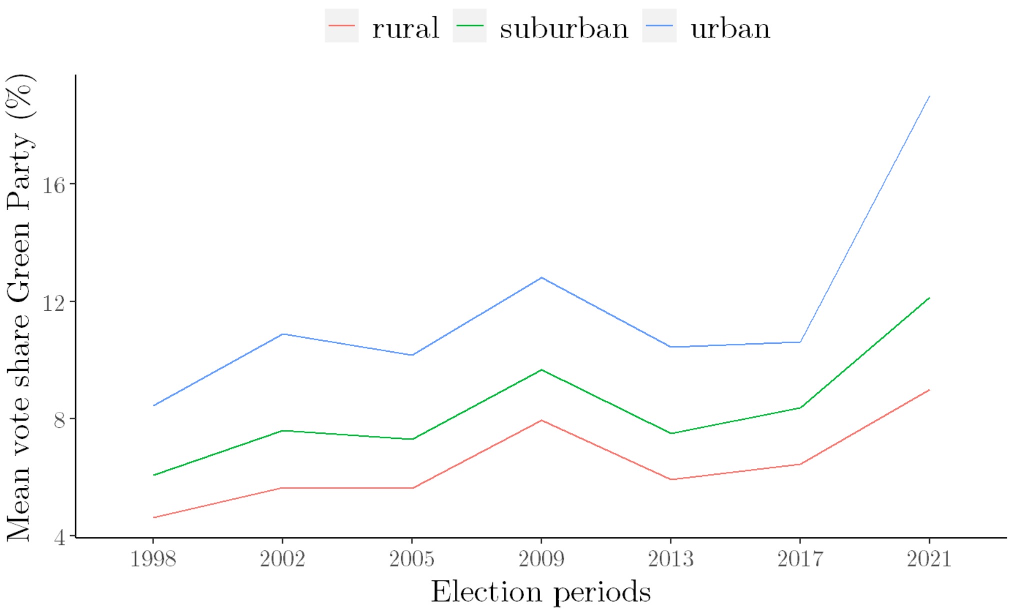
Figure 2 – Spatio-temporal distribution of municipalities where a turbine is installed for the first time. The dark blue areas are municipalities without turbines until the 2021 election period. The lighter the color, the later the first turbine was installed (yellow is the most recent 2021 election period).



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 3). This underlines the political revelance and brings up the question if the political divide might increase further if more even wind turbines are being constructed.



(a)



(b)

Figure 3 – Number of turbines constructed (a) and the vote share for the Green Party (b) in areas with different types of urbanization

4 Data Set Construction

4.1 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 broadly.[2] The official data on federal election results from 1998 to 2021 come from the Federal Returning Officer. Covariate data 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) . 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 has 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 publication by the Federal Returning Officer. We also exclude 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 adjusted dataset consists of a panel of 10,575 for the 1998 to 2017 election periods and 10,402 for 2021.

4.2 Wind Turbine Visibility

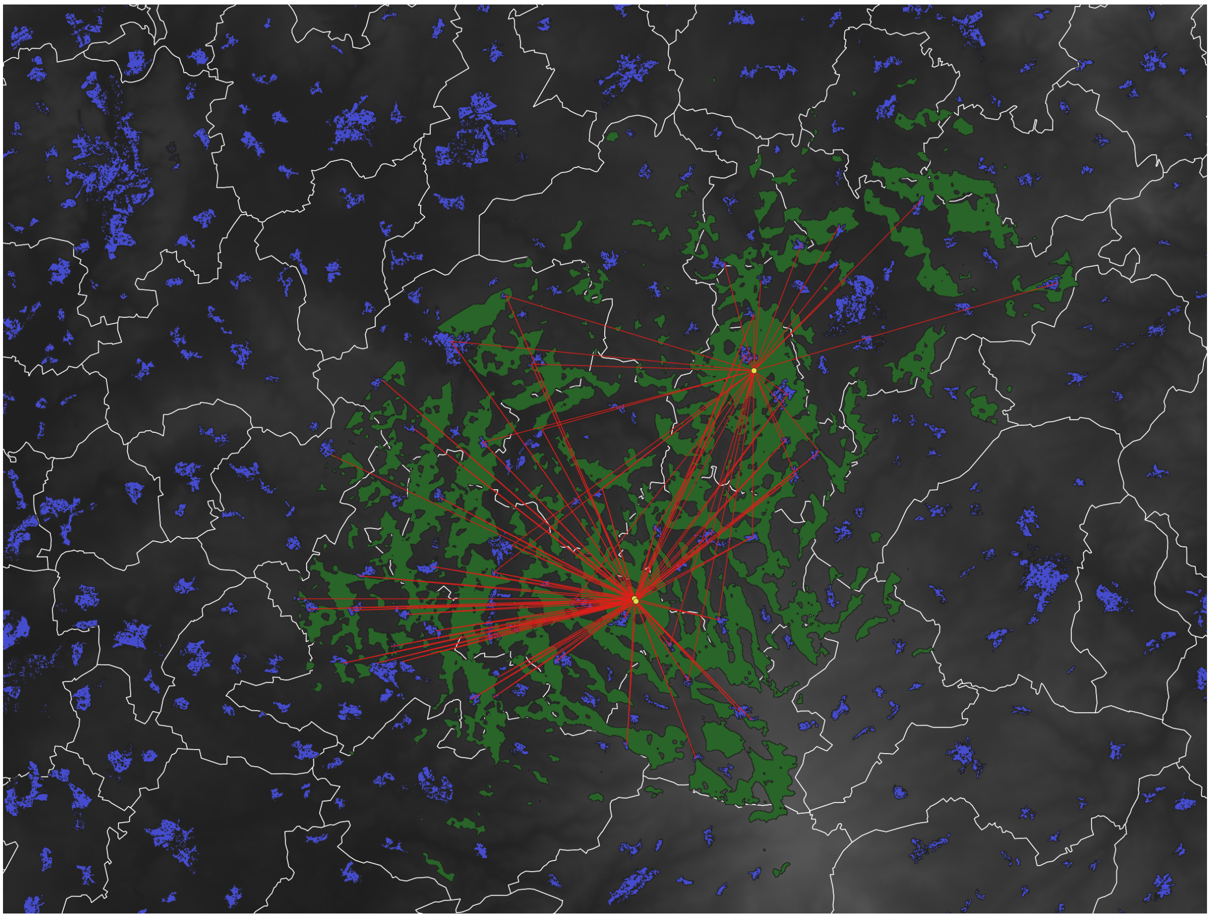
For our spatial analysis, we use fine-grained data on the position of wind turbines in Germany based on the federal network agencies data base adjusted by Eichhorn et al. (2019). We combine the geo-coded turbine data including their hub heights and construction dates with the digital surface model EU-DEM, 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. To further analyze the relationship between distance and voting responses, we also calculate the intervisibility distances, i.e., the distance between each settlement and the visible turbines.[3] Figure 4 visualizes the intervisibility network for turbines constructed within the 2013 election period (2010-2013) in Hesse. Each cell of the resulting viewshed grid represents the sum of visible turbines within a certain distance. Second, we superimpose

[2]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.

[3]The visible distance was calculated from the centroid of the settlement's visible part to the turbine.

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.

Figure 4 – 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



4.3 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 (Hobman et al., 2012, Horbaty et al., 2012, Gardt et al., 2021). Furthermore, they 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.[4] Overall, anti-wind initiatives have formed in nine percent of all municipalities in Germany. In those with wind turbines, the figure is over 15 percent, while it is only six percent across municipalities without 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 5.4.

5 Econometric Methods

Our empirical model is based on Difference-in-Difference, 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. Previous research (e.g. Otteni and Weisskircher, 2021) estimates the impact of this staggered treatment adaptation (i.e., the impact of building an additional turbine or the kW/hr generated by those turbines within the administrative boundary) on election outcomes using a two-way fixed effects (TWFE) model over multiple time periods and treatment timings. We use a similar approach, but estimate the effect separately for each group of municipalities visually exposed in the same election period, following a framework resembling the group-time average treatment effect proposed by Callaway and Sant'Anna (2021). From now on, we are referring to all municipalities first visually exposed in the same election period as a Timing Group g.[5] Since the data covers seven election periods in which all turbines were built, we have seven Timing Groups, for each of which we estimate the immediate effect on the results of the subsequent election.[6]

Analysing each Timing Group individually can reveal how voting responses might change over time. Furthermore, Goodman-Bacon (2021), Callaway and Sant'Anna (2021) and Abraham and Sun (2018) show that any TWFE model with multiple treatment timings can be decomposed into a weighted average of all possible 2x2 Difference-in-Difference (DiD) estimators in the panel. This implies that municipalities visually exposed in earlier election periods also serve as Control Groups for municipalities treated at a later time, while the weights of each 2x2 DiD estimator depend not only on the relative size of the Timing Groups, but also on the variation in the treatment variables. If the effects of wind turbines on election outcomes vary over time or are

[4] 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.

[5] 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 $g = 2009$.

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

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, but also quieter.

While Goodman-Bacon (2021), Callaway and Sant'Anna (2021) and Abraham and Sun (2018) consider the case of a binary treatment, these problems with staggered adoptions of the TWFE models also arise with a treatment with finite number of ordered values (De Chaisemartin and d'Haultfoeuille, 2020) or continuous treatment (Callaway et al., 2021). By comparing only the change in election outcomes between one pre-visible election period and one post-visible election period for each Timing Group separately, we avoid these potential problems of TWFE 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.

5.1 Treatment Groups

The treatment group in each election period (i.e., Timing Group) consists of municipalities visual exposed for the first time to turbines up to six kilometer, an estimated threshold distance for dominant visual impact (Breuner, 2001, CPRW, 1999). 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 in more than ten percent of residential areas. The distance at which a wind turbine is perceived as intrusive is subjective, so that a cut-off value cannot be clearly defined. To ensure that there is not yet an effect of turbines at a distance greater than 6 km in the pre-treatment period ($g-1$), we restrict the treatment group to municipalities with no visual exposure in their pre-treatment period up to a distance of 7 km, due to the ambiguity of the extent to which turbines have an effect in the buffer zone. In Section 7, we alter the distance to five and seven kilometer for robustness.
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 by turbines installed earlier (Figure A-2).

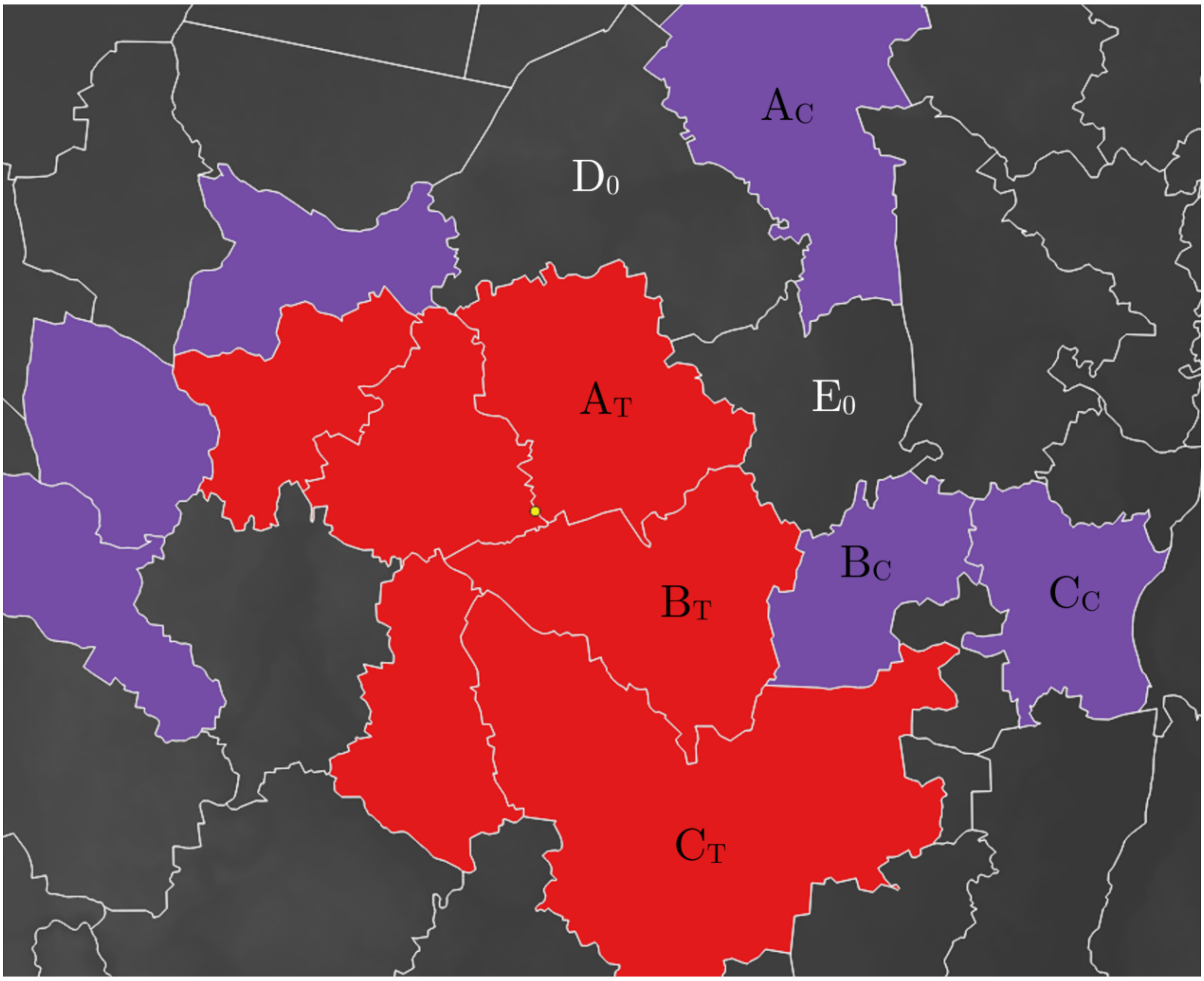
5.2 Control Groups

Similar municipalities that are geographically close to the treated ones, but have no turbines in sight, are used as a Control Group, up to a buffer distance of seven kilometer, again to avoid treatment spillover to turbines further away than the treatment threshold of six kilometer. If the change in vote share of the Control Group is equal to the counterfactual change in vote share of the treated group, we estimate the average effect of turbine visibility on support for renewable energy policies. 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. To do so, we iteratively match each visually exposed municipality to a control municipality that is geographically closest to the treated one within the same administrative level as those might share cultural, political and socioeconomic similarities (Tobler's first law of geography, Tobler (1970)). For each municipality in Timing Group g, we match a municipality in the same county that is not or not yet visually affected by wind turbines based on the smallest Euclidean distance between their centroids. We restrict the matching to pairs with the same urbanization status according to the DEGURBA classification since voters in urban and rural areas could have systematically different voting behavior regardless of their 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. If there is no control municipality in the same county and with the same urbanization status as the treatment municipality, we look for the closest municipality in the same federal state. 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.[7] Matching is done without replacement, meaning that each treated municipality in each Timing Group g is matched to an unique control municipality. If multiple treated municipalities have to same nearest neighbour, the one with the smallest euclidean distance is matched to the control one. Thus, the treatment group of each Timing Group has the same number of observation as its control group. Figure 5 illustrates this matching

[7] 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 influenced by the local candidate.

algorithm with an example.

Figure 5 – Example of the matching procedure in Bavaria with municipalities visually exposed (red) to a wind turbine (yellow) and control municipalities (purple): Treatment municipality A_T is matched with control municipality A_C since it is the closest municipality in the same county, has the same urbanization status, and is without anti-wind power initiatives in its territory. D_0 and E_0 are not considered due to visual exposure between 6 and 7 km, i.e., their residential areas are visually exposed within the buffer zone. For the two treatment municipalities B_T and C_T, B_C is the closest. Since B_T is closer to B_C than C_T is, B_T and B_C are matched, and C_T is paired with the second closest control municipality that meets all criteria (C_C).



Hence, municipalities j without visual exposure and citizen initiatives in both periods within the smallest administrative level possible, having the same degree of urbanization and the smallest euclidean distance to the treated municipality m are used as comparisons.

5.3 Baseline Model: Seen versus unseen

In the first specification, each Timing Group consists of all municipalities visually exposed for the first time, independent where the visible turbine is located. The binary treatment variable takes the value of one if turbines are seen for the first time in election period

$t = g$ in more than ten percent of the residential areas of municipality m within a radius of six kilometer:

$$D_{mt} = \begin{cases} 1 & \text{if } sharevisible_{mt} > 0.1 \\ 0 & otherwise \end{cases}$$

Hence, we compare the change in vote share before and after the visual exposure with the change of similar municipalities not visually exposed at time $t = g$, defined by eq. (1), with G indicating if the municipality belongs to Timing Group g and D_g an dummy indicator if a municipality is already treated at $t = g$.

$$ATT(g) = E[Y_g - Y_{g-1}, G = g, D_g = 1] - E[Y_g - Y_{g-1}, G \neq g, D_g = 0] \tag{1}$$

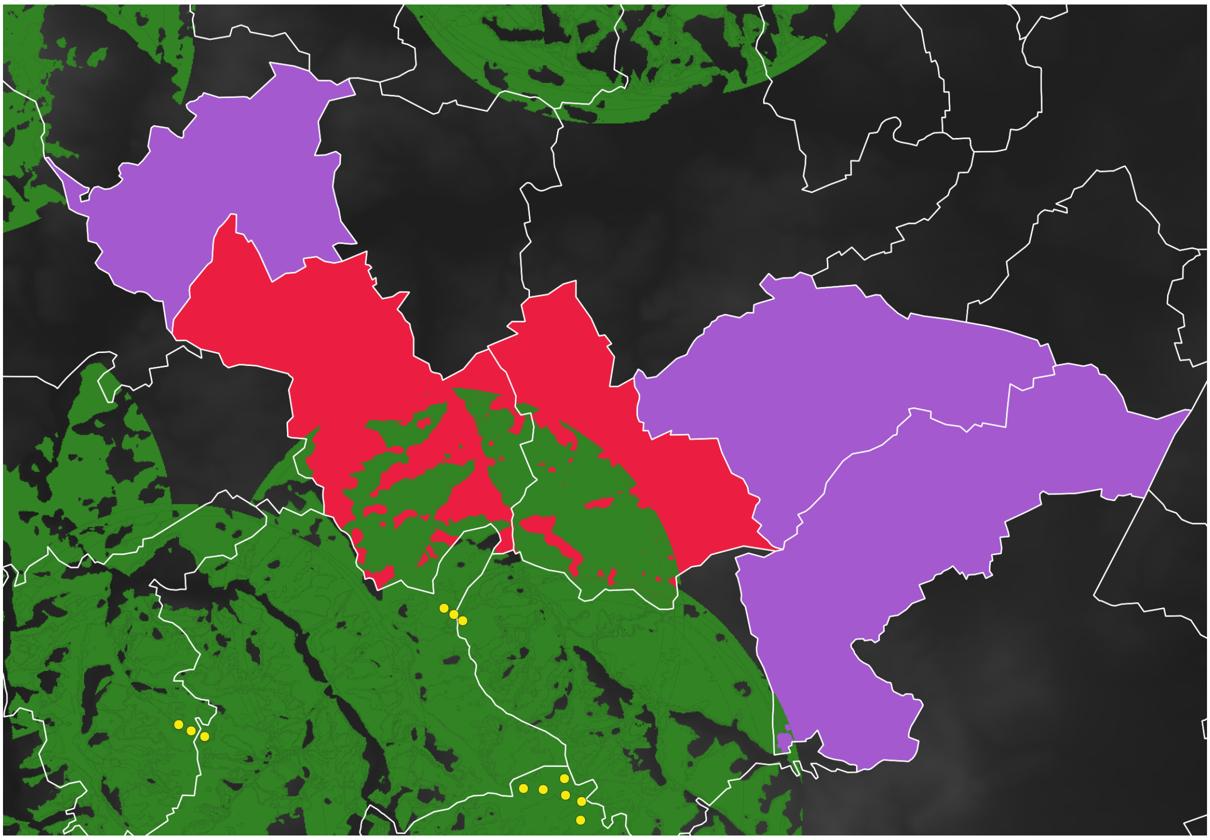
Assuming parallel trends and no anticipation, eq. (1) targets the average effect of visual exposure for municipalities seeing a turbine for the first time. While common pre-treatment outcomes are not necessary nor sufficient to provide evidence for post parallel trends (Kahn-Lang and Lang, 2020) it supports the assumption's plausibility. Figure A-5 plots the vote share for each Timing Group and its corresponding Control Group over time, supporting the assumption. Moreover, we shift the treatment timing for each Timing Group to all possible pre-treatment election periods and discuss and address the assumption of no anticipation in Section 7.

5.4 External Exposure Model: Inter-municipal visibility

The baseline specification is straightforward, yet one might be concerned about endogeneity 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. A potential negative effect for early Timing Groups could be masked by an opposite positive effect of higher support for these projects, resulting in small and insignificant estimates. In addition, there could be systematic heterogeneity in the effect due to differences in agreements with turbine operators, the municipal administration, and local residents. Jobert et al. (2007), Lienhoop (2018) or Schwarz (2020) suggest that participation plays a key role in how the local population perceives these projects. Municipal governments and community groups can involve them 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). If differences in participation determine both which municipalities receive a wind turbine and influences residents' attitudes, we face an issue of simultaneity. In addition, in some cases, citizens participate financially by lending land to turbine operators, paying reduced electricity tariffs, or join community energy cooperatives to participate in energy production themselves (Radtke et al., 2022).[8]

Finally, municipalities not only participate in site determination decisions but also reap some revenue in terms of trade taxes generated by wind turbines.[9] This increased revenue might play a role in public goods provision.

Figure 6 – 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. The lighter the background, the higher the elevation



In short, the placement of wind turbine in municipalities is not random and might go in line with varying agreements and/or benefits at the local level that shape residents' attitudes. Unfortunately, no such data is available on a nationwide scale so that we can control for it. Yet, to contour some of the unobserved heterogeneity and

[8]While financial participation is usually associated with an increase in acceptance, Cass et al. (2010) and Knauf (2022) suggest that people who generally oppose local wind turbine projects may perceive payments as a form of bribery.

[9]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, which they in turn are involved in developing. In addition to participating in siting decisions, municipalities can also participate financially. First, 70 percent of the trade tax revenue generated remains in the municipality where the wind turbine is located, which contributes to regional economic development and enhances the municipal budget, potentially increasing the level of public goods available to citizens. Municipalities can also become involved as energy providers by establishing municipal energy companies (so called "Stadtwerke") (Mez and Schneider, 2007), keeping the energy value chain in the municipality and thus increasing local participation.

potential endogeneity, we use the additional variation that wind turbines can be seen from municipalities without turbines themselves. It is conceivable that residents in adjacent municipalities which can also see the turbines have been less involved in the local administrative processes than the municipalities actually hosting a turbine. In the more restrictive External Exposure Model, we therefore limit 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 6). Although residents of adjacent municipalities may have some opportunities to participate in the form of agreements with the operator or administration of the municipality in which the facilities are located, their ability to participate is plausibly smaller. Thus, visual exposure of wind turbines is more random to people living in a municipality without such turbines than to those living in a municipality with turbines and the possibility of potential benefits such as financial participation and improved provision of public goods are limited. Consequently, wind turbines may be perceived more homogeneously in these externally exposed municipalities. For this model, we also inspect the election outcomes of both groups in the pre-treatment periods (Figure A-6) and shift the treatment timing to all possible $t < g$ pre-treatment election periods (Figure C-7).

5.5 Estimation

The ATT for both models and each Timing Group $g = 2002, ..., 2021$ is estimated via eq. (2) given by the slope parameter of the interaction of the treatment dummy D_{m_g} and $post_t$, a dummy whether the observation is in the pre- or post-treatment period. In order to make the parallel trend assumption more plausible, we also estimate the model with an inclusion of potential relevant socioeconomic covariates $X_{m_g t}$, controlling for the municipal population, the share of workers with a university degree, the distance to the nearest metropolis and the per person income tax revenue.

$$Y_{m_g t} = \eta(D_{m_g}) + \alpha(post_t) + \beta(D_{m_g} * post_t) + X'_{m_g t}\gamma + \epsilon_{m_g t} \tag{2}$$

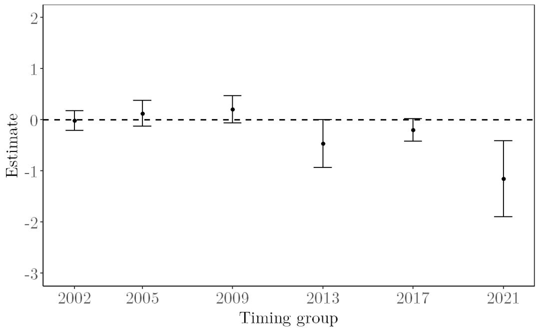
In this specification, β corresponds to the average effect of visual exposure on the election outcome for Timing Group g.

6 Preliminary Results

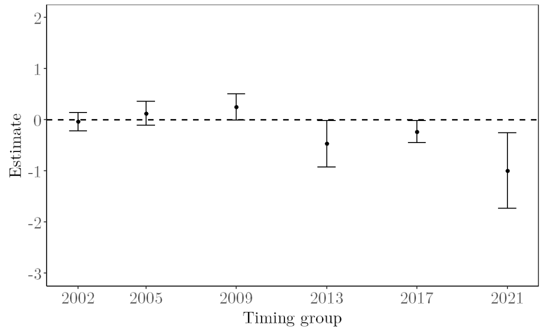
Figure 7 illustrate the estimates at a distance of six kilometer for the six Timing Groups (2002 to 2021). The estimated ATT suggest that the voting change after visual exposure from turbines has increased in magnitude over the last decades.

Figure 7 – Estimates for each Timing Group, 95 percent CI

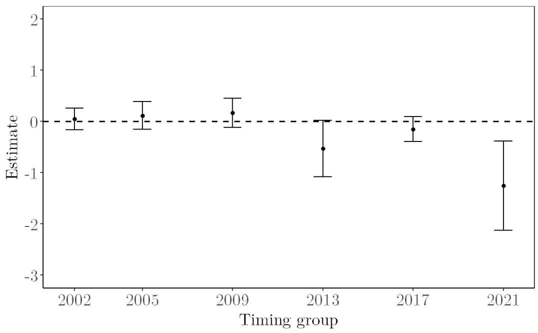
(a) Baseline Model with covariates



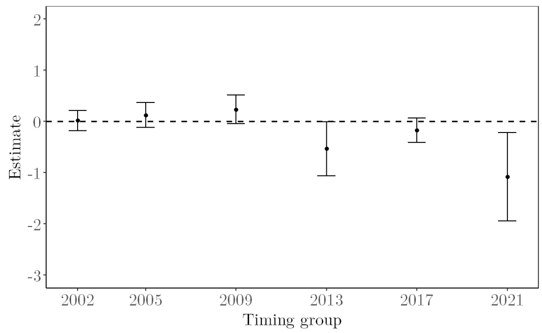
(b) Baseline Model without covariates



(c) External Model with covariates



(d) External Model without covariates



The point estimates are small in magnitude and insignificant for the first half of the sample period (1998, 2002, 2005) (Section B.1). Yet, visibility is associated with a significant decrease in Green party vote share for the municipalities first visually in the 2013, 2017 and 2021 election periods (Table 6), with the magnitude being particularly high in the most recent election.

While there is already a slightly negative trend in the 2013 and 2017 election periods, the estimated effects of the 2021 Timing Group are considerably higher, ranging from -1.0 to -1.2 percentage points, significant at the five percent level and at the one percent level when controlling for covariates.

The results for the External Exposure Model are similar, (**??**), but the magnitude of the effect for the 2021 Timing Group is stronger, with a decrease in Green Party vote share associated with the visual exposure of 1.3 percentage points and significant on a one percent level for the specification with covariates and a decrease of 1.1 percentage point without the inclusion, significant on a five percent level (**??**). The results are consistent with Jobert et al. (2007), Lienhoop (2018), or Schwarz (2020), as these municipalities are expected to have less opportunities to participate in the project, a critical factor for wind energy acceptance. As outlined in Section 5.4, the upward bias due to potential endogeneity may also be smaller, resulting in a slightly stronger negative effect. Interestingly, the coefficient on the 2009 Timing Group is positive and significant

Table 1 – Results 6km, 2021 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Baseline Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	1.5* (0.8)		1.8 (1.2)	
share university degree (%)	0.5*** (0.1)		0.6*** (0.1)	
log income tax revenue (PC)	2.8 (1.7)		2.0 (1.9)	
log population (N)	0.5* (0.3)		0.6* (0.3)	
post	2.0*** (0.6)	3.1*** (0.5)	1.8*** (0.5)	2.9*** (0.4)
visible	-0.4 (0.5)	-1.1** (0.5)	-0.4 (0.5)	-1.2** (0.6)
post × visible	-1.2*** (0.4)	-1.0** (0.4)	-1.3*** (0.4)	-1.1** (0.4)
Fit statistics				
Observations	200	200	148	148
R^2	0.51367	0.12710	0.53450	0.11729

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

at the ten percent level without controlling for covariates in the baseline model, possibly also reflecting this upward bias due to self-selection and unobserved heterogeneity. The estimates of the External Exposure Model for the 2009 Timing Group are not significant, supporting the notion that enogeneity is lowered. We discuss these dynamics in more detail in Section 7.3, where we correct for anticipation.

7 Robustness Tests

7.1 Alternative distance thresholds

One of the major threats to the validity of the results is the small number of municipalities in later Timing Groups, especially in the 2021 group. Also, the threshold distance of six kilometer is to some extent arbitrary. To increase the number of observations per group and to check how the estimations vary, we extend the distance threshold to seven kilometers. Furthermore, we decrease the distance to five kilometer while retaining the buffer zone between treated and control municipalities of one kilometer in all specifications. With a threshold distance of seven kilometer and a buffer up to eight kilometer, the effects are similar for most Timing Groups with a slightly smaller effect for the 2013 Timing Group and a higher one for the 2021 Timing Group (Table C.3). The effect for the 2017 Timing Group are insignificant. When decreasing the threshold to five kilometer, the effects are slightly stronger for the 2013 and 2021 Timing Group but also stay insignificant for the 2017 Timing Group.

7.2 Event study

To further test the assumption of a parallel trend, we perform a series of falsification tests by shifting the treatment time to all pre treatment election periods $t < g$ and also aggregating the results in event time, given by eq. (3), where e refers to event time and P refers to the relative group size of g. The results are not significant (Figure C-7) for most of the pre-treatment election periods, providing further evidence of unbiased estimation. For the 2013 Timing Group, we estimate a positive effect for one election prior to installation (i.e., 2009) that is significant at the 10 percent level, indicating a positive anticipation effect. Similar to the small but significant positive effects in some of the specifications for the 2009 Timing Group, the overall attitude toward wind energy in this election period appears to be quite positive among those visually exposed for the first time and in those municipalities where these installations were still in the planning phase. We discuss this positive effect further in the following Section 7.3.

$$\theta(e) = \sum_{g=2}^{T} 1\{g + e \leq T\} ATT(g, g+e) P(G_g = 1 | g + e \leq T) \tag{3}$$

7.3 Anticipation

In Germany, the duration of the planning and approval of a wind turbine is on average 4.75 years (FA Wind, 2015). These procedures include location assessments such as sound and shadow forecasts and public debates. Thus, voters might reveal their support or rejection at the ballot box before the turbine is commissioned at an earlier election period and therefore bias the estimates. To control for potential anticipation effects, we re-estimate the model by shifting the base pre-treatment period from $g - 1$ to $g - \delta - 1$ where δ represents the number of anticipation periods (eq. (4). An anticipation of one election period ($\delta = 1$) increases the difference between the pre-treatment election and the earliest date a turbine is constructed to four years which arguably should account for most of the anticipation effect. Although this relaxes the assumption of no anticipation, it also limits the number of Timing Groups for which we can estimate the response, since it is not possible to estimate the effect for the second Timing Group ($g = 2002$), given that voters in these municipalities already anticipate visual exposure or are already exposed to the construction site in the first election period, implying that there is no untreated period to compare to.

$$ATT(g, \delta) = E[Y_g - Y_{g-\delta-1}, G = g, D_{g+\delta} = 1] - E[Y_g - Y_{g-\delta-1}, G \neq g, D_{g+\delta} = 0] \quad (4)$$

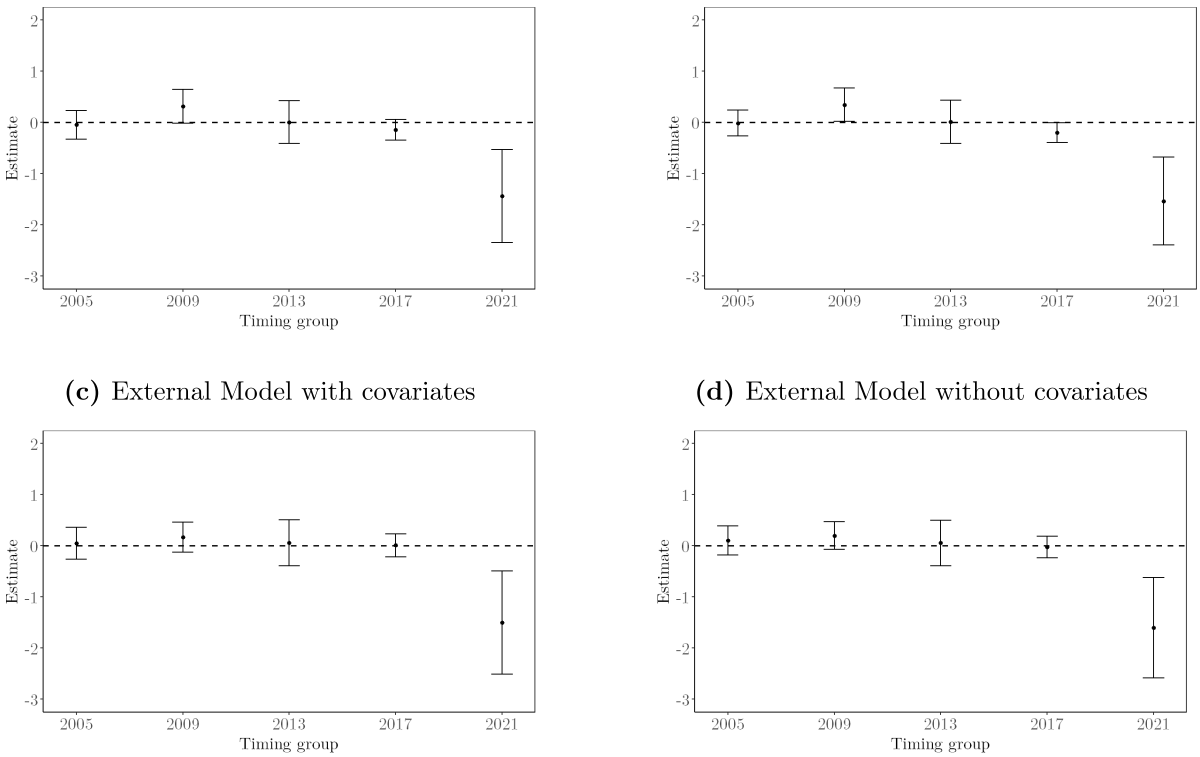
Figure 8 – Estimates (accounting for anticipation) for each Timing Group, 95 percent CI

(a) Baseline Model with covariates

(b) Baseline Model without covariates

(c) External Model with covariates

(d) External Model without covariates



The results when anticipation is taken into account (Figure 8, regression tables are in Section C.1) are similar to the main results for the 2021 time group and partially for the 2017 time group, while they are insignificant and small for the 2013 time group in most specifications. As we saw in the event study in Section 7.2, a positive anticipation effect was followed by a negative effect once the turbines were visible for the 2013 Timing Group. Thus, the negative effect for the 2013 election period in the main specification is largely explained by a prior positive anticipation effect. These projects may have been initially viewed positively because of potential environmental benefits and economic incentives presented during the planning and announcement phases. However, this positive perception may have waned once the wind turbines were installed. Once they are visible, residents are confronted with their impact on the surrounding landscape. Furthermore, these results may hint at insufficient community engagement during the planning phase, which may contribute to a change in perception. As discussed in

Section 5.4, residents may have felt they were not adequately consulted or involved in the decision-making process, making them more likely to oppose the project once it is visible from their neighborhood.

8 Interpretation and Discussion

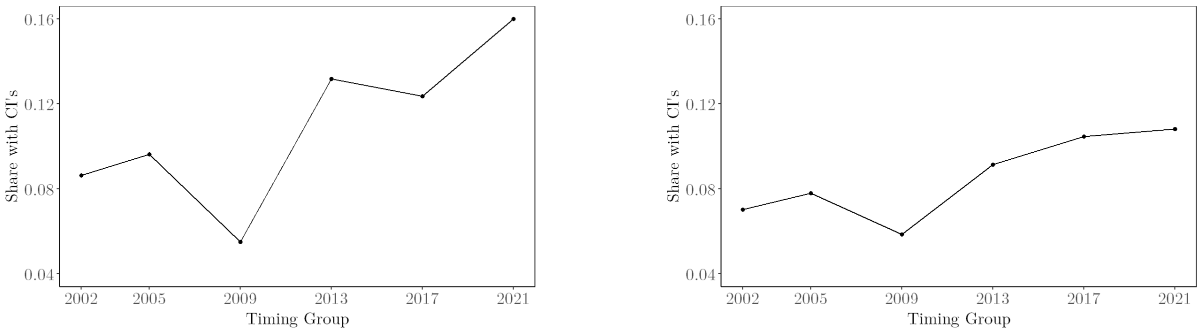
Our preliminary results suggest that building a wind turbine that is visible from a settlement does not come with strong negative impact on the Green party's local vote share in early election periods up to 2009, but the pattern has changed in more recent years. Voters now seem to react less favorably to the construction of wind turbines in their visible surroundings. Various factors might play a role in explaining this development.
First of all, wind turbines have already been built for many years in those regions which were geographically appropriate and where arguably local politicians as well as voters might have been more supportive. 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 that explain the varying effects over time. Moreover, this might be mirrored in the finding of Allcott (2015) 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.

The estimation results are also reflected in the number of citizens' initiatives that have emerged in later treated municipalities. Up to the 2009 Timing Group of the baseline model, the share of municipalities with reported citizens' initiatives is less than ten percent, after which it increases with each election, with over 15 percent of all municipalities having an initiative within their municipal boundaries in the 2021 time group (Figure 9). While the share of municipalities with an initiative is lower in the External Exposure Model municipalities, the share is also highest in the latest Timing Group. 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. Moreover, the small share of initiatives in the 2009 time group is additional evidence that there was indeed less political resistance in these municipalities, which may further explain the positive effect for some specifications.

Besides the effect of early and late adopters of wind energy generation, the public debate about climate action also plays a role. In the years up to the 2021 election, the

Figure 9 – Share of municipalities with a citizens' initiative per Timing Group

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



'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, gaining more prominence and fielding a candidate for chancellor for the first time.[10] Against the backdrop of this overall environmental agenda, the local effects of renewable energy propagation, namely the construction of wind turbines close the certain settlements, have been on more people's minds.

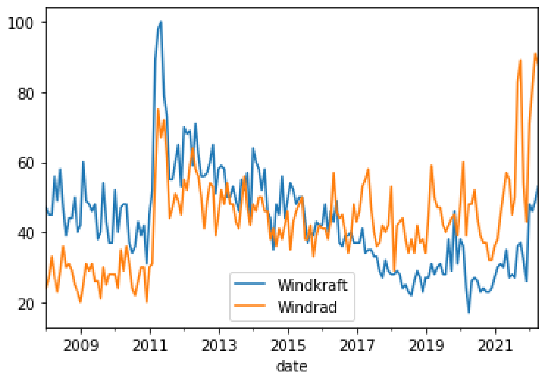
This is also illustrated by Google trends results of the German terms "Windkraft" ("Wind energy") and "Windrad" ("Wind turbine") from January 2008 to April 2022. Figure 10 shows that there is a notable jump in spring 2011 coinciding with the Fukushima nuclear disaster and the German government's decision to end the generation of nuclear energy. In the following years, fewer and fewer searches were conducted with the wind energy term as a concept, but more about wind turbines at the individual level. 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.

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 an indication that these municipalities may be less involved in the construction and operation of the turbines, which, as Jobert et al. (2007), Lienhoop (2018) or Schwarz (2020) has shown, may lead to lower acceptance of wind energy development. As a next step, we are investigating the owner structure of all installed turbines to get more information about who participates in the local projects.

One caveat of our study is that we cannot measure the potential wind energy benefits

[10] 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).

Figure 10 – Google trends search volumes for 'Windkraft' ('Wind energy') and 'Windrad' ('Wind turbine')



of local residents in the form of cheaper electricity. Depending on the wind turbine operator, some local households are eligible to cheaper electricity, with the details varying across Germany (Diermann, 2023). It would be interesting to see to what extent these monetary benefits influence the acceptance of wind turbines despite their visibility.

There are obviously other aspects to consider, as well as some more caveats. Crucially, our study only measures 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. On the other hand, this focus on the Green party brings with it the advantage of a clean identification. We might go as far as to suggest that strongly negative effect can be interpreted as NIMBY behavior: These are potential Green voters, hence those who are purportedly in favor of renewable energy, yet vote against the Greens once a visible wind turbine 'in their own backyard' is built.

9 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 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, which 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

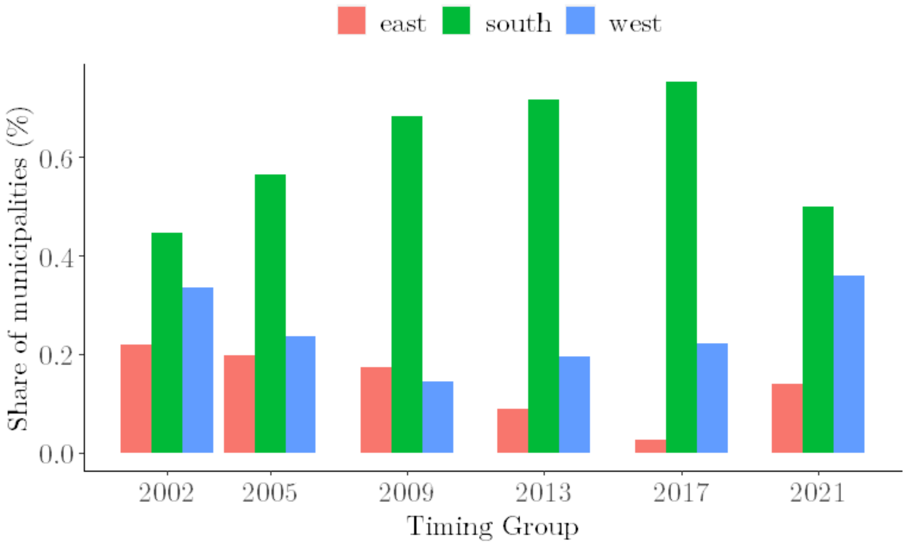


Figure A-2 – Number of municipalities per Timing Group first visually exposed up to a 6km

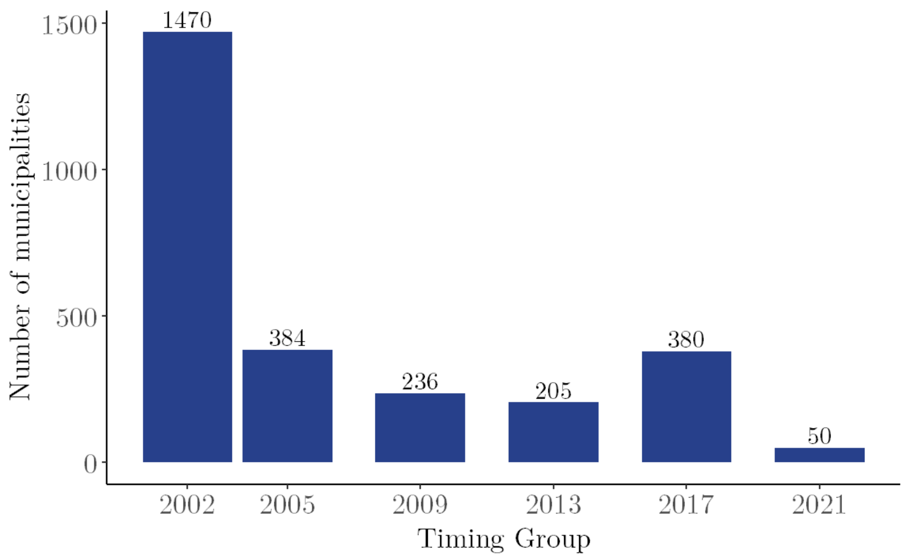


Figure A-3 – Mean distance to the closest visible turbine for each Timing Group

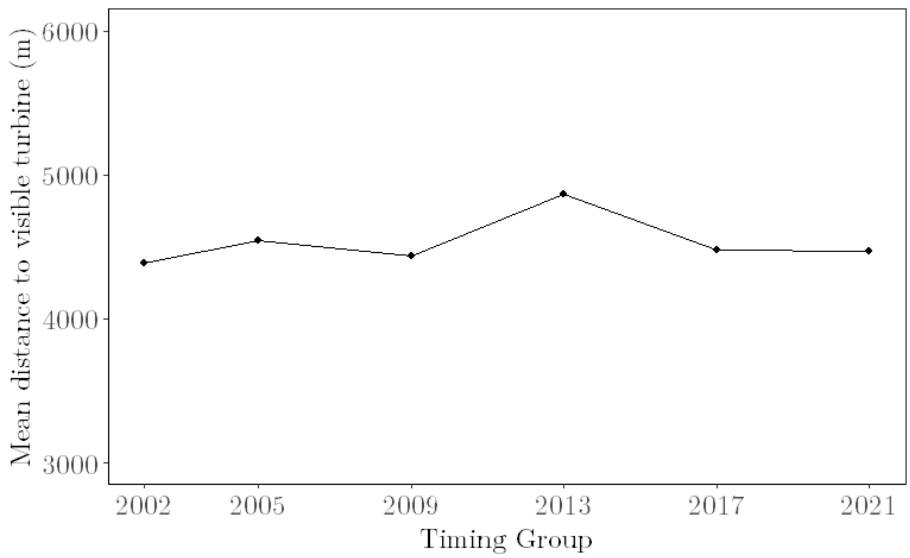
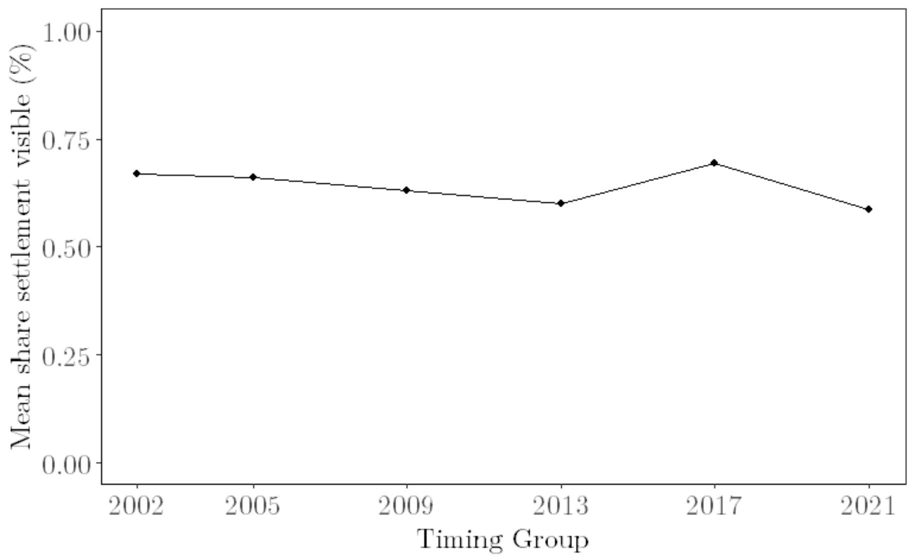


Figure A-4 – Mean share of the settlement area visually exposed for each Timing Group



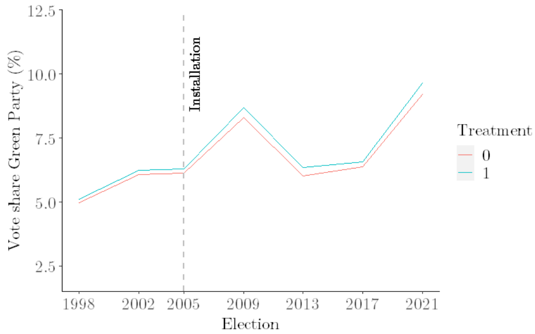
A.2 Parallel trends

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.

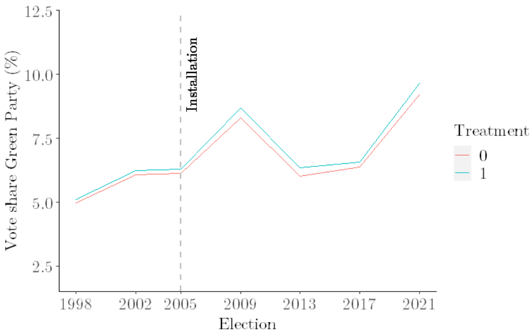
Figure A-5 – Baseline Model Green Party vote share

(a) 2002

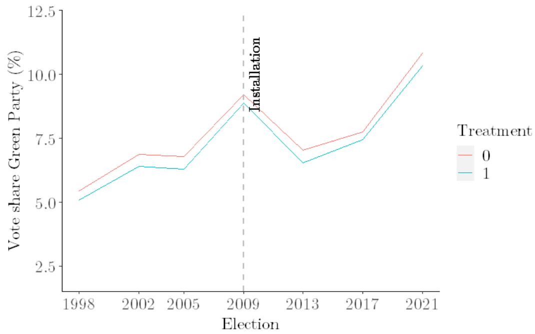
(b) 2005



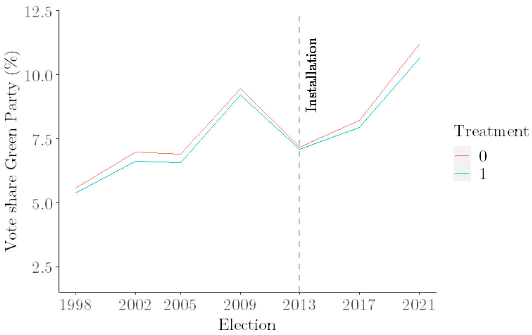
(c) 2009



(d) 2013



(e) 2017



(f) 2021

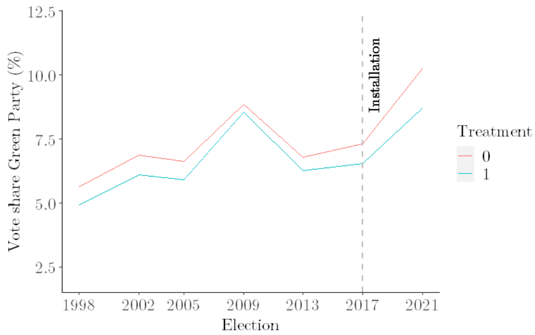
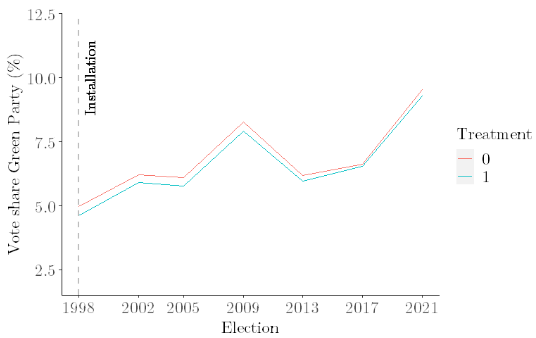
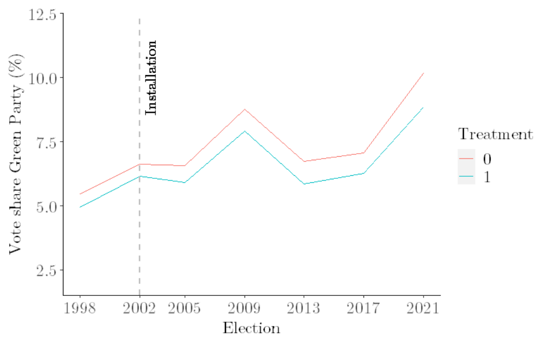


Figure A-6 – External Exposure Model Green Party vote share

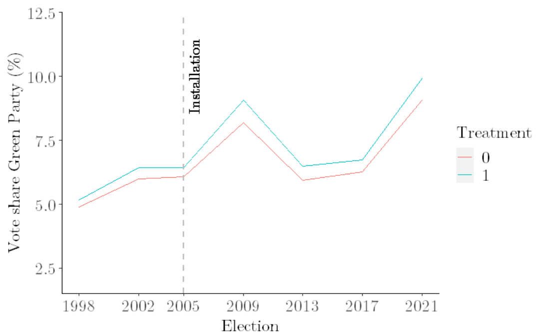
(a) 2002



(b) 2005



(c) 2009



(d) 2013

(e) 2017

(f) 2021

B Appendix: Additional Results

B.1 Estimation results for the 2002 to 2017 Timing Groups

Table B-1 – Results 6km, 2002 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Baseline Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	-0.3* (0.2)		-0.3 (0.2)	
share university degree (%)	0.2*** (0.05)		0.2*** (0.05)	
log income tax revenue (PC)	2.5*** (0.1)		2.5*** (0.1)	
log population (N)	-0.2*** (0.05)		-0.2*** (0.05)	
post	1.2*** (0.1)	1.3*** (0.1)	1.3*** (0.1)	1.3*** (0.1)
visible	-0.1 (0.1)	-0.2* (0.1)	-0.2 (0.1)	-0.2* (0.1)
post × visible	-0.02 (0.1)	-0.04 (0.09)	0.04 (0.1)	0.01 (0.1)
Fit statistics				
Observations	5,768	5,768	4,240	4,240
R^2	0.33761	0.05085	0.32812	0.05354

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table B-2 – Results 6km, 2005 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Baseline Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	-0.9 (0.6)		-0.9 (0.7)	
share university degree (%)	0.3*** (0.09)		0.2*** (0.09)	
log income tax revenue (PC)	3.2*** (0.4)		3.1*** (0.4)	
log population (N)	-0.1 (0.1)		-0.2 (0.1)	
post	-0.2* (0.1)	-0.2* (0.1)	-0.2 (0.1)	-0.2 (0.1)
visible	-0.3 (0.2)	-0.4 (0.2)	-0.2 (0.2)	-0.3 (0.2)
post × visible	0.1 (0.1)	0.1 (0.1)	0.1 (0.1)	0.1 (0.1)
Fit statistics				
Observations	1,536	1,536	1,232	1,232
R^2	0.35247	0.00265	0.33973	0.00136

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table B-3 – Results 6km, 2009 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Baseline Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	-0.1 (0.3)		0.006 (0.3)	
share university degree (%)	0.4*** (0.09)		0.4*** (0.1)	
log income tax revenue (PC)	3.7*** (0.3)		3.9*** (0.4)	
log population (N)	-0.3** (0.2)		-0.3* (0.2)	
post	0.5** (0.2)	2.1*** (0.2)	0.5* (0.3)	2.1*** (0.2)
visible	3×10^{-5} (0.2)	-0.08 (0.2)	-0.05 (0.2)	-0.1 (0.2)
post × visible	0.2 (0.1)	0.2* (0.1)	0.2 (0.1)	0.2 (0.1)
Fit statistics				
Observations	936	936	752	752
R^2	0.36517	0.10971	0.35680	0.10842

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table B-4 – Results 6km, 2013 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Baseline Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	-0.5 (0.6)		-0.6 (0.6)	
share university degree (%)	0.2** (0.1)		0.2** (0.1)	
log income tax revenue (PC)	3.4*** (0.6)		3.5*** (0.7)	
log population (N)	-0.2 (0.3)		-0.1 (0.3)	
post	-2.9*** (0.3)	-1.9*** (0.2)	-3.0*** (0.3)	-1.9*** (0.2)
visible	0.1 (0.3)	0.03 (0.3)	0.2 (0.3)	0.2 (0.3)
post × visible	-0.5* (0.2)	-0.5** (0.2)	-0.5* (0.3)	-0.5* (0.3)
Fit statistics				
Observations	820	820	656	656
R^2	0.30518	0.09596	0.30840	0.09911

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table B-5 – Results 6km, 2017 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Baseline Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	-0.08 (0.5)		-0.08 (0.6)	
share university degree (%)	0.3*** (0.05)		0.4*** (0.06)	
log income tax revenue (PC)	1.0** (0.4)		0.9* (0.4)	
log population (N)	0.1 (0.2)		0.1 (0.2)	
post	0.1 (0.2)	1.1*** (0.2)	0.06 (0.2)	1.1*** (0.2)
visible	0.02 (0.2)	-0.05 (0.2)	-0.1 (0.2)	-0.2 (0.2)
post × visible	-0.2* (0.1)	-0.2** (0.1)	-0.2 (0.1)	-0.2 (0.1)
Fit statistics				
Observations	1,516	1,516	1,108	1,108
R^2	0.19660	0.02338	0.21732	0.02257

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

C Appendix: Robustness Checks

C.1 Results accounting for anticipation

Table C-6 – Results 6km accounting for anticipation, 2005 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Base Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	-0.9 (0.6)		-0.9 (0.7)	
share university degree (%)	0.2*** (0.09)		0.2** (0.09)	
log income tax revenue (PC)	2.6*** (0.3)		2.5*** (0.3)	
log population (N)	-0.06 (0.1)		-0.1 (0.1)	
post	1.0*** (0.2)	1.0*** (0.1)	1.0*** (0.2)	1.0*** (0.1)
visible	-0.1 (0.2)	-0.2 (0.2)	-0.1 (0.2)	-0.2 (0.2)
post × visible	-0.05 (0.1)	-0.02 (0.1)	0.05 (0.2)	0.1 (0.1)
Fit statistics				
Observations	1,380	1,380	1,116	1,116
R^2	0.30462	0.02662	0.28854	0.02690

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-7 – Results 6km accounting for anticipation, 2009 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Base Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	-0.3 (0.3)		-0.2 (0.3)	
share university degree (%)	0.3*** (0.09)		0.4*** (0.1)	
log income tax revenue (PC)	3.8*** (0.4)		4.0*** (0.4)	
log population (N)	-0.4* (0.2)		-0.4* (0.2)	
post	0.4 (0.3)	2.1*** (0.2)	0.4 (0.3)	2.1*** (0.2)
visible	-0.1 (0.2)	-0.2 (0.2)	-0.2 (0.2)	-0.2 (0.2)
post × visible	0.3* (0.2)	0.3** (0.2)	0.2 (0.1)	0.2 (0.1)
Fit statistics				
Observations	844	844	672	672
R^2	0.37980	0.10487	0.36076	0.09691

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-8 – Results 6km accounting for anticipation, 2013 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Base Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	-0.8* (0.4)		-0.8** (0.4)	
share university degree (%)	0.3*** (0.07)		0.3*** (0.08)	
log income tax revenue (PC)	2.3*** (0.3)		2.2*** (0.4)	
log population (N)	-0.2 (0.3)		-0.1 (0.3)	
post	-1.5*** (0.3)	0.3 (0.2)	-1.5*** (0.3)	0.2 (0.2)
visible	-0.4* (0.2)	-0.5** (0.2)	-0.4* (0.2)	-0.5** (0.2)
post × visible	0.004 (0.2)	0.01 (0.2)	0.06 (0.2)	0.05 (0.2)
Fit statistics				
Observations	640	640	496	496
R^2	0.31408	0.00995	0.30399	0.00760

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-9 – Results 6km accounting for anticipation, 2017 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Base Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	-0.1 (0.6)		-0.2 (0.6)	
share university degree (%)	0.4*** (0.06)		0.4*** (0.06)	
log income tax revenue (PC)	1.0** (0.4)		0.9** (0.5)	
log population (N)	0.1 (0.2)		0.1 (0.2)	
post	-2.8*** (0.3)	-1.1*** (0.2)	-2.9*** (0.2)	-1.2*** (0.2)
visible	-0.01 (0.3)	-0.08 (0.3)	-0.3 (0.2)	-0.3 (0.2)
post × visible	-0.1 (0.1)	-0.2** (0.1)	0.006 (0.1)	-0.03 (0.1)
Fit statistics				
Observations	1,452	1,452	1,068	1,068
R^2	0.19726	0.02699	0.21885	0.02779

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-10 – Results 6km accounting for anticipation, 2021 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Base Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	1.1** (0.5)		1.2* (0.7)	
share university degree (%)	0.5*** (0.1)		0.5*** (0.1)	
log income tax revenue (PC)	5.0*** (0.8)		4.6*** (1.0)	
log population (N)	0.4** (0.2)		0.5*** (0.2)	
post	0.5 (0.8)	4.0*** (0.7)	0.5 (0.9)	3.9*** (0.7)
visible	-0.04 (0.4)	-0.5 (0.4)	-0.2 (0.4)	-0.7 (0.5)
post × visible	-1.4*** (0.5)	-1.5*** (0.4)	-1.5*** (0.5)	-1.6*** (0.5)
Fit statistics				
Observations	200	200	148	148
R^2	0.59906	0.18423	0.60361	0.18388

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

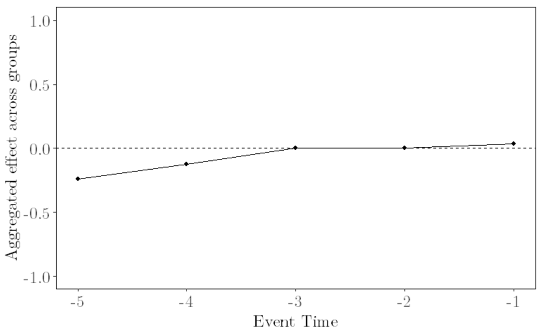
C.2 Event study

We shift the treatment timing to all possible pre-treatment election periods, and subsequently aggregate the data in event time. 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 a pre-treatment election period for any e < 0.

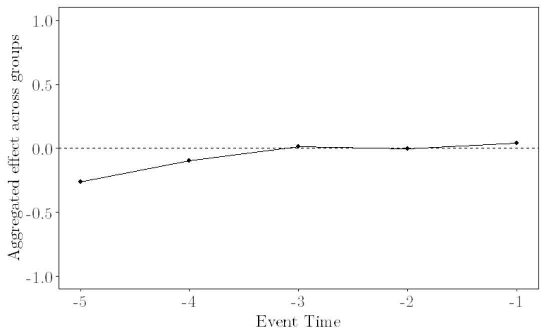
Figure **??** visualizes the aggregated (i.e., weighted averages) estimation results per event time. The tables below report all the results disaggregated.

Figure C-7 – Aggregated event study in event time

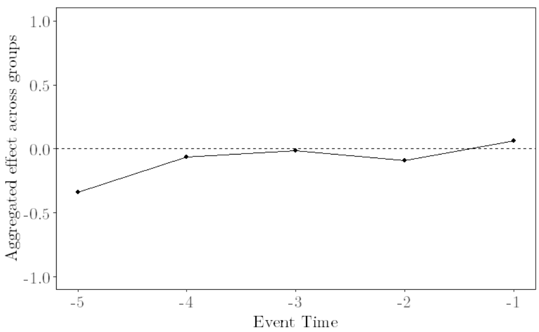
(a) Baseline Model with covariates



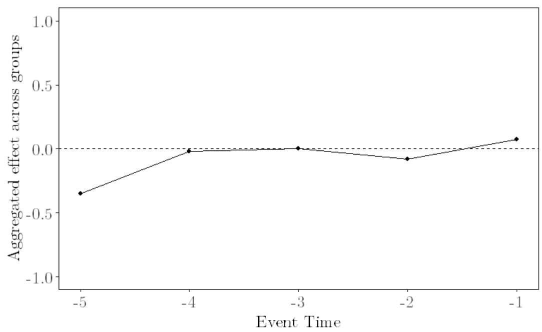
(b) Baseline Model without covariates



(c) External Exposure Model with covariates



(d) External Exposure Model without covariates



C.2.1 Event study results of the Baseline Model

Table C-11 – Event study results Baseline Model with covariates 6km, 2005 Timing Group

Dependent Variable:	vote share Green Party (%)	
	e = 0	e = -1
Model:	(1)	(2)
Variables		
Constant	-1.8	-1.9
	(6.1)	(5.8)
log distance large city	-0.9	-0.9
	(0.6)	(0.6)
share university degree (%)	0.3***	0.3***
	(0.09)	(0.08)
log income tax revenue (PC)	3.2***	3.0***
	(0.4)	(0.3)
log population (N)	-0.1	-0.1
	(0.1)	(0.1)
post	-0.2*	1.3***
	(0.1)	(0.1)
visible	-0.3	-0.1
	(0.2)	(0.2)
post × visible	0.1	-0.2
	(0.1)	(0.1)
Fit statistics		
Observations	1,536	1,536
R^2	0.35247	0.34003

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-12 – Event study results Baseline Model without covariates 6km, 2005 Timing Group

Dependent Variable:	vote share Green Party (%)	
	e = 0	e = -1
Model:	(1)	(2)
Variables		
Constant	6.7***	5.4***
	(0.4)	(0.3)
post	-0.2*	1.3***
	(0.1)	(0.1)
visible	-0.4	-0.2
	(0.2)	(0.2)
post × visible	0.1	-0.2
	(0.1)	(0.1)
Fit statistics		
Observations	1,536	1,536
R^2	0.00265	0.03368

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-13 – Event study results Baseline Model with covariates 6km, 2009 Timing Group

Dependent Variable:	vote share Green Party (%)		
	e = 0	e = -1	e = -2
Model:	(1)	(2)	(3)
Variables			
Constant	-11.9***	-5.3**	-2.2
	(3.5)	(2.5)	(2.9)
log distance large city	-0.1	-0.4*	-0.5**
	(0.3)	(0.2)	(0.2)
share university degree (%)	0.4***	0.3***	0.3***
	(0.09)	(0.08)	(0.08)
log income tax revenue (PC)	3.7***	3.0***	2.3***
	(0.3)	(0.3)	(0.3)
log population (N)	-0.3**	-0.3*	-0.2*
	(0.2)	(0.1)	(0.1)
post	0.5**	0.05	1.0***
	(0.2)	(0.1)	(0.1)
visible	3×10^{-5}	-0.05	-0.09
	(0.2)	(0.2)	(0.1)
post × visible	0.2	0.01	0.02
	(0.1)	(0.09)	(0.1)
Fit statistics			
Observations	936	932	932
R^2	0.36517	0.32252	0.28468

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-14 – Event study results Baseline Model without covariates 6km, 2009 Timing Group

Dependent Variable:	vote share Green Party (%)		
	e = 0	e = -1	e = -2
Model:	(1)	(2)	(3)
Variables			
Constant	6.2***	6.1***	5.0***
	(0.3)	(0.3)	(0.2)
post	2.1***	0.08	1.1***
	(0.2)	(0.1)	(0.1)
visible	-0.08	-0.1	-0.08
	(0.2)	(0.2)	(0.2)
post × visible	0.2*	0.02	-0.03
	(0.1)	(0.09)	(0.1)
Fit statistics			
Observations	936	932	932
R^2	0.10971	0.00060	0.04605

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-15 – Event study results Baseline Model with covariates 6km, 2013 Timing Group

Dependent Variable:	vote share Green Party (%)			
	e = 0	e = -1	e = -2	e = -3
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	-5.6	-0.7	8.5	7.8
	(9.3)	(8.3)	(7.2)	(6.2)
log distance large city	-0.5	-0.7	-1.2**	-1.1***
	(0.6)	(0.6)	(0.5)	(0.4)
share university degree (%)	0.2**	0.3***	0.3***	0.3**
	(0.1)	(0.1)	(0.1)	(0.1)
log income tax revenue (PC)	3.4***	2.5***	2.1***	1.7***
	(0.6)	(0.4)	(0.3)	(0.4)
log population (N)	-0.2	-0.2	-0.3	-0.3
	(0.3)	(0.2)	(0.2)	(0.2)
post	-2.9***	1.2***	-0.3	1.4***
	(0.3)	(0.3)	(0.2)	(0.2)
visible	0.1	-0.3	-0.2	-0.2
	(0.3)	(0.2)	(0.2)	(0.2)
post × visible	-0.5*	0.4*	-0.07	-0.03
	(0.2)	(0.2)	(0.1)	(0.1)
Fit statistics				
Observations	820	820	820	820
R^2	0.30518	0.34769	0.34441	0.35094

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-16 – Event study results Baseline Model without covariates 6km, 2013 Timing Group

Dependent Variable:	vote share Green Party (%)			
	e = 0	e = -1	e = -2	e = -3
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	9.1***	6.9***	7.1***	5.5***
	(0.6)	(0.4)	(0.5)	(0.3)
post	-1.9***	2.3***	-0.2	1.6***
	(0.2)	(0.3)	(0.2)	(0.2)
visible	0.03	-0.4*	-0.3	-0.2
	(0.3)	(0.2)	(0.2)	(0.2)
post $\times$ visible	-0.5**	0.4*	-0.05	-0.09
	(0.2)	(0.2)	(0.1)	(0.1)
Fit statistics				
Observations	820	820	820	820
R^2	0.09596	0.12758	0.00478	0.07562

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-17 – Event study results Baseline Model with covariates 6km, 2017 Timing Group

Dependent Variable:	vote share Green Party (%)				
	e = 0	e = -1	e = -2	e = -3	e = -4
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Constant	-1.4	-11.9**	-9.4*	-3.5	-0.8
	(6.7)	(5.9)	(5.0)	(4.7)	(4.7)
log distance large city	-0.08	0.04	-0.2	-0.6	-0.6*
	(0.5)	(0.5)	(0.4)	(0.4)	(0.4)
share university degree (%)	0.3***	0.3***	0.3***	0.4***	0.3***
	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)
log income tax revenue (PC)	1.0**	3.3***	3.0***	2.8***	2.1***
	(0.4)	(0.5)	(0.4)	(0.3)	(0.4)
log population (N)	0.1	-0.05	-0.1	-0.2	-0.1
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)
post	0.1	-3.2***	1.5***	-0.05	1.1***
	(0.2)	(0.2)	(0.2)	(0.1)	(0.2)
visible	0.02	-0.02	0.05	0.1	0.08
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)
post × visible	-0.2*	0.02	-0.05	-0.03	0.05
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Fit statistics					
Observations	1,516	1,516	1,516	1,512	1,512
R^2	0.19660	0.27770	0.33539	0.28027	0.27188

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-18 – Event study results Baseline Model without covariates 6km, 2017 Timing Group

Dependent Variable:	vote share Green Party (%)				
	e = 0	e = -1	e = -2	e = -3	e = -4
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Constant	7.2***	9.4***	6.8***	6.8***	5.5***
	(0.3)	(0.3)	(0.3)	(0.3)	(0.2)
post	1.1***	-2.2***	2.6***	-0.06	1.3***
	(0.2)	(0.1)	(0.1)	(0.09)	(0.2)
visible	-0.05	-0.07	-0.07	-0.02	-0.02
	(0.2)	(0.3)	(0.2)	(0.2)	(0.2)
post × visible	-0.2**	0.02	0.003	-0.02	0.007
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Fit statistics					
Observations	1,516	1,516	1,516	1,512	1,512
R^2	0.02338	0.10359	0.14106	0.00017	0.04854

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-19 – Event study results Baseline Model with covariates 6km, 2021 Timing Group

Dependent Variable:	vote share Green Party (%)					
	e = 0	e = -1	e = -2	e = -3	e = -4	e = -5
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	-34.1***	-25.7***	-25.7***	-16.9***	-11.4**	-15.8**
	(12.3)	(9.3)	(6.0)	(5.2)	(5.4)	(6.8)
log distance large city	1.5*	1.4**	1.0**	0.7	0.3	0.7
	(0.8)	(0.6)	(0.5)	(0.5)	(0.5)	(0.7)
share university degree (%)	0.5***	0.4***	0.4***	0.5***	0.5***	0.5***
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)
log income tax revenue (PC)	2.8	2.1	3.6***	2.3***	2.3***	2.5***
	(1.7)	(1.4)	(0.7)	(0.5)	(0.4)	(0.5)
log population (N)	0.5*	0.3	0.08	0.04	-0.06	-0.3
	(0.3)	(0.2)	(0.2)	(0.1)	(0.1)	(0.2)
post	2.0***	-0.4	-3.4***	1.1***	-0.6**	1.0**
	(0.6)	(0.4)	(0.4)	(0.4)	(0.3)	(0.4)
visible	-0.4	-0.2	-0.3	-0.3	-0.6*	-0.2
	(0.5)	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)
post × visible	-1.2***	-0.3	0.07	-0.01	0.3	-0.4
	(0.4)	(0.3)	(0.3)	(0.4)	(0.2)	(0.2)
Fit statistics						
Observations	200	200	200	200	200	200
R^2	0.51367	0.36716	0.45620	0.46292	0.41418	0.33258

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-20 – Event study results Baseline Model without covariates 6km, 2021 Timing Group

Dependent Variable:	vote share Green Party (%)					
	e = 0	e = -1	e = -2	e = -3	e = -4	e = -5
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	7.6***	6.7***	8.8***	6.5***	7.0***	5.8***
	(0.8)	(0.5)	(0.6)	(0.4)	(0.6)	(0.5)
post	3.1***	0.9**	-2.1***	2.3***	-0.5*	1.2***
	(0.5)	(0.4)	(0.2)	(0.3)	(0.2)	(0.4)
visible	-1.1**	-0.5	-0.5	-0.6	-0.9**	-0.6
	(0.5)	(0.4)	(0.5)	(0.4)	(0.4)	(0.4)
post × visible	-1.0**	-0.5*	0.02	0.06	0.3	-0.4
	(0.4)	(0.3)	(0.2)	(0.3)	(0.2)	(0.2)
Fit statistics						
Observations	200	200	200	200	200	200
R^2	0.12710	0.03017	0.12571	0.15627	0.02551	0.05030

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-21 – Event study results External Exposure Model with covariates 6km, 2005 Timing Group

Dependent Variable:	vote share Green Party (%)	
	e = 0	e = -1
Model:	(1)	(2)
Variables		
Constant	-0.9	-1.6
	(6.7)	(6.4)
log distance large city	-0.9	-0.8
	(0.7)	(0.7)
share university degree (%)	0.2***	0.2***
	(0.09)	(0.09)
log income tax revenue (PC)	3.1***	3.0***
	(0.4)	(0.3)
log population (N)	-0.2	-0.2
	(0.1)	(0.1)
post	-0.2	1.2***
	(0.1)	(0.1)
visible	-0.2	-0.1
	(0.2)	(0.2)
post × visible	0.1	-0.09
	(0.1)	(0.1)
Fit statistics		
Observations	1,232	1,232
R^2	0.33973	0.32956

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

C.2.2 Event study results of the External Exposure Model

Table C-22 – Event study results External Exposure Model without covariates 6km, 2005 Timing Group

Dependent Variable:	vote share Green Party (%)	
	e = 0	e = -1
Model:	(1)	(2)
Variables		
Constant	6.6***	5.4***
	(0.4)	(0.3)
post	-0.2	1.2***
	(0.1)	(0.1)
visible	-0.3	-0.2
	(0.2)	(0.2)
post × visible	0.1	-0.07
	(0.1)	(0.1)
Fit statistics		
Observations	1,232	1,232
R^2	0.00136	0.03197

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-23 – Event study results External Exposure Model with covariates 6km, 2009 Timing Group

Dependent Variable:	vote share Green Party (%)		
	e = 0	e = -1	e = -2
Model:	(1)	(2)	(3)
Variables			
Constant	-14.2***	-6.0**	-2.2
	(4.2)	(3.0)	(3.5)
log distance large city	0.006	-0.3	-0.4*
	(0.3)	(0.2)	(0.2)
share university degree (%)	0.4***	0.3***	0.2**
	(0.1)	(0.1)	(0.1)
log income tax revenue (PC)	3.9***	3.0***	2.2***
	(0.4)	(0.3)	(0.4)
log population (N)	-0.3*	-0.3*	-0.2*
	(0.2)	(0.2)	(0.1)
post	0.5*	0.02	1.0***
	(0.3)	(0.2)	(0.2)
visible	-0.05	-0.09	-0.2
	(0.2)	(0.2)	(0.2)
post × visible	0.2	-0.01	0.07
	(0.1)	(0.1)	(0.2)
Fit statistics			
Observations	752	748	748
R^2	0.35680	0.29795	0.25574

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-24 – Event study results External Exposure Model without covariates 6km, 2009 Timing Group

Dependent Variable:	vote share Green Party (%)		
	e = 0	e = -1	e = -2
Model:	(1)	(2)	(3)
Variables			
Constant	6.2***	6.2***	5.0***
	(0.3)	(0.3)	(0.2)
post	2.1***	0.07	1.2***
	(0.2)	(0.1)	(0.2)
visible	-0.1	-0.1	-0.1
	(0.2)	(0.2)	(0.2)
post × visible	0.2	-0.01	0.006
	(0.1)	(0.1)	(0.2)
Fit statistics			
Observations	752	748	748
R^2	0.10842	0.00053	0.04646

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-25 – Event study results External Exposure Model with covariates 6km, 2013 Timing Group

Dependent Variable:	vote share Green Party (%)			
	e = 0	e = -1	e = -2	e = -3
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	-6.0	1.0	9.8	8.9
	(9.1)	(8.5)	(7.5)	(6.3)
log distance large city	-0.6	-0.8	-1.3**	-1.2**
	(0.6)	(0.6)	(0.5)	(0.4)
share university degree (%)	0.2**	0.3***	0.3**	0.3**
	(0.1)	(0.1)	(0.1)	(0.1)
log income tax revenue (PC)	3.5***	2.4***	1.9***	1.6***
	(0.7)	(0.4)	(0.3)	(0.4)
log population (N)	-0.1	-0.2	-0.3	-0.2
	(0.3)	(0.3)	(0.2)	(0.2)
post	-3.0***	1.2***	-0.3	1.4***
	(0.3)	(0.4)	(0.2)	(0.2)
visible	0.2	-0.3	-0.2	-0.2
	(0.3)	(0.2)	(0.2)	(0.2)
post × visible	-0.5*	0.5*	-0.07	0.04
	(0.3)	(0.2)	(0.1)	(0.1)
Fit statistics				
Observations	656	656	656	656
R^2	0.30840	0.32923	0.31325	0.32670

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-26 – Event study results External Exposure Model without covariates 6km, 2013 Timing Group

Dependent Variable:	vote share Green Party (%)			
	e = 0	e = -1	e = -2	e = -3
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	9.2***	7.0***	7.2***	5.6***
	(0.6)	(0.4)	(0.5)	(0.3)
post	-1.9***	2.2***	-0.2	1.6***
	(0.2)	(0.3)	(0.2)	(0.2)
visible	0.2	-0.3	-0.2	-0.2
	(0.3)	(0.2)	(0.2)	(0.2)
post × visible	-0.5*	0.5**	-0.04	-0.02
	(0.3)	(0.2)	(0.1)	(0.1)
Fit statistics				
Observations	656	656	656	656
R^2	0.09911	0.12446	0.00415	0.08165

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-27 – Event study results External Exposure Model with covariates 6km, 2017 Timing Group

Dependent Variable:	vote share Green Party (%)				
	e = 0	e = -1	e = -2	e = -3	e = -4
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Constant	-0.9	-9.1	-7.3	-2.0	0.9
	(7.3)	(6.5)	(5.3)	(5.1)	(5.1)
log distance large city	-0.08	-0.03	-0.3	-0.7	-0.7*
	(0.6)	(0.5)	(0.5)	(0.5)	(0.4)
share university degree (%)	0.4***	0.3***	0.4***	0.4***	0.4***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
log income tax revenue (PC)	0.9*	2.9***	2.8***	2.8***	1.9***
	(0.4)	(0.6)	(0.4)	(0.3)	(0.5)
log population (N)	0.1	-0.05	-0.1	-0.2	-0.1
	(0.2)	(0.2)	(0.2)	(0.2)	(0.1)
post	0.06	-3.2***	1.4***	-0.04	1.1***
	(0.2)	(0.2)	(0.2)	(0.1)	(0.2)
visible	-0.1	-0.2	-0.1	0.07	-0.01
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)
post × visible	-0.2	0.1	-0.1	-0.1	0.07
	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)
Fit statistics					
Observations	1,108	1,108	1,108	1,104	1,104
R^2	0.21732	0.28241	0.33766	0.28816	0.27761

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-28 – Event study results External Exposure Model without covariates 6km, 2017 Timing Group

Dependent Variable:	vote share Green Party (%)				
	e = 0	e = -1	e = -2	e = -3	e = -4
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Constant	7.2***	9.4***	6.9***	6.9***	5.6***
	(0.3)	(0.4)	(0.3)	(0.3)	(0.2)
post	1.1***	-2.2***	2.5***	-0.02	1.4***
	(0.2)	(0.1)	(0.1)	(0.1)	(0.2)
visible	-0.2	-0.3	-0.2	-0.05	-0.08
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)
post × visible	-0.2	0.1	-0.07	-0.1	0.03
	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)
Fit statistics					
Observations	1,108	1,108	1,108	1,104	1,104
R^2	0.02257	0.09925	0.12467	0.00055	0.05069

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-29 – Event study results External Exposure Model with covariates 6km, 2021 Timing Group

Dependent Variable:	vote share Green Party (%)					
	e = 0	e = -1	e = -2	e = -3	e = -4	e = -5
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	-34.5**	-26.0**	-25.7***	-16.6**	-13.1*	-20.8**
	(13.2)	(10.3)	(6.7)	(6.1)	(6.5)	(9.0)
log distance large city	1.8	1.6	0.9	0.5	0.4	1.1
	(1.2)	(1.0)	(0.7)	(0.7)	(0.7)	(1.0)
share university degree (%)	0.6***	0.5***	0.4***	0.6***	0.6***	0.6***
	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)	(0.2)
log income tax revenue (PC)	2.0	1.7	3.7***	2.4***	2.4***	2.7***
	(1.9)	(1.6)	(0.8)	(0.6)	(0.4)	(0.6)
log population (N)	0.6*	0.3	0.1	0.1	-0.05	-0.4**
	(0.3)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)
post	1.8***	-0.4	-3.5***	1.0**	-0.7**	1.1*
	(0.5)	(0.6)	(0.4)	(0.4)	(0.3)	(0.5)
visible	-0.4	-0.3	-0.4	-0.5	-0.8*	-0.2
	(0.5)	(0.4)	(0.4)	(0.5)	(0.5)	(0.4)
post × visible	-1.3***	-0.3	0.02	0.06	0.3	-0.6*
	(0.4)	(0.4)	(0.3)	(0.4)	(0.3)	(0.3)
Fit statistics						
Observations	148	148	148	148	148	148
R^2	0.53450	0.37717	0.44108	0.44503	0.39842	0.32830

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-30 – Event study results External Exposure Model without covariates 6km, 2021 Timing Group

Dependent Variable:	vote share Green Party (%)					
	e = 0	e = -1	e = -2	e = -3	e = -4	e = -5
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	7.6***	6.6***	8.7***	6.5***	7.0***	5.8***
	(0.9)	(0.5)	(0.7)	(0.5)	(0.6)	(0.6)
post	2.9***	1.0*	-2.1***	2.2***	-0.6*	1.2**
	(0.4)	(0.6)	(0.3)	(0.3)	(0.3)	(0.5)
visible	-1.2**	-0.7	-0.6	-0.8	-1.2**	-0.6
	(0.6)	(0.5)	(0.5)	(0.6)	(0.5)	(0.5)
post × visible	-1.1**	-0.5	-0.04	0.2	0.3	-0.6*
	(0.4)	(0.4)	(0.3)	(0.4)	(0.3)	(0.3)
Fit statistics						
Observations	148	148	148	148	148	148
R^2	0.11729	0.03618	0.12624	0.15114	0.03915	0.04576

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

C.3 Estimation results with the alternative maximum distance of 7 km

Table C-31 – Results 7km, 2002 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Baseline Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	-0.4* (0.2)		-0.3 (0.2)	
share university degree (%)	0.3*** (0.05)		0.2*** (0.05)	
log income tax revenue (PC)	2.6*** (0.1)		2.5*** (0.1)	
log population (N)	-0.2*** (0.06)		-0.2*** (0.06)	
post	1.3*** (0.1)	1.3*** (0.1)	1.3*** (0.1)	1.3*** (0.1)
visible	-0.1 (0.1)	-0.2* (0.1)	-0.08 (0.1)	-0.2 (0.1)
post × visible	-0.06 (0.1)	-0.09 (0.09)	-0.008 (0.1)	-0.04 (0.1)
Fit statistics				
Observations	6,328	6,328	4,928	4,928
R^2	0.32353	0.05093	0.31352	0.05369

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-32 – Results 7km, 2005 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Baseline Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	-1.1 (0.7)		-1.1 (0.8)	
share university degree (%)	0.3*** (0.08)		0.2** (0.08)	
log income tax revenue (PC)	3.2*** (0.4)		3.1*** (0.4)	
log population (N)	-0.07 (0.1)		-0.1 (0.1)	
post	-0.2* (0.1)	-0.2* (0.1)	-0.2 (0.1)	-0.2 (0.1)
visible	-0.4* (0.2)	-0.4* (0.2)	-0.3 (0.2)	-0.3 (0.2)
post × visible	0.1 (0.1)	0.1 (0.1)	0.1 (0.1)	0.1 (0.1)
Fit statistics				
Observations	1,616	1,616	1,348	1,348
R^2	0.32822	0.00327	0.32015	0.00157

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-33 – Results 7km, 2009 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Baseline Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	-0.5 (0.4)		-0.5 (0.4)	
share university degree (%)	0.3*** (0.08)		0.3*** (0.1)	
log income tax revenue (PC)	3.6*** (0.3)		3.7*** (0.4)	
log population (N)	-0.3* (0.2)		-0.3* (0.1)	
post	0.5* (0.2)	2.0*** (0.2)	0.5 (0.3)	2.0*** (0.2)
visible	-0.05 (0.2)	-0.1 (0.2)	-0.05 (0.2)	-0.1 (0.3)
post × visible	0.2 (0.2)	0.3 (0.2)	0.3 (0.2)	0.4* (0.2)
Fit statistics				
Observations	908	908	764	764
R^2	0.38051	0.10068	0.37648	0.10750

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-34 – Results 7km, 2013 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Baseline Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	-0.6 (0.6)		-0.7 (0.6)	
share university degree (%)	0.3*** (0.08)		0.3*** (0.08)	
log income tax revenue (PC)	4.0*** (0.5)		4.1*** (0.5)	
log population (N)	-0.2 (0.3)		-0.2 (0.3)	
post	-3.2*** (0.2)	-2.0*** (0.1)	-3.2*** (0.3)	-2.0*** (0.2)
visible	-0.05 (0.2)	-0.09 (0.3)	-0.07 (0.3)	-0.06 (0.3)
post × visible	-0.3** (0.1)	-0.3* (0.1)	-0.4* (0.2)	-0.3* (0.2)
Fit statistics				
Observations	828	828	680	680
R^2	0.40735	0.09650	0.40316	0.09477

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-35 – Results 7km, 2017 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Baseline Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	-0.02 (0.5)		0.007 (0.6)	
share university degree (%)	0.3*** (0.06)		0.4*** (0.06)	
log income tax revenue (PC)	0.9** (0.4)		1.0** (0.4)	
log population (N)	0.1 (0.2)		0.06 (0.3)	
post	0.2 (0.2)	1.2*** (0.2)	0.1 (0.2)	1.2*** (0.2)
visible	0.08 (0.2)	-0.006 (0.2)	-0.06 (0.2)	-0.1 (0.2)
post × visible	-0.09 (0.1)	-0.2 (0.2)	-0.04 (0.2)	-0.09 (0.2)
Fit statistics				
Observations	1,608	1,608	1,252	1,252
R^2	0.21874	0.02826	0.23299	0.02729

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-36 – Results 7km, 2021 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Baseline Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	1.7** (0.7)		2.3** (0.9)	
share university degree (%)	0.5*** (0.1)		0.5*** (0.1)	
log income tax revenue (PC)	2.7 (1.8)		2.1 (1.9)	
log population (N)	0.6** (0.2)		0.6*** (0.2)	
post	2.0*** (0.6)	3.0*** (0.5)	2.1*** (0.6)	3.1*** (0.6)
visible	0.3 (0.5)	-0.6* (0.4)	0.2 (0.4)	-0.6 (0.4)
post × visible	-1.3*** (0.5)	-1.1** (0.4)	-1.4** (0.5)	-1.2** (0.5)
Fit statistics				
Observations	224	224	180	180
R^2	0.48968	0.10758	0.49367	0.10520

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

C.4 Estimation results with the alternative maximum distance of 5 km

Table C-37 – Results 5km, 2002 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Baseline Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	-0.3 (0.2)		-0.2 (0.2)	
share university degree (%)	0.2*** (0.05)		0.2*** (0.05)	
log income tax revenue (PC)	2.5*** (0.1)		2.5*** (0.1)	
log population (N)	-0.2*** (0.05)		-0.2*** (0.06)	
post	1.2*** (0.1)	1.2*** (0.1)	1.3*** (0.1)	1.3*** (0.1)
visible	-0.2 (0.1)	-0.3** (0.1)	-0.2*** (0.07)	-0.2*** (0.08)
post × visible	-0.03 (0.1)	-0.06 (0.09)	-0.04 (0.1)	-0.08 (0.1)
Fit statistics				
Observations	5,140	5,140	3,476	3,476
R^2	0.34507	0.04865	0.34249	0.05470

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-38 – Results 5km, 2005 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Baseline Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	-0.3 (0.4)		-0.06 (0.4)	
share university degree (%)	0.3*** (0.09)		0.2*** (0.09)	
log income tax revenue (PC)	3.0*** (0.3)		2.9*** (0.3)	
log population (N)	0.008 (0.1)		0.02 (0.1)	
post	-0.2* (0.1)	-0.2* (0.1)	-0.2 (0.1)	-0.2 (0.1)
visible	-0.1 (0.2)	-0.2 (0.2)	-0.06 (0.2)	-0.2 (0.2)
post × visible	0.1 (0.1)	0.1 (0.1)	0.1 (0.1)	0.2 (0.1)
Fit statistics				
Observations	1,468	1,468	1,088	1,088
R^2	0.34314	0.00121	0.34252	0.00083

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-39 – Results 5km, 2009 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Baseline Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	0.1 (0.3)		0.2 (0.4)	
share university degree (%)	0.3*** (0.08)		0.3*** (0.1)	
log income tax revenue (PC)	3.8*** (0.3)		3.7*** (0.4)	
log population (N)	-0.3** (0.1)		-0.2 (0.1)	
post	0.7*** (0.3)	2.2*** (0.2)	0.7** (0.3)	2.3*** (0.2)
visible	0.5*** (0.2)	0.4** (0.2)	0.6** (0.2)	0.5** (0.2)
post × visible	0.2 (0.1)	0.2 (0.1)	0.2 (0.2)	0.2 (0.2)
Fit statistics				
Observations	908	908	644	644
R^2	0.36728	0.12909	0.32661	0.13099

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-40 – Results 5km, 2013 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Baseline Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	-0.4 (0.6)		-0.2 (0.6)	
share university degree (%)	0.1 (0.1)		0.1 (0.1)	
log income tax revenue (PC)	3.8*** (0.5)		3.9*** (0.6)	
log population (N)	-0.08 (0.2)		-0.04 (0.2)	
post	-2.9*** (0.3)	-1.9*** (0.2)	-3.0*** (0.3)	-2.0*** (0.2)
visible	0.1 (0.3)	0.09 (0.2)	0.1 (0.3)	0.2 (0.2)
post × visible	-0.4* (0.2)	-0.4* (0.2)	-0.5* (0.3)	-0.4* (0.2)
Fit statistics				
Observations	768	768	560	560
R^2	0.31780	0.10259	0.31541	0.11392

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-41 – Results 5km, 2017 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Baseline Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	-0.1 (0.6)		-0.1 (0.6)	
share university degree (%)	0.3*** (0.05)		0.3*** (0.05)	
log income tax revenue (PC)	1.1** (0.5)		1.2** (0.6)	
log population (N)	0.003 (0.2)		-0.006 (0.2)	
post	0.08 (0.2)	1.0*** (0.1)	-0.06 (0.2)	0.9*** (0.1)
visible	-0.09 (0.2)	-0.1 (0.2)	-0.3 (0.2)	-0.3 (0.2)
post × visible	-0.1 (0.1)	-0.2 (0.1)	0.02 (0.1)	-0.008 (0.1)
Fit statistics				
Observations	1,488	1,488	1,000	1,000
R^2	0.17052	0.02194	0.17547	0.02095

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table C-42 – Results 5km, 2021 Timing Group

Dependent Variable:	vote share Green Party (%)			
	Baseline Model		External Exposure Model	
Model:	(1)	(2)	(3)	(4)
Variables				
log distance large city	0.6 (0.7)		0.9 (0.9)	
share university degree (%)	0.3^{***} (0.1)		0.5^{***} (0.1)	
log income tax revenue (PC)	2.5 (1.7)		1.6 (1.6)	
log population (N)	0.7^{***} (0.2)		0.8^{***} (0.2)	
post	2.4^{***} (0.6)	3.2^{***} (0.6)	2.2^{***} (0.6)	3.1^{***} (0.5)
visible	-0.3 (0.5)	-0.9^{**} (0.4)	-0.2 (0.5)	-0.8 (0.5)
post × visible	-1.3^{**} (0.6)	-1.2^{**} (0.6)	-1.7^{**} (0.6)	-1.6^{**} (0.6)
Fit statistics				
Observations	204	204	140	140
R^2	0.45886	0.12676	0.50601	0.12541

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*