The Shape of Democracy: Jurisdiction Boundaries and the Siting of Renewable Energy Infrastructure

Carsten Andersen, *Aarhus University*
Michael Hankinson, *George Washington University*
Asya Magazinnik, *Hertie School*
Martin Vinæs Larsen, *Aarhus University*
Peter B. Mortensen, *Aarhus University*

Political science has long studied how the size and shape of jurisdictions influence representation and governance, but much less is known about their effects on policy outcomes. This paper addresses that gap by examining how local jurisdictional structure shapes the siting of wind turbines—a critical challenge for the green energy transition. We develop a theoretical model which predicts how the division of voters into local jurisdictions influence the siting of wind turbines (or:.. which predicts how the geographical distribution of voters within local jurisdictions influence the siting of wind turbines). Using data on all Danish wind turbines built between 2007 and 2021, and exploiting Denmark's 2007 municipal reform, which changed local boundaries while leaving the landscape unchanged, we show that shifts in local electorates strongly affect turbine siting. These results highlight how the political geography of local governments shapes renewable energy deployment, raising concerns about equity, efficiency, and democratic legitimacy in decentralized climate policy.

Work in progress, please do not cite without permission

This version: July 7, 2025.

Few questions in politics are more enduring than how to define the size and shape of political communities. In empirical political science, scholars have debated these features in terms of the administrative costs of running political systems (e.g., Blom-Hansen, Houlberg and Serritzlew 2014; Ostrom 2009) as well as their implications for democratic representation, participation, and fairness (Almond and Verba 1963; Blom-Hansen et al. 2016; Caughey, Tausanovitch and Warshaw 2017; Dahl 2008; Denters et al. 2014; Gerring and Veenendaal 2020; Lassen and Serritzlew 2011; Warshaw 2019). This research highlights how the drawing of jurisdictional boundaries influences citizen representation, political participation, and political efficacy, and shapes how resources are managed, with significant consequences for democratic functioning and economic performance. However, much less attention has been paid to how the size and shape of jurisdictions affect policy outcomes.

This article addresses that question by examining how jurisdictional size and shape interact to influence policy outcomes, using the siting of wind turbines as a critical case. Wind turbines are central to the transition away from fossil fuels, making their timely deployment a global priority (Quaschning 2019). In many countries, the authority to approve turbine locations rests with local governments (see Appendix A), placing these decisions squarely within the realm of local jurisdictional politics. Beyond their importance for decarbonization, wind turbines also exemplify a broader class of policy challenges known as locally unwanted land uses (LULUs). Because turbines generate both local costs and broader societal benefits, their siting decisions reveal how jurisdictional boundaries can shape distributive outcomes. In particular, the share of voters directly affected by a turbine will depend on the overall size of a jurisdiction but also on its shape, which determines the spatial distribution of voters relative to project locations. In turn, these boundaries structure whose preferences local politicians prioritize, and whose concerns can be more easily ignored.

To formalize these ideas, we develop a theoretical model of renewable energy infrastructure siting in decentralized political systems. The model captures how local politicians weigh the economic and political benefits of wind energy projects (Urpelainen and Zhang 2022) against the risks of local opposition (Stokes 2016; Stokes et al. 2023). A key insight is that the size and shape of jurisdictions determine how voters are distributed across space, which in turn affects local politicians' incentives over where to site turbines. As a result, turbine placement decisions reflect not only economic and technical considerations, but also the political geography of municipalities—in particular, whose preferences matter most within and across jurisdictional lines. Jurisdictions with identical population sizes but different shapes may expose different shares of their electorate to a turbine's impacts, creating distinct political pressures. Furthermore, the drawing of jurisdictional boundaries creates border areas where the preferences of those just inside the line are given greater weight than those living just across it, even if both groups experience the same negative externalities. This highlights an important yet understudied democratic consequence of how local jurisdictions are structured.

We test our model empirically by analyzing the placement of all wind turbines constructed in Denmark. Over recent decades, Denmark has built thousands of turbines, creating a rich dataset for evaluating our model's predictions. Specifically, we divide the country into 1x1 km grid cells and overlay these with municipal boundaries to link turbine siting decisions to local political jurisdictions. Using our theoretical model and detailed administrative data, we calculate an "approval score" that represents the proportion of voters likely to approve a given turbine site, and then examine how this aligns with actual siting decisions. Our findings support the model's predictions: the spatial distribution of voters within jurisdictions appears to be a key factor shaping turbine placement.

A central inferential challenge, however, is that the observed relationship may be confounded by the underlying distribution of people and infrastructure, which could jointly determine both jurisdictional borders and turbine siting. To address these concerns, we exploit a 2007 municipal boundary reform that redrew most local jurisdictional borders. This reform fundamentally changed the size and shape of municipalities, altering the composition of local electorates while leaving the physical geography of turbine sites unchanged. We leverage this reform to calculate changes in the approval score for each grid cell before and after the boundary shift. We then examine whether locations experiencing an increase in approval score after the reform were more likely to receive turbines in the post-reform period. These reform-induced changes do not predict turbine siting before the reform, suggesting that the reform was plausibly exogenous to other factors driving turbine development. Further supporting this interpretation, controlling for topographic factors known to influence turbine placement does not substantially affect the estimated effects.

The study makes three contributions to debates about jurisdictional structure and policy-making. First, it moves beyond questions of representation and efficiency to focus on how jurisdictional boundaries shape policy outcomes. Second, it shows how the size and shape of jurisdictions jointly interact to structure these outcomes, highlighting the political geography of who is affected by decisions. Third, by applying these ideas to the siting of renewable energy infrastructure—a critical component of the transition away from fossil fuels (Bolet, Green and Gonzalez-Eguino 2024; Hazlett and Mildenberger 2020; Hughes and Lipscy 2013; Stokes 2020)—the study sheds new light on the political challenges of achieving decarbonization, where local governments must balance national goals with local resistance.

Jurisdiction Lines and the Siting of Renewable Energy Projects

Debates about the appropriate size and shape of jurisdictions are central to political science (Treisman 2007). This literature has examined questions of scale and optimal jurisdiction size (Blom-Hansen, Houlberg and Serritzlew 2014; Gerring and Veenendaal 2020; Lassen and Serritzlew 2011), the benefits of competition between local governments (Tiebout 1956), the challenges of horizontal coordination (Ostrom 2009), fiscal governance (Oates 1972), and other institutional trade-offs (Treisman 2007). However, it has paid far less attention to how the drawing of jurisdictional boundaries affects the placement of facilities with broad social benefits but localized costs, such as renewable energy projects.

The drawing of jurisdictional boundaries is a central element of political architecture. Boundaries define which residents belong to a given community and which do not, shaping the allocation of political accountability and influence. As a result, people who live close to one another may fall under different local governments, separated by these borders. When those borders divide communities, residents just outside a boundary may bear the costs of decisions taken by a neighboring local government—decisions they cannot politically contest. These patterns can concentrate political costs or benefits within certain areas depending on how boundaries are drawn. A large literature on pollution exporting has shown, for instance, that undesirable facilities such as coal-fired power plants or waste sites are sometimes placed near jurisdictional borders to shift negative externalities onto neighboring populations who cannot hold decision makers accountable (Konisky and Woods 2010; Morehouse and Rubin 2021). Yet we know little about how these same dynamics might unfold for beneficial but locally costly facilities.

This question is particularly pressing for renewable energy projects. Renewable technologies like solar parks and wind turbines are essential to achieving climate goals, but their siting imposes highly localized costs on nearby residents. For example, turbines can lower house prices (Andersen and Hener 2023) and generate intense local opposition even in regions with strong public support for renewable energy (Stokes 2016; Stokes et al. 2023). Such opposition reflects broader resistance to so-called locally unwanted land uses (LULUs), where communities reject projects with local costs despite broader societal benefits (de Benedictis-Kessner and Hankinson 2019; Devine-Wright 2009; Furuseth 1990; Marble and Nall 2021; Trounstine 2009). Yet studies of LULUs and wind energy have largely neglected how the size and shape of jurisdictional boundaries might structure these political incentives. At the same time, wind projects may bring local benefits, including tax revenues and job creation (Urpelainen and Zhang 2022), and can be politically advantageous if climate policy is popular among voters. What remains unclear is how local politicians weigh these competing pressures, and whether the political architecture of their jurisdictions—its size and spatial configuration—conditions these siting decisions.

In the theoretical model presented below, we argue that the size and shape of jurisdictions affect where key infrastructure, such as wind turbines, is located, since electorally accountable representatives seek to minimize the share of the associated costs borne by their own constituents. In brief, we expect that local politicians will attempt to site turbines in ways that minimize the political costs to their own constituents, taking advantage of how jurisdictional boundaries separate those they represent from nearby residents across the border.

Although our argument is broadly applicable to a wide range of contexts, it has three scope conditions. First, it applies to policymaking in systems where local governments exercise control over land use within their jurisdiction. This is usually the case for renewable energy. Although climate goals and energy policy are set at the national level, permitting the development of renewable energy is often left to local governments (Cruz 2018; Pettersson et al. 2010, see also Appendix A). This means local politicians have some discretion over where to place renewable energy facilities. The level of formal discretion varies from country to country, and some countries, including the United States, are considering exempting these types of projects from local control. However, even in areas where local governments have little formal authority, we know that local politicians can be effective in blocking projects by lobbying state or national governments or by negotiating with developers to place projects where local politicians prefer. As such, it seems safe to assume that local elected officials will almost always try to exert control over what gets built where in their jurisdictions.

Our second condition is that this discretion is checked by some degree of electoral accountability to local constituencies for the land use decisions politicians make, in particular about the supply and spatial location of wind turbines. This requires that voters be able to observe sufficiently proximate wind turbines; that they attribute the construction of this infrastructure to decisions made by their local representatives; and that they punish or reward their representatives with their vote at least in part on the basis of these decisions. In line with this assumption, Stokes (2016) finds that voters in Canada punish local incumbents who were responsible for permitting these turbines (see also Isaksson and Gren 2024).

The third premise of our argument is that although many citizens support efforts to combat climate change in principle, they frequently oppose renewable energy projects when these developments are sited near their communities. Stokes et al. (2023) documents significant opposition to wind energy projects in both the US and Canada. This aligns with broader research that consistently demonstrates resistance to locally unwanted land uses (de Benedictis-Kessner and Hankinson 2019; Devine-Wright 2009; Furuseth 1990; Marble and Nall 2021; Sandman 1985; Stokes 2016; Trounstine 2009). However, wind energy projects also bring potential benefits such as job creation and revenue to local governments (Urpelainen and Zhang 2022). Therefore, in jurisdictions where the median voter supports climate action, the construction of wind turbines could yield electoral advantages.

Together, these three conditions suggest that electorally motivated politicians will prioritize placing wind turbines in areas of their jurisdictions that minimize their constituents' exposure to the turbines' real or perceived negative effects. However, from a local politician's perspective, the suitability of a given parcel of land for turbine construction depends on several factors: the number of voters in proximity relative to the jurisdiction's overall population; the perceived costs and benefits of the turbine to voters; and how these perceptions vary with distance from the turbine. In what follows, we develop a theoretical model that is based on these considerations and which generates testable predictions about how the siting decisions of electorally motivated local politicians are influenced by the geographical shape of the jurisdiction.

A Formal Model of How Jurisdictions shape Wind Turbine Siting

In this section, we develop a parsimonious model that takes as input only the spatial distribution of voters over a municipality—as well as some minimal functional form assumptions on voter utilities—and produces as output a municipality-wide approval score for a proposal to site a wind turbine at a given location within that jurisdiction. We have already argued that an electorally motivated local politician will take the constituency's approval into account when deciding where in the municipality to site a new wind turbine. By enabling us to compute what that approval score would be for any given parcel of land, our model yields testable predictions about where wind turbines are located.

Our formal analysis begins at the level of a voter living in a spatial location i in a municipality M. To keep matters simple—and to match the structure of the data we will eventually use in our empirical analysis—we can divide the municipality into small grid cells. Let voters derive some fixed benefit b from a wind turbine project and experience a cost c that is a function of the distance between their own location, i.e., the grid cell in which they live, and the proposed turbine location. Thus, the utility to a voter who lives in the grid cell i of a turbine located in the grid cell j is given by the following.

$$U_v(i,j) = b - c(i,j) \tag{1}$$

This utility function captures the non-spatial nature of support for climate action, in contrast with the spatial nature of not-in-my-backyard opposition to new turbine construction. The benefits of a turbine include the energy contributed to the electrical grid and the offset of carbon emissions; a sizable increase in local GDP and tax revenues (Brunner and Schwegman 2022; De Silva, McComb and Schiller 2016; Scheifele and Popp 2024); and, potentially, modest impacts on local employment, although the evidence is mixed (Costa and Veiga 2021; De Silva, McComb and Schiller 2016; Scheifele and Popp 2024). Importantly, these benefits all accrue to the nation, the climate, or the municipality, but not specifically to the turbine's closest neighbors.

In contrast, the costs are spatially concentrated around the turbine's location. The main drivers of local opposition to wind turbines are environmental impacts, including effects on both wildlife and the human environment, such as aesthetics and noise, as well as concerns about property values (Susskind et al. 2022). Previous research suggests that these impacts are felt—or at least capitalized into home prices—at distances of up to 4 km from the turbine when the project is directly visible (Jarvis Forthcoming).

Our cost function $c(i,j)$ captures how intensely the voter experiences the costs of a turbine as a function of its distance from the voter's own spatial location. We assume that these costs increase as the voter's distance to the turbine decreases, with the most proximate voters experiencing the strongest opposition. In addition, we expect that these costs *change* more dramatically at smaller distances than at large ones: for instance, voters care a lot whether the turbine is 100 or 200 meters from them, whereas they are largely indifferent between a turbine located halfway across the municipality and fully on the opposite side of the municipality. We capture this assumption with the cost function:

$$c(i,j) = k\left(\frac{1}{d(i,j)+q}\right)^2 \tag{2}$$

where $d(i,j)$ is the distance between voter location i and turbine location j. The parameters k and q control the shape of the cost function experienced by voters, in particular how intensely the costs are felt relative to the benefit as well as how these costs decay over space.

In Figure 1, we illustrate this functional form with sample parameter values of $b = 1$, $k = 1$, and $q = 0$. The figure plots voter utility, U_v, on the y axis, as a function $d(i,j)$—the distance between a voter at location i and a turbine at location j—on the x axis. Here, the voter experiences significant costs when the turbine is up to one unit of distance away, and it is over this interval that the voter experiences the largest utility gains from moving further away from the turbine. The voter's losses plateau after two units of distance, such that the voter is nearly indifferent between a turbine positioned four or ten units away.

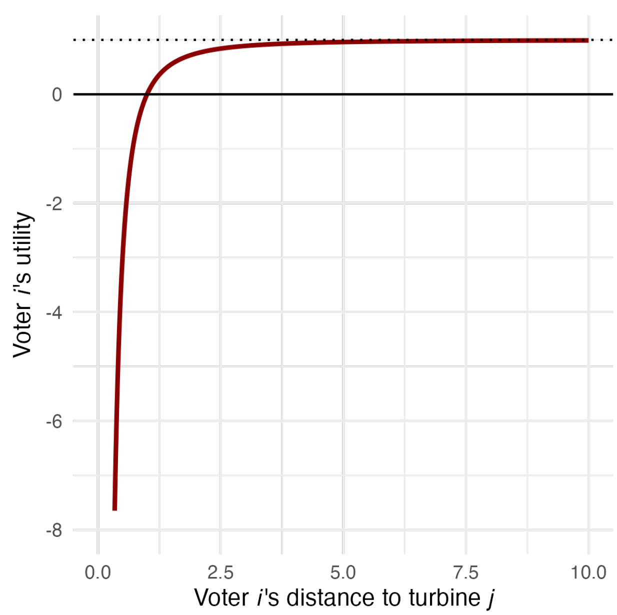


Figure 1: Plot of utility function: $U_v = b - k\left(\frac{1}{d(i,j)+q}\right)^2$ for $b = 1$, $k = 1$, and $q = 0$. Distance $d(i,j)$ is shown on x-axis and utility is shown on the y-axis.

With this utility structure in place, we can define the conditions under which a voter will support or oppose an exogenous proposal to site a wind turbine at a particular location. We define this *vote choice* variable, $A_{i,j}$, as a binary indicator of support from a voter living at location i to site a turbine at location j. This binary indicator of support may be interpreted either as the voter's decision if the proposal were voted on directly by the constituency or as a vote to retain or replace the politician that approved this proposal in the subsequent election. We assume that voters will support the proposal if their utility from the proposal passing exceeds the utility from it failing. If the proposal fails, all voters receive a reservation utility of 0: they neither receive the benefits nor pay the costs. Then, we can write $A_{i,j}$ as follows:

$$A_{i,j} = \begin{cases} 1 & \text{if } U_v > 0 \to b > c(i,j) \\ 0 & \text{if } U_v < 0 \to b < c(i,j) \\ \text{coin flip between 1 and 0} & \text{if } U_v = 0 \to b = c(i,j) \end{cases} \tag{3}$$

It remains to aggregate $A_{i,j}$ over all voters in the municipality to generate an overall *approval score*, A_j, that represents the proportion of the municipality's voters that support the construction of a wind turbine in grid cell j. We compute this vote share as the average of $A_{i,j}$ in all grid cells $i \in M$, weighted by the population in each grid cell:

$$A_j = \frac{\sum_{i \in M} A_{i,j} P_i}{\sum_{i \in M} P_i} \tag{4}$$

where P_i is the population of voters who live in grid cell i.

The ability to compute the approval score, A_j, for every grid cell $j \in M$ allows us to compare the viability of different parcels of land in a municipality for the siting of wind turbines from a political, rather than technical or economic, vantage point. Although we expect that technical and economic considerations also play a role, our model generates empirically testable predictions about where turbines are likely to go when local politics is a key factor. In particular, we expect that the probability that a turbine is sited in grid cell j increases in A_j. Of course, we do not expect politics to be the only consideration. Rather, our argument is that within the realm of technical feasibility, the political incentives captured by A_j will have some effect, and political considerations may outweigh technical or economic efficiency if politicians are sufficiently concerned about electoral outcomes.

Empirical Context

We examine these theoretical predictions in Denmark, a nation with a long history of wind power development. From the 1970s onward, government subsidies and tax deductions encouraged wind investment, initially resulting in small turbines owned privately or through cooperatives, often by farmers. By the late 1990s, however, subsidies were phased out, and turbines grew significantly larger, concentrating ownership among large-scale corporate investors.

A crucial feature of the Danish case is the 2007 municipal reform, which fundamentally reshaped the country's political geography. This large-scale administrative overhaul consolidated 271 municipalities into 98 larger units, redrawing jurisdictional boundaries for the vast majority of local governments (Blom-Hansen, Houlberg and Serritzlew 2014). The reform dramatically increased the size of the average municipality, fundamentally redrawing the boundaries between local jurisdictions, with the explicit aim of improving administrative efficiency and public service provision (Blom-Hansen, Houlberg and Serritzlew 2014). The reform offers a valuable opportunity to identify the effects of jurisdiction size and shape on siting outcomes. Because the physical landscape and wind resources remained unchanged while political boundaries shifted, we can isolate how changes to jurisdictional structure—both in size and spatial configuration—affect local decision-making about wind turbine placements.

Beyond this reform, several features of the Danish context make it an ideal setting to test our theoretical model. First, Danish local governments have significant discretion over wind turbine siting. Although national guidelines restrict where turbines cannot be placed, local governments retain primary authority to decide where turbines will be allowed, subject to these constraints (Naturstyrelsen, Miljøministeriet 2015). Municipalities designate turbine zones through local planning processes, balancing national renewable energy targets with local environmental, landscape, and community concerns. They must also adhere to minimum distance requirements from residences—typically four times the turbine's height—to mitigate noise and visual impacts. Public consultations are critical, as local governments engage in hearings and impact assessments to address citizen concerns and potential opposition.[1]

Second, there has been substantial wind turbine construction. During the period we study, thousands of turbines were built, allowing us to estimate the likelihood of turbine placement with considerable precision.

Third, although there is broad political support for wind energy construction in Denmark, consistent with its longstanding climate and renewable energy commitments (Larsen and Hvidkjær 2025), individual projects often encounter significant not-in-my-backyard (NIMBY) opposition (Hevia-Koch and Ladenburg 2019). This creates a politically challenging environment in which local governments must navigate the tension between ambitious national energy goals and local resistance.

Data

We use the Danish National Grid created by Statistics Denmark. This subdivides Denmark into 45,604 1 km by 1 km grid cells. We obtain data on the location of all wind turbines in the period 2007-2021 from the Danish Energy Agency. We combine this with information on the population of each grid cell, municipal borders, and data on the topography of each grid cell.[2]

Dependent Variable Our key outcome variable is whether any turbine is built in the grid cell during the period 2007-2021. In this period around 3,000 turbines have been sited, which means that only a small fraction of the 45,604 grid cells have had a turbine sited (<1%). Therefore, it makes sense to only distinguish between whether or not any turbines have been constructed.

[1] Once approved, wind turbine installation follows a structured permitting and construction process. Developers must obtain environmental and building permits, ensure compliance with noise limits and grid connection requirements, and coordinate site preparation, turbine assembly, and grid integration. The process concludes with technical inspections and operational testing before the turbines become fully functional.

[2] Thanks to Kim Sønderskov and Niels Nyholt for providing the data on population distributions.

However, results are similar regardless of how we define the dependent variable (e.g., in terms of counts, see Appendix G).

We can visualize trends in turbine construction by looking at the share of cells in general that hosted a turbine within that height band in a given year. We calculate the mean of the dependent variable for each height band across all cells within each year, which is effectively the percent of cells where it equals 1 for that year. Figure 2 shows the trends for all turbines in the dataset.

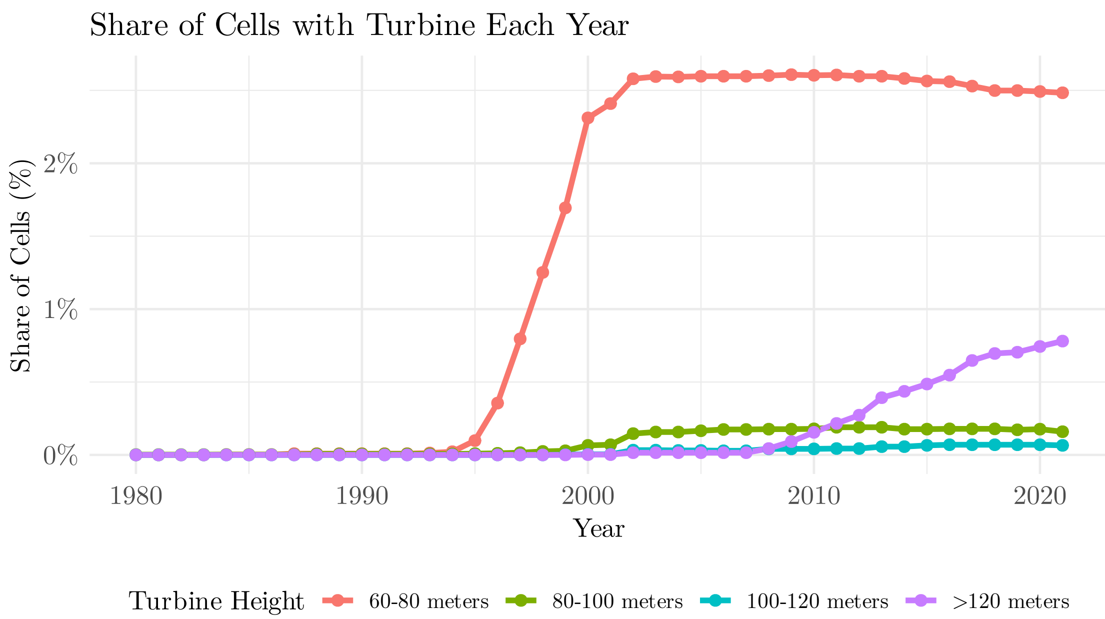


Figure 2: Share of cells hosting turbines in a given year, using height bands.

After explosive growth of 60-80-meter-tall turbines in the late 1990s, the share of cells hosting these midsize turbines plateaus and then begins to decline. That is because many of these turbines were taken down in the mid-2010's and immediately replaced with very tall (>120 meter) turbines, which began to appear around 2008.

In defining our dependent variable, we focus on whether a single turbine that is at least 80 meters tall is built on the grid. The 80-meter threshold balances several considerations. Taller turbines are more visible and impactful on perceptions of the local environment, making them more likely to face opposition and requiring more strategic placement by politicians. Second, taller turbines dominate recent developments, while smaller ones are rarely built today, making our focus more relevant to contemporary policymakers. At the same time, the 80-meter threshold also ensures comparability over time, as it captures the tallest turbines consistently installed both before and after the 2007 reform. If we were to focus on very tall turbines ($> 120m$), then we would have a dependent variable without variation before 2010.

Independent Variable Our treatment is the share of a municipality's population expected to approve of a proposed wind turbine at a given grid cell. We estimate this quantity using our theoretical model (Equation 4), which takes as inputs the grid-cell population counts in a municipality. Calculating the municipality-wide "approval score" requires selecting values for the parameters q and k, which determine how approval decays over distance.[3] To ensure these parameters reflect real-world patterns, we select them empirically based on prior research and an objective criterion—maximizing the predictive power of the model.

To do so, we generate a grid of candidates over the range of plausible values that accord with intuitions and expectations derived from prior research. Our grid includes q values from 0 to 1, inclusive, incremented by 0.1, as well as k values from 1 to 20, inclusive, incremented by 1, generating a total of 220 candidate pairs. We conduct a calibration exercise over this grid using data from the pre-reform period (1998-2006).[4] First, we randomly split the pre-reform data into a training set (70%) and a test set (30%). Because tall turbine siting is a rare event, we oversample the treated observations in the training set to achieve better performance. For each candidate pair of parameter values, we compute the approval score and use it as an input into a support vector machine (SVM) classification model along with a set of additional measures of topography, wind capacity, and distance to the coastline. The prediction target is whether there is at least one turbine present in the grid cell. The model is run on the training set and predictions are generated for the test set. Then we compare these predictions to the true values and compute an F1 score, which balances precision and recall.[5]

[3] We normalize the b parameter to 1.

[4] We select 1998 as the start of the pre-reform period because that is the first year in which a tall turbine appears in the data.

[5] Precision is the proportion of all positive cases identified by our model that is actually correct. Recall is the

Through this process, we select parameter values of $k = 15$ and $q = 0.4$. Figure 3 plots the voter's utility as a function of distance to the turbine for the chosen parameters. We see that the decay in the cost happens most intensely over the first 2 km and that the function starts to plateau after 5 km. Encouragingly, this pattern is consistent with previous findings that the effects of new, tall turbines on home prices are felt up to distances of 4 km (Jarvis Forthcoming). However, as we show in Appendix Figure C3, our results remain qualitatively robust across a wide range of parameter values. For a more detailed discussion of the parameter tuning process, please see Appendix C.

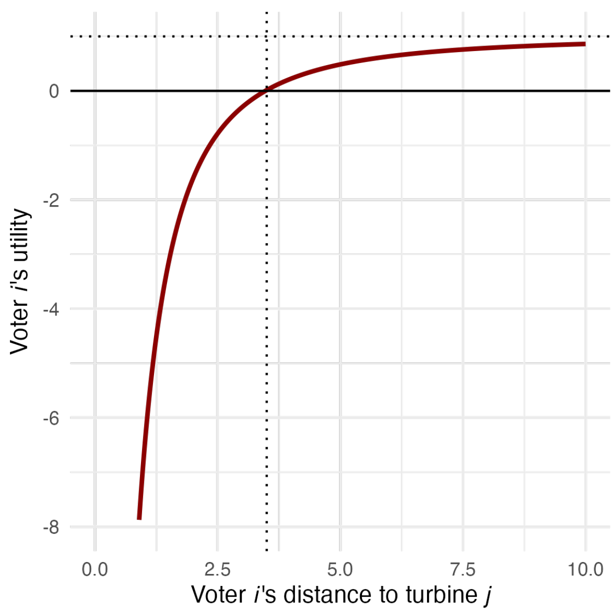


Figure 3: The utility function for the optimal parameter values: $b = 1$, $k = 15$, $q = 0.4$. Dashed horizontal line represents the non-spatial benefit, $b = 1$. Dashed vertical line marks where the benefit equals the cost, at a distance of 3.5 km.

With approval scores in hand, we can visualize how they relate to post-reform turbine siting, starting with the municipalities of Holstebro and Lolland. These are informative municipalities as they are hotbeds of turbine siting, but are quite different geographically and politically. Lolland is a large island in southern Denmark and has generally supported liberal parties in the Danish

proportion of all positive cases in the data that is correctly identified by our model. The F1 score is the harmonic mean of the two. We repeat this process twenty times per candidate pair of parameter values to smooth over any noise from sampling the training data, and compute the average F1 score over the 20 iterations.

parliament. In contrast, Holstebro is a largely landlocked municipality on the western edge of Denmark and has supported conservative parties in parliamentary elections. Both municipalities have similar land area ($\sim$ 840 km squared), although Holstebro has 50 percent more residents (60,000 compared to 40,000 residents in Lolland).

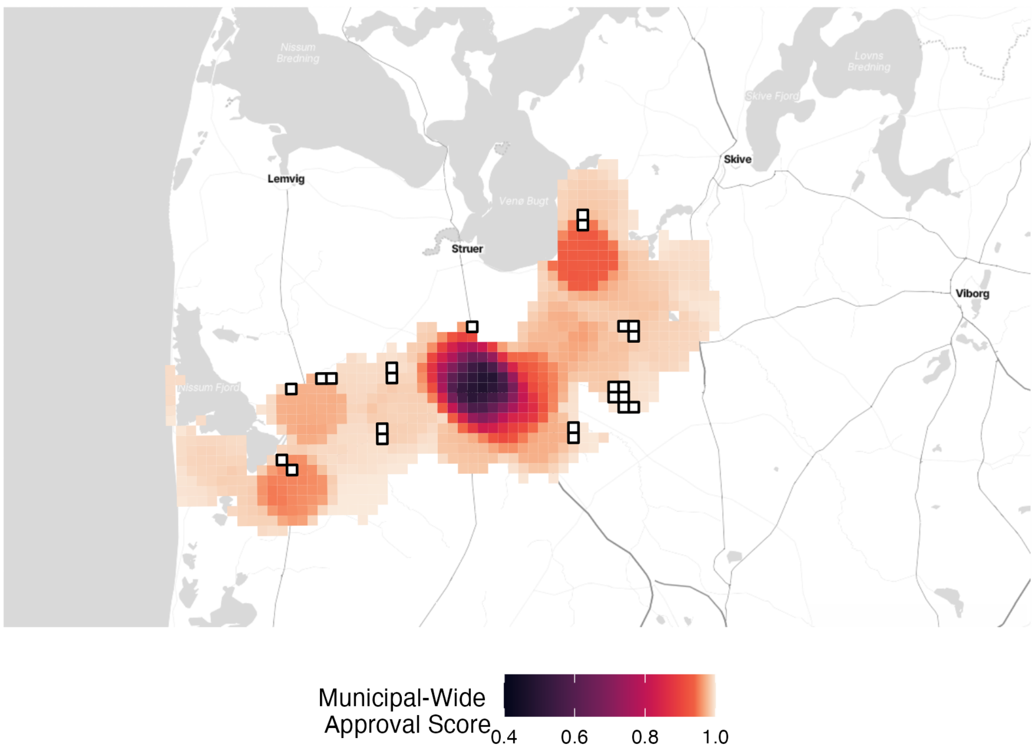


Figure 4: Map of Holstebro, Denmark. Cells are shaded based on expected municipal wide approval score for siting a turbine within that cell. White cells indicate a turbine was built there post-2007.

Figure 4 shows Holstebro, Denmark. The approval scores are depicted using shading. Dark purple areas are those where siting a turbine would be most unpopular. For example, the darkest part of the map is the center of the town of Holstebro. Here, less than 50 percent of voters municipality-wide would support the location of a wind turbine. In contrast, light-shaded cells are locations where our theoretical model predicts that turbines should win majority support. These are largely along the east and west ends of the municipality, where there are fewer residents as a share of the overall population. The white cells show the actual distribution of turbines built between 2007 and 2021. The location largely followed the pattern of approval scores, staying outside the central and unpopular region.

Figure 5 shows Lolland, Denmark. Again, dark purple areas have low approval scores where we would not expect turbine siting. Since Lolland is a multi-core municipality, turbines are likely to be politically feasible either between the cores or on the northern islands of the municipality. This is supported by the actual placement of the turbines.

These visualizations provide some suggestive evidence that our approval score performs well in predicting turbine sites. In addition, they show how the approval score outperforms more naive heuristics, such as proximity to borders or areas with a low population density. Although these traits are correlated with the approval score, our model directly integrates them to provide a clearer picture of municipality-wide electoral support for this locally unwanted infrastructure. In the analyses below, we demonstrate the explanatory power of the approval score in predicting turbine siting using a regression model that links siting decisions to the approval score while controlling for potential confounder variables.[6]

Analytical Strategy

We leverage the 2007 Danish municipal reform to study how jurisdictional structure influences turbine siting decisions. This reform merged hundreds of smaller municipalities into larger jurisdictions, redrawing their size and shape for nearly two-thirds of local governments (Blom-Hansen, Houlberg and Serritzlew 2014). These changes shifted the composition of local electorates—and thus altered our approval score measure for a given location—even though physical factors like topography, wind conditions, or land use remained constant.

Our approach is therefore similar to a first-difference design, examining whether changes in approval scores induced by the reform predict changes in turbine siting (i.e., new turbines). By comparing the same grid cells before and after a shift in their jurisdictional boundaries, we hold

[6]Approval scores for every municipality in Denmark are visualized in Appendix B.

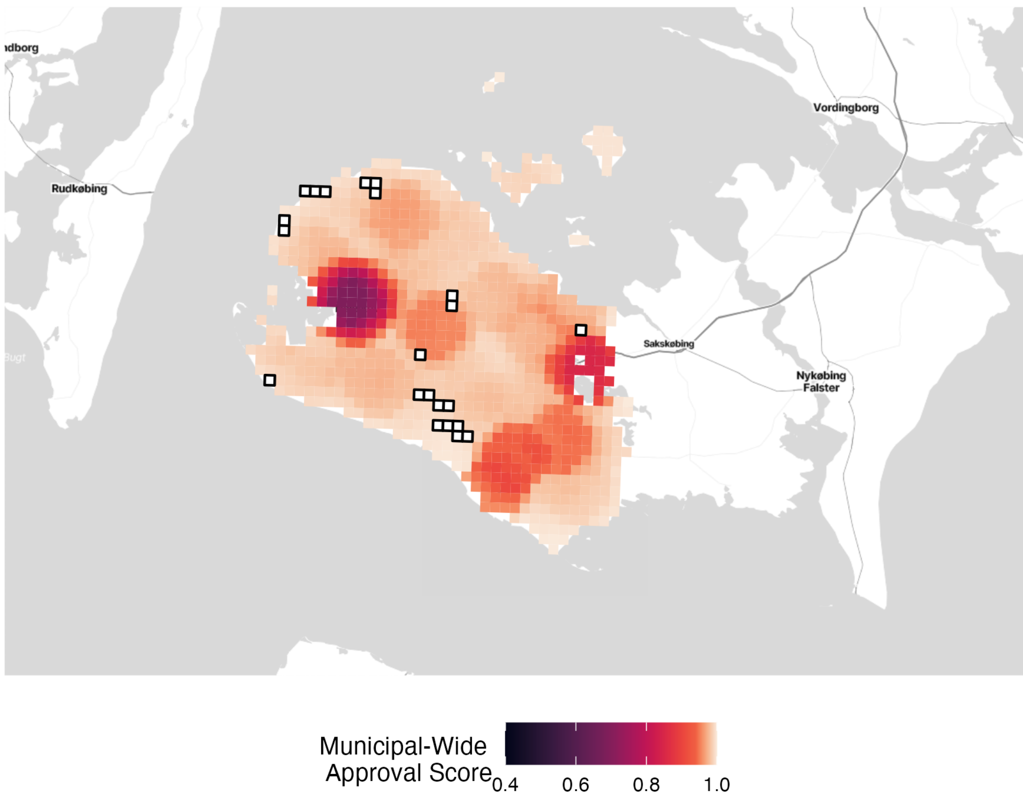
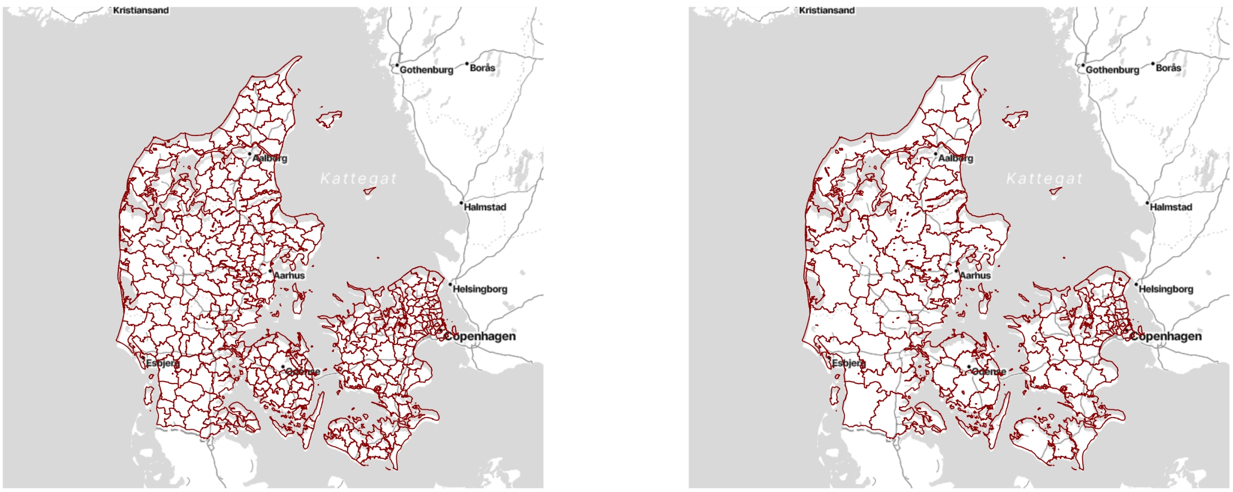


Figure 5: Map of Lolland, Denmark. Cells are shaded based on expected municipal wide approval score for siting a turbine within that cell. White cells indicate a turbine was built there post-2007.

constant time-invariant features of the grid cell that might otherwise confound the relationship between political geography and turbine siting.

Figure 6 illustrates the reconfiguration of municipal boundaries before and after the reform, showing how the electorate to which local politicians were accountable changed. Figure 7 documents the distribution of resulting approval-score shifts. Many grid cells saw little change, but a substantial fraction experienced large increases—sometimes more than 30 percentage points—due to being folded into new, more geographically dispersed municipalities.



Pre-2007 2007-present

Figure 6: Changing Borders of Danish Municipalities

A key remaining threat to inference is that areas where post-reform approval rose might also be, for other reasons, more suitable for turbine siting. To address this, we include a limited set of theoretically motivated controls. Topography, for example, influences settlement patterns and hence the built environment, which can affect approval scores while also impacting wind capacity, since structures and terrain can disrupt wind flow. Rugged areas may be harder to develop, while coastal areas often face stricter aesthetic constraints. We therefore control for (1) the elevation of each grid cell's centroid, (2) the standard deviation of elevation surrounding each grid cell (as a ruggedness measure), and (3) the distance to the coastline (Rediske et al. 2021; Wimhurst, Nsude and Greene 2023). We also directly include each grid cell's estimated wind capacity from available data.

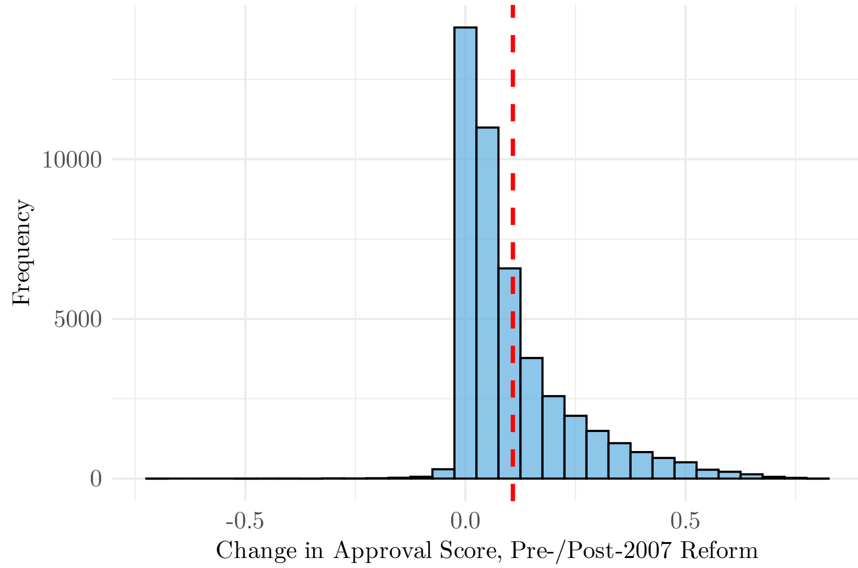


Figure 7: Change in average approval scores from the pre-reform (1980-2006) to the post-reform period (2007-2021) across grid cells. Red line signifies the average change.

As an additional robustness check, we conduct a placebo test, examining whether reform-induced changes in approval scores predict turbine siting before the reform took place. Finding no such relationship would strengthen the interpretation that the post-reform association is plausibly causal, rather than reflecting a persistent, unobserved confounder.

In modeling turbine siting, we rely on a logit framework because the outcome—whether any turbine is sited in a grid cell—is binary. However, turbine placement is a rare event, occurring in fewer than one percent of grid cells. Standard logistic regression struggles in such "rare event" contexts because maximum likelihood estimation can produce biased and unstable coefficients. In particular, with sparse events, MLE often underestimates event probabilities, inflates standard errors, and risks separation—where coefficients go to infinity if a predictor perfectly classifies the outcome (King and Zeng 2001).

To address these issues, we use the Firth logit estimator (Firth 1993), which adds a penalty to the likelihood function, effectively shrinking extreme coefficients toward more reasonable values. This correction improves coefficient stability and confidence interval coverage, and is specifically recommended for rare-event data where standard logistic regression fails. Firth's method has the added advantage of avoiding separation problems by ensuring finite, interpretable coefficients even when a predictor perfectly predicts turbine placement in a few cells (Rainey and McCaskey 2021; Zorn 2005).

Finally, we cluster Huber-White standard errors at the municipal level to account for correlation within municipalities and ensure valid inference.

Results

Before turning to the main analysis of the reform's effects, we first describe the cross-sectional relationship between approval scores and turbine placement during the post-reform period from 2007 to 2021. This descriptive exploration helps illustrate how the distribution of approval scores relates to observed siting patterns in the data, without making any causal claims. We focus on the post-reform period because it is when most tall turbines (height $> 80m$) were built and when the new municipal boundaries were in effect, allowing us to use a single approval score per grid cell and avoiding complications from pre- and post-reform differences.

Figure 8 presents a scatter plot illustrating the descriptive relationship between approval scores and turbine siting. Notably, no turbines are sited in areas with an approval score below 0.4, while nearly all turbines are sited in areas where the approval score exceeds 0.9—indicating that, according to our model, about 90 percent of the local electorate would approve of a turbine in that location. This pattern suggests that, in practice, turbines tend to be placed only in areas with overwhelming local support, which may reflect how strong local opposition from a minority can block projects even if a majority supports them. This descriptive relationship also highlights its strongly nonlinear form, underscoring the need for a model like the Firth logit to address rare-event data rather than relying on simple linear approaches.

We also formally estimate the cross-sectional relationship between approval scores and turbine siting using standard logit and Firth logit models. Four specifications are estimated: (1) a bivariate model; (2) a model controlling for topographic factors (hilliness, distance to the coast, elevation,

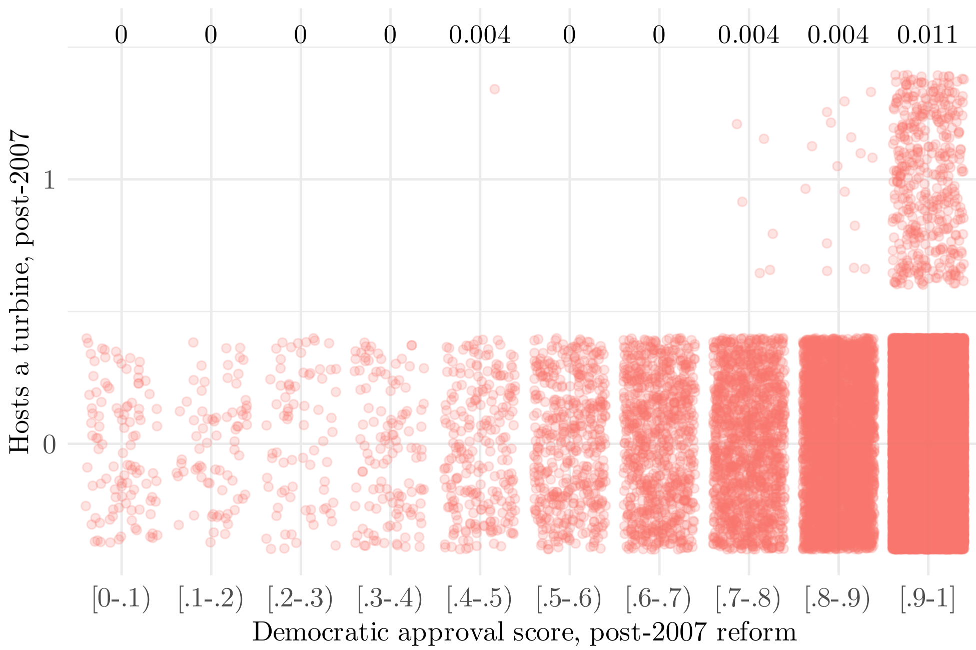


Figure 8: Relationship between approval score and the probability of hosting a turbine in a grid cell for turbines sited between 2007 and 2021. Red dots represent individual grid cells. Numbers at top represent conditional probabilities of hosting a turbine in a grid cell given its approval score.

wind capacity); (3) a model with municipality fixed effects; and (4) a model that also controls for distance to municipal borders (binned as 0–1 km, 1–3 km, 3–5 km, and 5–10 km). While model (3) is our preferred specification, we also include model (4) to test whether our approval score still has explanatory power after controlling for proximity to the border—a related measure that has been used in the literature to capture the same interjurisdictional dynamics, but that is unable to account fully for jurisdictional size, shape, and population density.

Figure 9 presents the main estimates, reporting the change in the odds ratio of turbine siting for a one-standard deviation increase in approval score (roughly 20 percentage points). Across all specifications, we find a statistically significant relationship between approval scores and siting.

In our preferred specification, which includes all controls and fixed effects, the odds ratio for a one-standard deviation increase in the approval score is 1.46. This means that a one-standard deviation increase in the approval score is associated with a 46 pct. higher odds of a turbine being sited. As turbine construction remains rare overall, the absolute probabilities stay low, but the pattern is still meaningful.

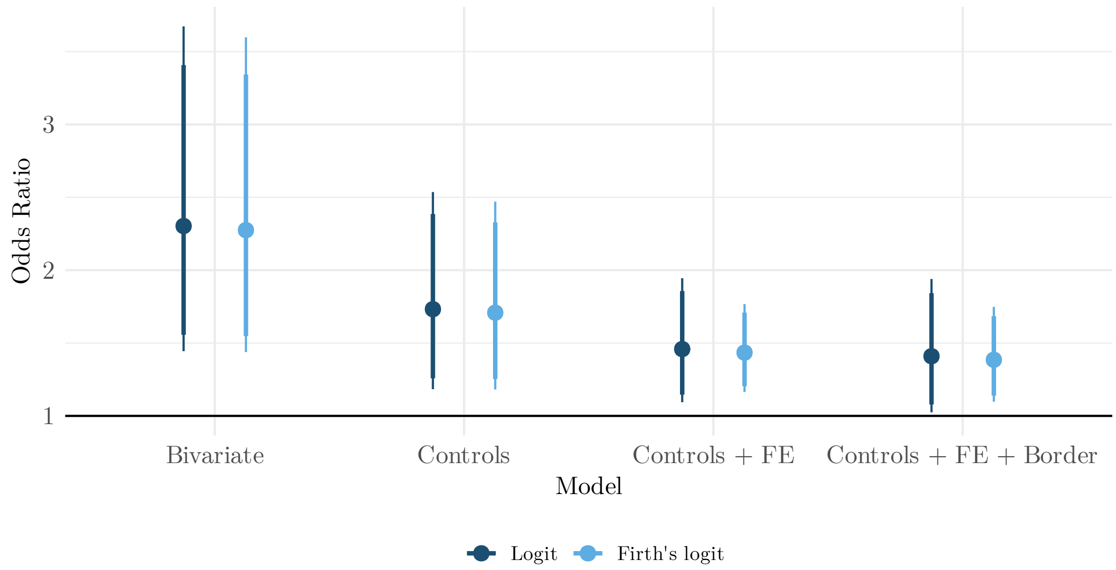


Figure 9: Relationship between a standard deviation increase in approval score and the odds ratio for the siting of a turbine in a grid cell. Thick lines represent 90% confidence intervals, thin lines are 95% confidence intervals. Turbines sited 2007-2021. See Tables E3 and E4 for tabular form.

Changes in Approval Scores and Siting Decisions

To better isolate the relationship between approval scores and turbine siting, we turn to a first-difference design that exploits changes over time. We construct an adjusted dependent variable coded as one if a new turbine was sited in a grid cell after 2007, and zero if no new turbine was placed or if a turbine was decommissioned. This approach captures how shifts in the political attractiveness of a location—driven by changes in its approval score after the reform—relate to subsequent siting, while holding constant any time-invariant factors that could jointly influence jurisdictional boundaries, population distributions, and turbine siting. Because we compare the same grid cells before and after their exposure to a boundary change, this design strengthens causal inference by focusing on local "shocks" to approval scores induced by the reform. These time-invariant controls include unchanging geographic or infrastructural characteristics at the grid-cell level, such as proximity to major cities.

We estimate models using both standard logit and Firth's logit, including bivariate models, models with topographic controls, municipality fixed effects, and distance-to-border controls. Figure 10 presents the key results. These results are robust to the inclusion of detailed topographic controls and municipality fixed effects, underscoring that the effect of changes in approval scores on turbine siting cannot be explained by differential trends in siting based on geographic or infrastructural features of grid cells

In our preferred specification, which incorporates both fixed effects and controls, a one-standard-deviation increase in approval corresponds to a 60 percent increase in the odds of turbine siting.

We also implement a placebo analysis to assess whether reform-driven changes in approval scores predict turbine siting before the reform. Finding no such relationship, as shown in Appendix F, increases our confidence that the post-reform associations are not simply driven by unobserved, time-invariant factors that might jointly influence approval scores and turbine placement. This strengthens the credibility of our design by showing that it is the changes in jurisdictional structure—rather than pre-existing differences—that are linked to changes in turbine siting after the reform.

Figure 11 examines the sensitivity of these results to varying the height cutoff for the turbines used to define the dependent variable. Across definitions of 60, 80, and 100 meters, the estimates remain broadly similar, with somewhat larger effects for taller turbines, which is intuitive since taller turbines are more likely to provoke stronger local opposition.

Overall, these findings have several important implications. First, they show that reform-driven changes in the approval score were strongly predictive of turbine siting, consistent with the model's predictions. A 10-percentage-point increase in approval score—about one standard deviation—raised the odds of turbine placement by roughly 50–60 percent. Second, by holding constant time-invariant grid-level factors, this approach isolates the role of local political support in shaping renewable energy siting decisions.

.

.

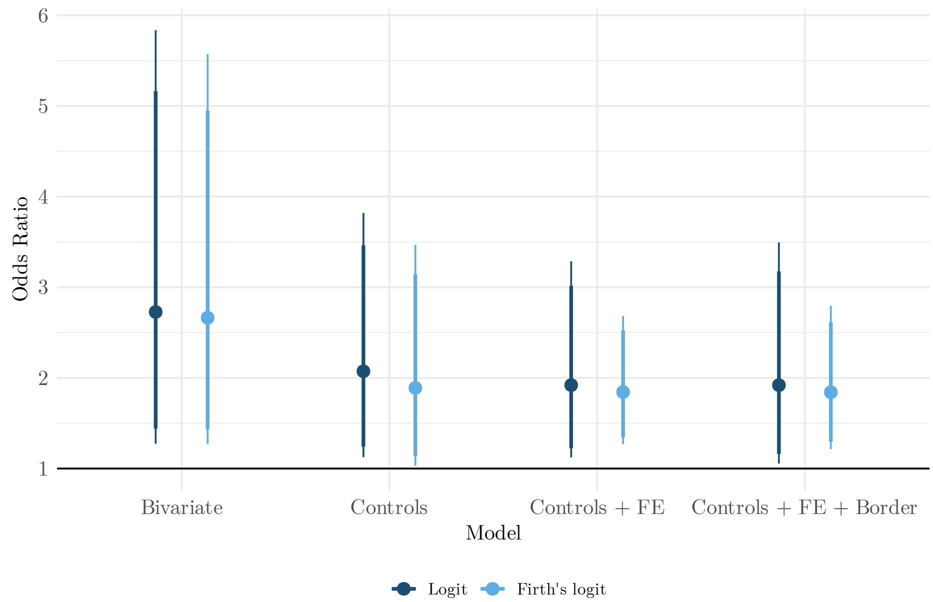


Figure 10: Effect of standardized change in approval score on binary indicator for gaining a turbine post-2007, exponentiated coefficients. See Tables E5 and E6 for tabular form. (1 standard deviation ≈ 0.1.)

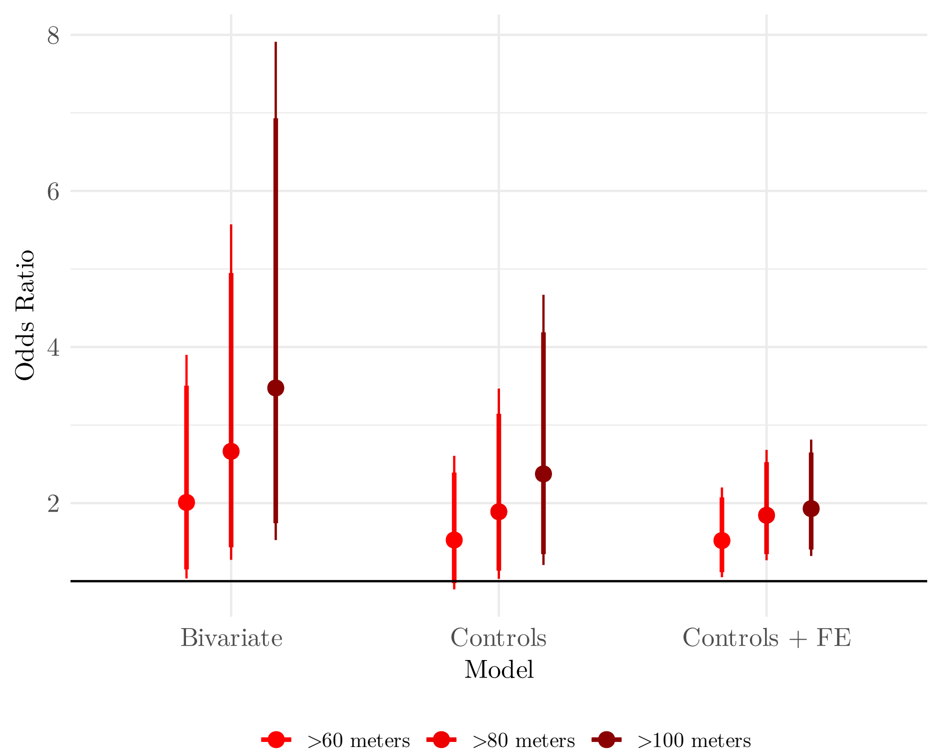


Figure 11: Effect from Firth's logit of standardized change in approval score on binary indicator for gaining a turbine post-2007 across different turbine heights, exponentiated coefficients. See Tables E7 and E8 for tabular form. (1 standard deviation ≈ 0.1.)

Neighboring Municipalities

A key potential criticism of the previous results is that they might simply reflect population density near turbine sites rather than any politically meaningful mechanism. This concern is less likely in the reform-based analysis, where the population distribution is largely stable, and only jurisdictional boundaries change to alter approval scores. Nonetheless, to further probe this issue, we disaggregate local population density around each grid cell into two components: residents living inside the municipality where the grid cell is located, and residents living in neighboring municipalities. If our argument about political incentives holds, then only the density of voters within the same municipality should meaningfully affect turbine siting, as local politicians are accountable only to their own electorate.

We test this by calculating the density of the local population within a 1.5 km radius of each grid cell, distinguishing between voters inside the municipality and those in adjacent municipalities. We then relate these measures to turbine siting using a Firth logit model, first in a bivariate specification, and then with the inclusion of topographic controls and municipality fixed effects.

Figure 12 presents these results. The figure shows that the population density of neighboring municipalities becomes largely irrelevant for turbine siting decisions once we include municipality fixed effects. In other words, when comparing sites within the same municipality, only the density of local voters within that municipality predicts turbine placement. This finding is consistent with the idea that siting decisions are primarily driven by local political considerations, reflecting the preferences and interests of voters to whom local politicians are directly accountable.

These results raise important concerns about the democratic legitimacy of decentralizing turbine siting decisions to local governments. By remaining unresponsive to residents of neighboring municipalities—who may be equally affected by turbine externalities but lack political influence over the permitting municipality—local governments can prioritize the interests of their own voters while disregarding broader regional impacts. Such patterns risk undermining public satisfaction with democratic processes and may exacerbate political polarization across municipal borders, particularly when harms are concentrated just outside the jurisdiction making the siting decision.

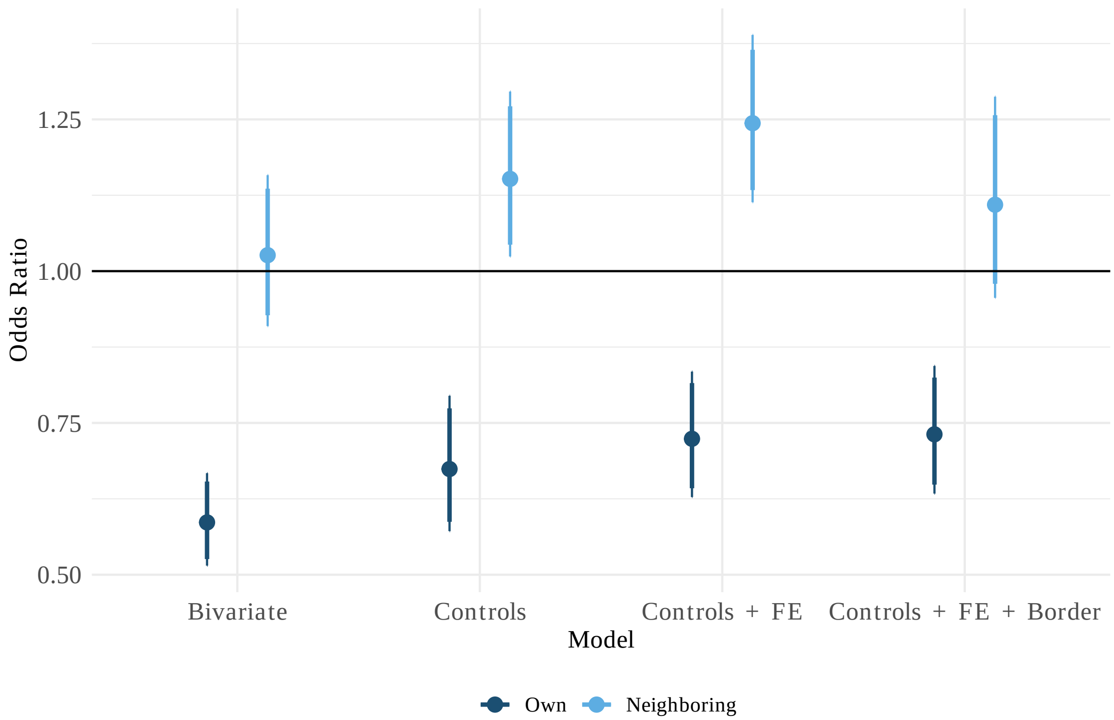


Figure 12: Relationship between a standard deviation increase in population density and the odds ratio for the siting of a turbine in a grid cell. Thick lines represent 90% confidence intervals, thin lines are 95% confidence intervals. See Tables E9 and E10 for tabular form.

Conclusion

This paper has examined how the size and shape of political jurisdictions structure local policy outcomes, using the siting of wind turbines in Denmark as a critical test case. While existing research has extensively explored the consequences of jurisdictional structure for representation and administrative efficiency, it has paid far less attention to how these features influence policy decisions. We argue that the size and shape of jurisdictions affect governments' incentives when siting unwanted land uses. Larger municipalities can place such facilities so that a smaller share of their own voters is directly affected. Moreover, irregularly shaped municipal borders can be exploited strategically to concentrate negative impacts on areas with relatively fewer within-municipality residents, thereby minimizing electoral costs. We formalize these insights in a theoretical model of renewable energy siting under decentralized authority, and test it using detailed administrative data and a rare natural experiment—Denmark's 2007 municipal reform—which affected the jurisdiction size and boundaries of Danish local governments.

Our findings highlight three main insights. First, the approval score derived from our model—capturing the share of voters in the municipality expected to support a turbine at a given location—strongly predicts turbine siting. Second, leveraging the municipal reform demonstrates that exogenous changes in the approval score, induced by boundary shifts, also influence siting outcomes. This strengthens causal claims that local political preferences, as structured by jurisdictional boundaries, systematically shape renewable energy development. Third, we show that these patterns are highly localized: only the preferences of voters within the permitting municipality predict turbine siting, while the interests of neighboring residents—who may still experience the costs—are largely disregarded.

These findings carry important implications. They underscore that local political geography can distort the allocation of renewable energy infrastructure, potentially undermining both efficiency and fairness in the transition away from fossil fuels. While local control over siting may enhance democratic legitimacy within municipalities, it can also create externalities that cross jurisdictional boundaries and erode regional cooperation. Future work might extend these insights to other types of locally unwanted land uses or to contexts beyond Denmark, exploring how different institutional designs could balance local accountability with broader collective goals.

In sum, this study demonstrates that the ways we draw and structure political jurisdictions do not merely affect how citizens are represented, but also profoundly shape the substance of policy itself. As societies accelerate efforts to decarbonize, understanding these jurisdictional effects will be crucial to ensuring that climate policy is both effective and democratically sustainable.

References

Almond, Gabriel A. and Sidney Verba. 1963. *The Civic Culture: Political Attitudes and Democracy in Five Nations*. Princeton, NJ: Princeton University Press.

Andersen, Carsten and Timo Hener. 2023. Wind Turbines, Shadow Flicker, and Real Estate Values. Technical report CESifo Working Paper.

Blom-Hansen, Jens, Kurt Houlberg and Søren Serritzlew. 2014. "Size, democracy, and the economic costs of running the political system." *American Journal of Political Science* 58(4):790–803.

Blom-Hansen, Jens, Kurt Houlberg, Søren Serritzlew and Daniel Treisman. 2016. "Jurisdiction size and local government policy expenditure: Assessing the effect of municipal amalgamation." *American Political Science Review* 110(4):812–831.

Bolet, Diane, Fergus Green and Mikel Gonzalez-Eguino. 2024. "How to get coal country to vote for climate policy: The effect of a "Just Transition Agreement" on Spanish election results." *American Political Science Review* 118(3):1344–1359.

Brunner, Eric J. and David J. Schwegman. 2022. "Commercial wind energy installations and local economic development: Evidence from U.S. counties." *Energy Policy* 165:112993.

Caughey, Devin, Chris Tausanovitch and Christopher Warshaw. 2017. "Partisan gerrymandering and the political process: Effects on roll-call voting and state policies." *Election Law Journal: Rules, Politics, and Policy* 16(4):453–469.

Clean Air Task Force. 2024. "New report shows the diversity of clean energy siting policies and permitting authorities across the country.". Accessed March 6, 2025.
URL: https://www.catf.us/2024/06/new-report-shows-diversity-clean-energy-siting-pol

Clean Energy Wire. 2025. "Surveying the Harvest: How to Build a Wind Farm in Germany.". Accessed March 6, 2025.
URL: https://www.cleanenergywire.org/factsheets/survey-harvest-how-build-wind-farm-germany

Costa, Hélia and Linda Veiga. 2021. "Local labor impact of wind energy investment: an analysis of Portuguese municipalities." *Energy Economics* 94:105055.

Cruz, Rizalino B. 2018. "The politics of land use for distributed renewable energy generation." *Urban Affairs Review* 54(3):524–559.

Dahl, Robert A. 2008. *Democracy and its Critics*. Yale university press.

de Benedictis-Kessner, Justin and Michael Hankinson. 2019. "Concentrated burdens: How self-interest and partisanship shape opinion on opioid treatment policy." *American Political Science Review* 113(4):1078–1084.

De Silva, Dakshina G., Robert P. McComb and Anita R. Schiller. 2016. "What Blows in with the Wind?" *Southern Economic Journal* 82(3):826–858.

Denters, Bas, Michael Goldsmith, Andreas Ladner, Poul Erik Mouritzen and Lawrence E Rose. 2014. Size and local democracy. In *Size and local democracy*. Edward Elgar Publishing.

Devine-Wright, Patrick. 2009. "Rethinking NIMBYism: The Role of Place Attachment and Place Identity in Explaining Place-protective Action." *Journal of Community & Applied Social Psychology* 19(6):426–441.

Firth, David. 1993. "Bias Reduction of Maximum Likelihood Estimates." *Biometrika* 80(1):27–38.

Furuseth, Owen J. 1990. "Impacts of a sanitary landfill: Spatial and non-spatial effects on the surrounding community." *Journal of Environmental Management* 31(3):269–277.

Gerring, John and Wouter Veenendaal. 2020. *Population and Politics: The Impact of Scale*. Cambridge University Press.

Hazlett, Chad and Matto Mildenberger. 2020. "Wildfire exposure increases pro-environment voting within democratic but not republican areas." *American Political Science Review* 114(4):1359–1365.

Hevia-Koch, Pablo and Jacob Ladenburg. 2019. "Where should wind energy be located? A review of preferences and visualisation approaches for wind turbine locations." *Energy Research & Social Science* 53:23–33.

Hughes, Llewelyn and Phillip Y Lipscy. 2013. "The Politics of Energy." *Annual Review of Political Science* 16(1):449–469.

IEA Wind. 2022. Wind Energy in Italy: Recent Trends and Future Prospects. Technical report International Energy Agency (IEA) Wind. Accessed March 6, 2025.
URL: https://iea-wind.org/wp-content/uploads/2022/12/Italy_k2.pdf

Isaksson, Zeth and Simon Gren. 2024. "Political expectations and electoral responses to wind farm development in Sweden." *Energy Policy* 186:113984.

Jarvis, Stephen. Forthcoming. "The Economic Costs of NIMBYism: Evidence from Renewable Energy Projects." *Journal of the Association of Environmental and Resource Economists* .

King, Gary and Langche Zeng. 2001. "Logistic Regression in Rare Events Data." *Political Analysis* 9(2):137–163.

Konisky, David M and Neal D Woods. 2010. "Exporting air pollution? Regulatory enforcement and environmental free riding in the United States." *Political Research Quarterly* 63(4):771–782.

Larsen, Martin Vinæs and Marc Hvidkjær. 2025. "Politisk Repræsentation i det Danske Lokaldemokrati." *Politica* .

Lassen, David Dreyer and Søren Serritzlew. 2011. "Jurisdiction size and local democracy: Evidence on internal political efficacy from large-scale municipal reform." *American Political Science Review* 105(2):238–258.

Marble, William and Clayton Nall. 2021. "Where self-interest trumps ideology: liberal homeowners and local opposition to housing development." *The Journal of Politics* 83(4):1747–1763.

Morehouse, John and Edward Rubin. 2021. "Downwind and out: The strategic dispersion of power plants and their pollution." *Available at SSRN 3915247* .

Nadaï, Alain and Olivier Labussière. 2014. Wind Energy Development in France: From State Regulation to Local Planning. In *Wind Power in Europe: Politics, Business and Society*, ed. Jens-Peter Fenger. Springer pp. 85–106.
URL: https://link.springer.com/chapter/10.1007/978-94-017-9843-3_5

Naturstyrelsen, Miljøministeriet. 2015. "Vejledning om planlægning for og tilladelse til opstilling af vindmøller.".

NFU Energy. 2022. "Wind Energy Guide.". Accessed March 6, 2025.
URL: https://www.nfuenergy.co.uk/sites/default/files/nfu_wind_guide_a4_4pg_-_feb_2022.pdf

Oates, Wallace E. 1972. *Fiscal federalism*. London: Edward Elgar Publishing.

Ostrom, Elinor. 2009. "A general framework for analyzing sustainability of social-ecological systems." *Science* 325(5939):419–422.

Pettersson, Maria, Kristina Ek, Kristina Söderholm and Patrik Söderholm. 2010. "Wind power planning and permitting: Comparative perspectives from the Nordic countries." *Renewable and Sustainable Energy Reviews* 14(9):3116–3123.

Quaschning, Volker V. 2019. *Renewable Energy and Climate Change*. John Wiley & Sons.

Rainey, Carlisle and Kelly McCaskey. 2021. "A Solution to Separation in Binary Response Models." *Political Analysis* 29(1):43–56.

Rediske, G, HP Burin, PD Rigo, CB Rosa, L Michels and JCM Siluk. 2021. "Wind Power Plant Site Selection: A Systematic Review." *Renewable and sustainable energy reviews* 148:111293.

Reuters. 2025. "How a Storm of Lawsuits Paralysed Wind Mills in Northwest Spain." *Reuters* . Accessed March 6, 2025.
URL: https://www.reuters.com/business/energy/how-storm-lawsuits-paralysed-wind-mills-northwest-spain-2025-01-14/

Sandman, Peter M. 1985. "Getting to maybe: some communications aspects of siting hazardous waste facilities." *Seton Hall Legis. J.* 9:437.

Scheifele, Fabian and David Popp. 2024. "Not in My Backyard? The Local Impact of Wind and Solar Parks in Brazil." *CESifo Working Paper Series* 11023.

Stokes, Leah. 2020. *Short Circuiting Policy: Interest Groups and the Battle Over Clean Energy and Climate Policy in the American States*. Oxford University Press.

Stokes, Leah C. 2016. "Electoral backlash against climate policy: A natural experiment on retrospective voting and local resistance to public policy." *American Journal of Political Science* 60(4):958–974.

Stokes, Leah, Emma Franzblau, Jessica R Lovering and Chris Miljanich. 2023. "Prevalence and predictors of wind energy opposition in North America." *Proceedings of the National Academy of Sciences* 120(40):e2302313120.

Susskind, Lawrence, Jungwoo Chun, Alexander Gant, Chelsea Hodgkins, Jessica Cohen and Sarah Lohmar. 2022. "Sources of Opposition to Renewable Energy Projects in the United States." *Energy Policy* 165.

Tiebout, Charles M. 1956. "A Pure Theory of Local Expenditures." *Journal of political economy* 64(5):416–424.

Treisman, Daniel. 2007. *The Architecture of Government: Rethinking Political Decentralization*. Cambridge University Press.

Trounstine, Jessica. 2009. "All Politics is Local: The Reemergence of the Study of City Politics." *Perspectives on Politics* 7(3):611–618.

Urpelainen, Johannes and Alice Tianbo Zhang. 2022. "Electoral Backlash or Positive Reinforcement? Wind Power and Congressional Elections in the United States." *The Journal of Politics* 84(3):1306–1321.

Warshaw, Christopher. 2019. "Local elections and representation in the United States." *Annual Review of Political Science* 22:461–479.

Wimhurst, Joshua J, Chinedu C Nsude and J Scott Greene. 2023. "Standardizing the Factors Used in Wind Farm Site Suitability Models: A Review." *Heliyon* 9(5).

Zorn, Christopher. 2005. "A Solution to Separation in Binary Response Models." *Political Analysis* 13(2):157–170.

Appendix: For Online Publication

Contents

A *Responsibility for Siting Renewable Energy Projects in Selected countries*

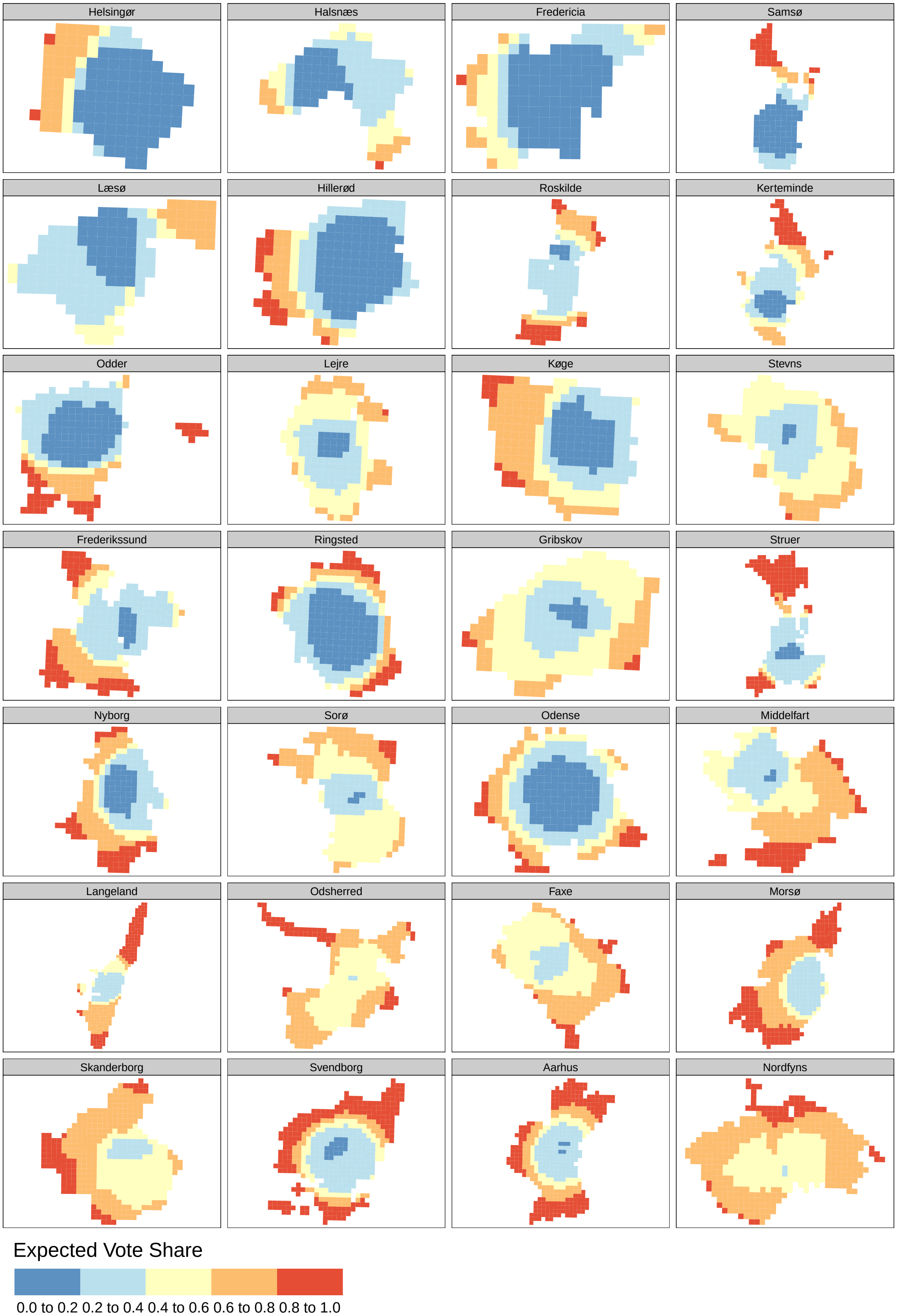
Table A1: Responsibility for Siting Renewable Energy Projects in Western Europe and the United States

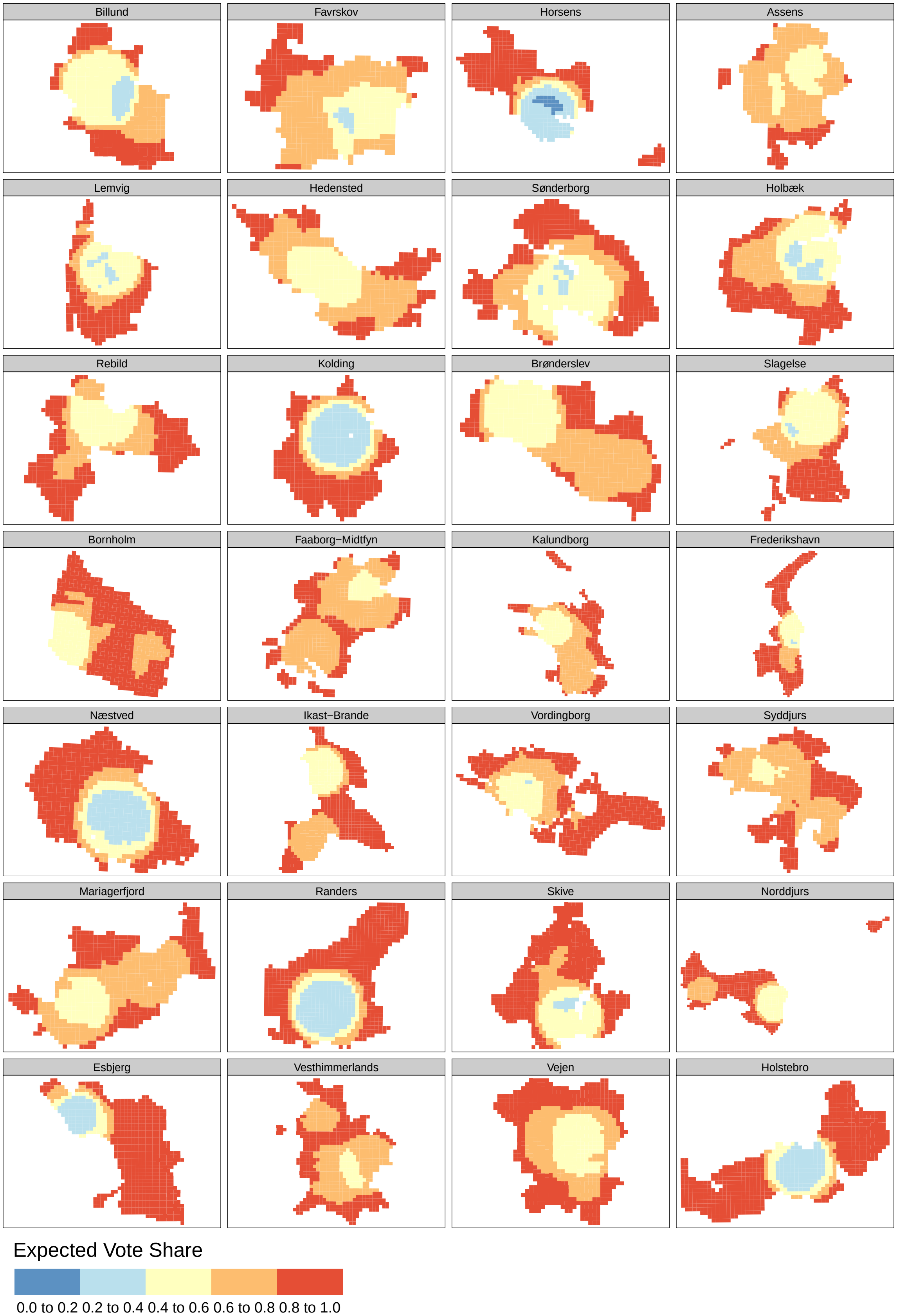
Country/Region	**Primary Responsibility**	**Details**
United States	Primarily Local Governments	Local zoning laws govern siting; however, state and federal agencies may influence through regulations and incentives. (Clean Air Task Force 2024)
Denmark	Local Municipalities	Municipalities are responsible for planning and permitting, aligning with national renewable energy goals. (Naturstyrelsen, Miljøministeriet 2015)
Germany	Shared (Federal, State, Local)	Federal government sets targets; states and local authorities handle planning and permitting, with community engagement. (Clean Energy Wire 2025)
France	Shared (Regional and Local)	Regional authorities oversee planning; local governments manage permitting and address public concerns. (Nadaï and Labussière 2014)
United Kingdom	Shared (National and Local)	Local councils approve most projects; larger projects are handled at the national level. (NFU Energy 2022)
Italy	Regional Authorities	Regions designate suitable areas and handle permitting under national guidelines. (IEA Wind 2022)
Spain	Shared (Regional and National)	Regional governments manage permitting; the national government oversees projects of strategic importance. (Reuters 2025)

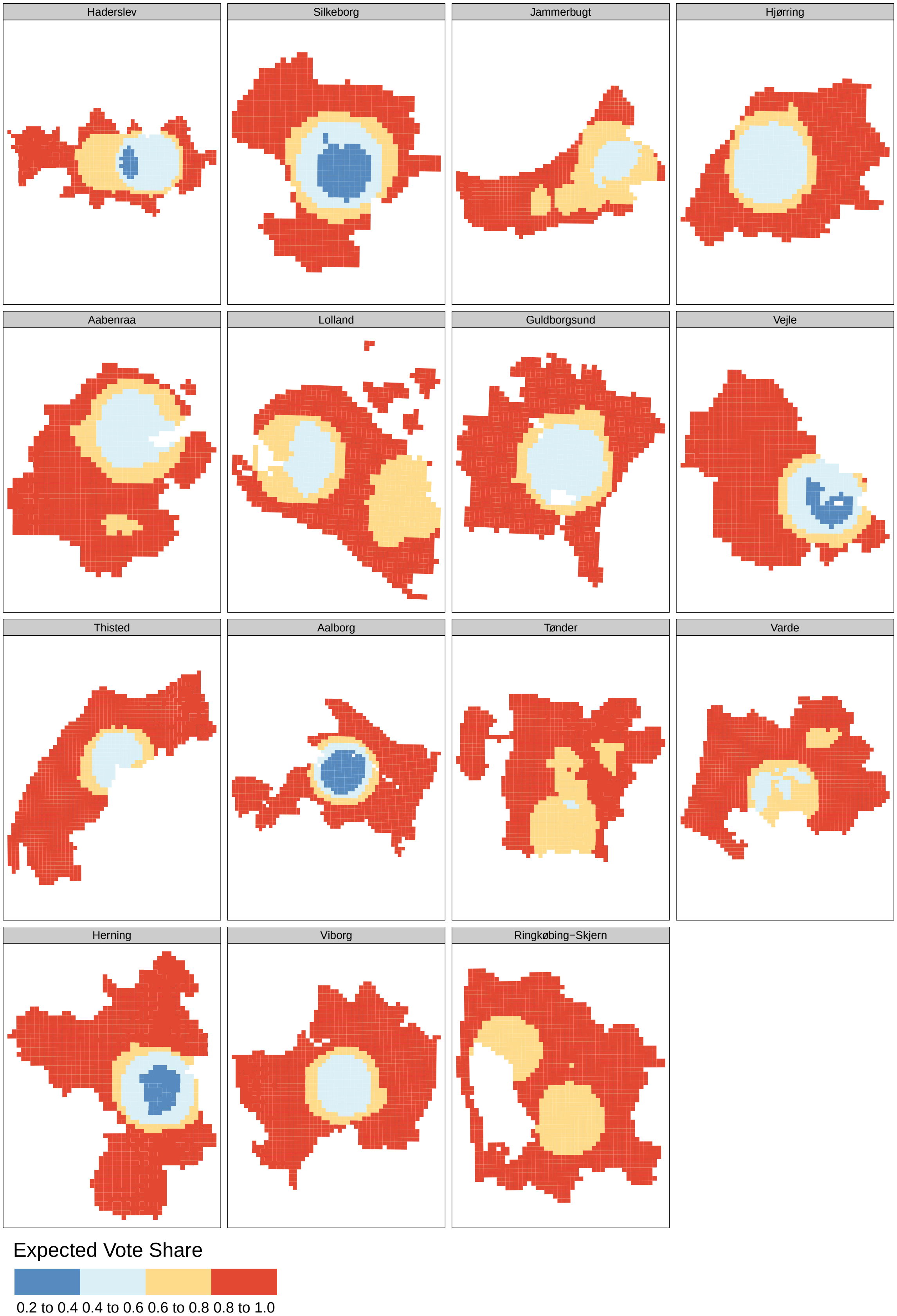
B Visualization of Prop. Approve Scores by Municipality

These visualizations show the the approval score, colored by quintile of the overall distribution, for each municipality in Denmark. Municipalities are ordered by land area.


Christiansø
Frederiksberg
Vallensbæk
Rødovre
Herlev
Glostrup
Brøndby
Dragør
Albertslund
Gladsaxe
Hvidovre
Gentofte
Ishøj
Ballerup
Hørsholm
Lyngby−Taarbæk
Solrød
Furesø
Greve
Allerød
Høje−Taastrup
Rudersdal
Tårnby
Fanø
København
Fredensborg
Egedal
Ærø
Expected Vote Share
0.0 to 0.2
0.2 to 0.4
0.4 to 0.6
0.6 to 0.8
0.8 to 1.0


Helsingør
Halsnæs
Fredericia
Samsø
Læsø
Hillerød
Roskilde
Kerteminde
Odder
Lejre
Køge
Stevns
Frederikssund
Ringsted
Gribskov
Struer
Nyborg
Sorø
Odense
Middelfart
Langeland
Odsherred
Faxe
Morsø
Skanderborg
Svendborg
Aarhus
Nordfyns
Expected Vote Share
0.0 to 0.2
0.2 to 0.4
0.4 to 0.6
0.6 to 0.8
0.8 to 1.0


Billund
Favrskov
Horsens
Assens
Lemvig
Hedensted
Sønderborg
Holbæk
Rebild
Kolding
Brønderslev
Slagelse
Bornholm
Faaborg−Midtfyn
Kalundborg
Frederikshavn
Næstved
Ikast−Brande
Vordingborg
Syddjurs
Mariagerfjord
Randers
Skive
Norddjurs
Esbjerg
Vesthimmerlands
Vejen
Holstebro
Expected Vote Share
0.0 to 0.2
0.2 to 0.4
0.4 to 0.6
0.6 to 0.8
0.8 to 1.0


Haderslev
Silkeborg
Jammerbugt
Hjørring
Aabenraa
Lolland
Guldborgsund
Vejle
Thisted
Aalborg
Tønder
Varde
Herning
Viborg
Ringkøbing−Skjern
Expected Vote Share
0.2 to 0.4
0.4 to 0.6
0.6 to 0.8
0.8 to 1.0

C Parameter Selection for the Voter's Utility Function

We model the utility experienced by a voter at location i from a turbine at location j according to the function:

$$U_v = b - k\left(\frac{1}{d(i,j)+q}\right)^2 \tag{C1}$$

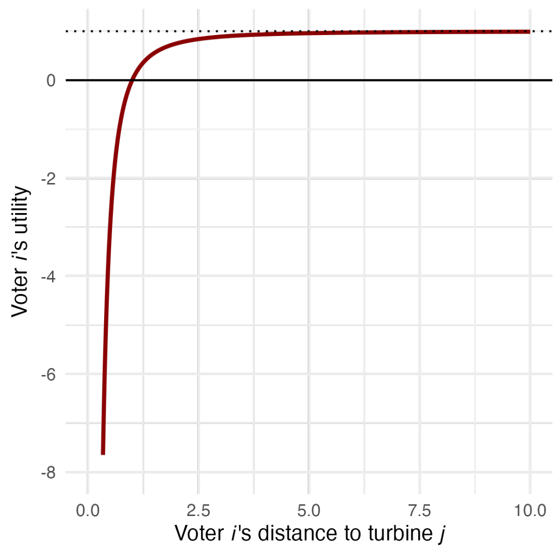
where $d(i,j)$ represents the Euclidean distance between locations i and j. We normalize the (non-spatial) benefit of a turbine, b, to 1. In this section, we describe our data-driven process for selecting the optimal values of the parameters k and q. These parameters control the shape of the cost function experienced by voters, in particular how intensely the costs are felt relative to the benefit as well as how these costs decay over space.

Figure C1 presents a few illustrative examples. In panel a, we plot the function with k set to 1 and q set to 0 for reference, so that U_v is simply $1-\left(\frac{1}{d(i,j)}\right)^2$. In panel b, we increase the parameter k to 20, keeping q fixed at 0. The resulting function has a more gradual and long-lasting decay, such that some costs are still felt at distances up to 10 km, compared to the baseline specification in panel a where most costs have dissipated by 2.5 km. Panel c illustrates the additional value of the q parameter in shifting the function horizontally, thereby controlling where it crosses $y=0$ (i.e., at what distance the benefit of the turbine begins to outweigh the cost). For example, setting $q=1$ compared to $q=0$, holding k constant at 20, shifts this threshold from approximately 4 km in panel b to 3 km in panel c.

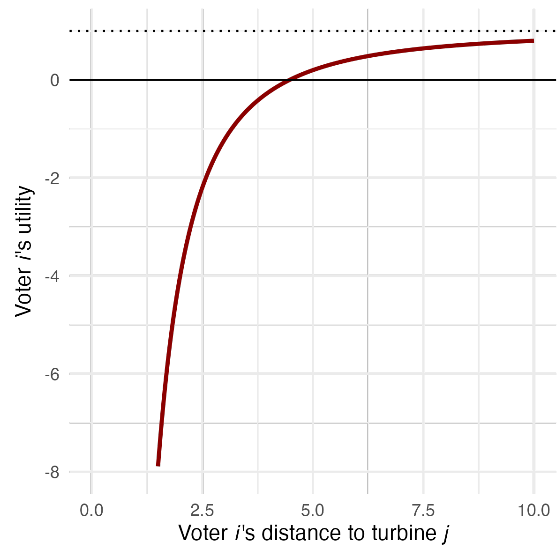
We find the values of k and q that make our model most predictive of turbine sitings. To do so, we generate a grid of candidates over the range of plausible values that accord with intuitions and expectations derived from prior research. We are mainly guided by findings on the effects of large and visible wind turbines on nearby property values. For instance, Jarvis (forthcoming) finds that these price effects are present at distances up to 4 km. Our grid includes q values from 0 to 1, inclusive, incremented by 0.1, as well as k values from 1 to 20, inclusive, incremented by 1, generating a total of 220 candidate pairs.

For each candidate pair, we run a support vector machine (SVM) classification model and assess its performance at predicting tall turbine sitings (>80 meters). We use the pre-reform data (1998-2006) for this calibration exercise.[7] The process proceeds as follows:

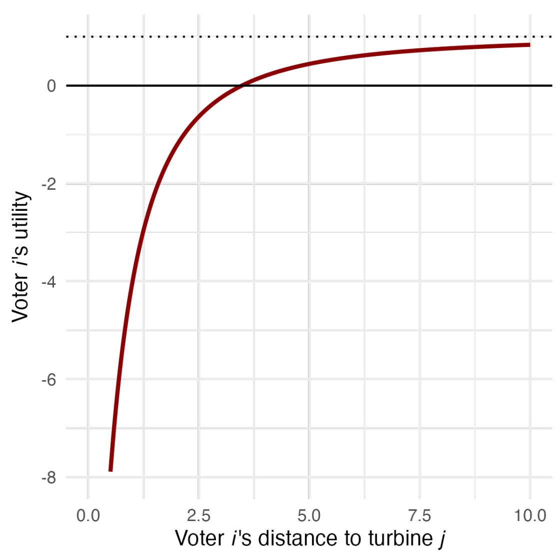
[7] We select 1998 as the start of the pre-reform period because that is the first year in which a tall turbine appears in the data.



(a) $b = 1,\ k = 1,\ q = 0$



(b) $b = 1,\ k = 20,\ q = 0$



(c) $b = 1,\ k = 20,\ q = 1$

Figure C1: The role of the k and q parameters in the utility model. Voter's utility function is given in Equation C1. Dashed horizontal line represents the non-spatial benefit, $b = 1$.

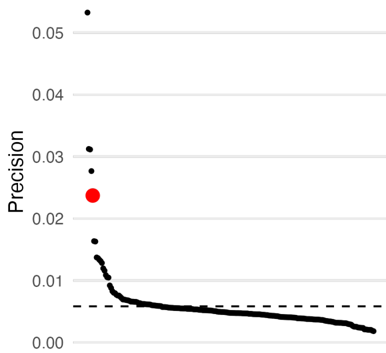
1. Begin with a data set that has one observation per grid cell for all grid cells in Denmark. For each grid cell, compute the municipality-wide approval score based on the municipality boundaries during that period as well as grid-cell-level population averaged over that period. The outcome is a binary indicator of whether a turbine over 80 meters was newly built in that grid cell at any point during that period.

2. Divide this data set into training and test data. The training set contains 70% of the sample and the test set the remaining 30%. Because tall turbine siting is a rare event in the data, we significantly oversample the treated observations in the training set to achieve better performance.

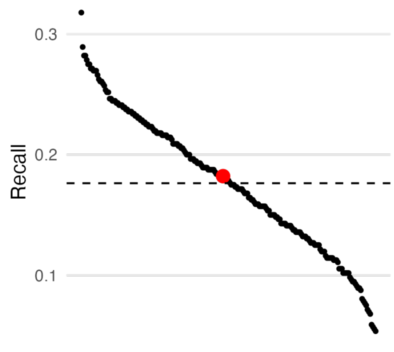
3. For each municipality-wide approval score (generated using each pair of candidate parameters), we run an SVM on the training data, also including the variables from our main analysis in the model. The model is then used to generate predictions in the test data and a confusion matrix is computed, giving us the true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN).

4. We repeat steps 2-3 20 times per candidate approval score to smooth over any noise from sampling the training data, and compute the averages of the following metrics over the 20 iterations:

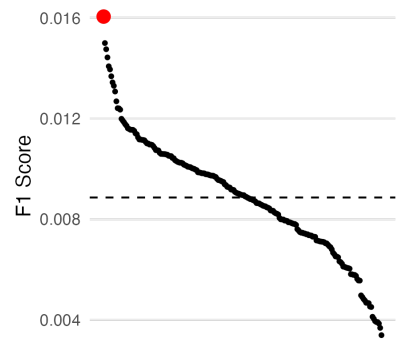
    - **Recall (true positive rate):** Of all *positive* cases in the data, the proportion *correctly* identified by our model: $\frac{TP}{TP+FN}$
    - **False negative rate:** Of all *positive* cases in the data, the proportion *incorrectly* identified by our model: $\frac{FN}{TP+FN}$
    - **Specificity (true negative rate):** Of all *negative* cases in the data, the proportion *correctly* identified by our model: $\frac{TN}{TN+FP}$
    - **False positive rate:** Of all *negative* cases in the data, the proportion *incorrectly* identified by our model: $\frac{FP}{TN+FP}$
    - **Precision:** Of all *positive* cases identified by our model, the proportion actually correct: $\frac{TP}{TP+FP}$
    - **F1 Score:** The harmonic mean of precision and recall: $2 \times \frac{Precision \times Recall}{Precision + Recall}$
    - **Accuracy:** Of all model predictions, the proportion actually correct: $\frac{TN+TP}{TN+TP+FN+FP}$



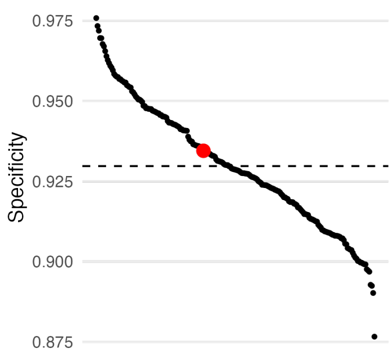
(a) Precision: $\frac{TP}{TP+FP}$



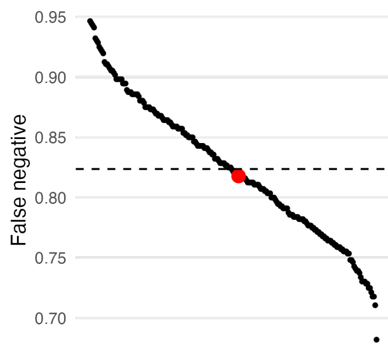
(b) Recall: $\frac{TP}{TP+FN}$



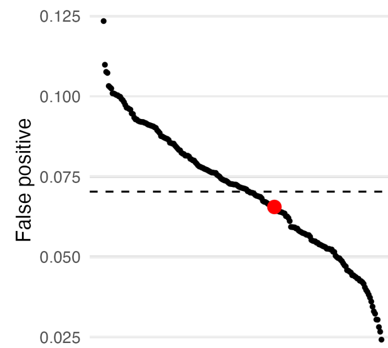
(c) F1 Score: $2\times\frac{Precision\times Recall}{Precision+Recall}$



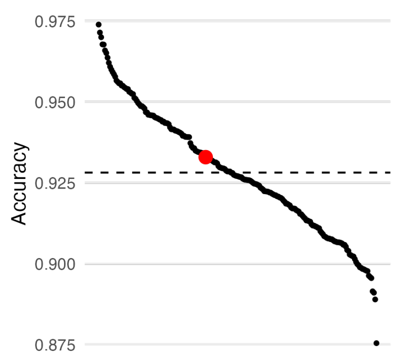
(d) Specificity: $\frac{TN}{TN+FP}$



(e) False negative rate: $\frac{FN}{TP+FN}$



(f) False positive rate: $\frac{FP}{TN+FP}$



(g) Accuracy: $\frac{TN+TP}{TN+TP+FN+FP}$

Figure C2: Performance metrics for the candidate parameter values. Performance for the chosen values ($k = 15,\ q = 0.4$) is highlighted in red. Dashed line shows mean performance among all candidates.

Figure C2 presents the results. We choose to maximize the F1 score and choose values of $k = 15$ and $q = 0.4$ to accomplish this goal. Figure 3 plots the voter's utility as a function of distance to the turbine for the chosen parameters. We see that the decay in the cost happens most intensely over the first 2 km and that the function starts to plateau after 5 km. This pattern is consistent with findings from the literature in economics on the effects of wind turbines on nearby home prices: for instance, Jarvis (Forthcoming) finds that effects on prices are felt at distances up to 4 km from new, tall turbines.

Finally, in Figure C3, we show the sensitivity of our main results to the choice of parameters. We show the point estimates and 95% confidence intervals from a logistic regression with our preferred specification from Figure 9, including all controls and municipality fixed effects. The point estimate corresponding to our chosen parameters is marked in red: a point estimate of 0.54 ($p < 0.001$), corresponding to an odds ratio of 1.71. The figure shows that our chosen parameter values yield some of the more conservative estimates of the effect of municipality-wide approval scores on turbine siting, which are mostly concentrated between 0.40 and 2.19 (corresponding to odds ratios of 1.50 and 4.20, respectively).

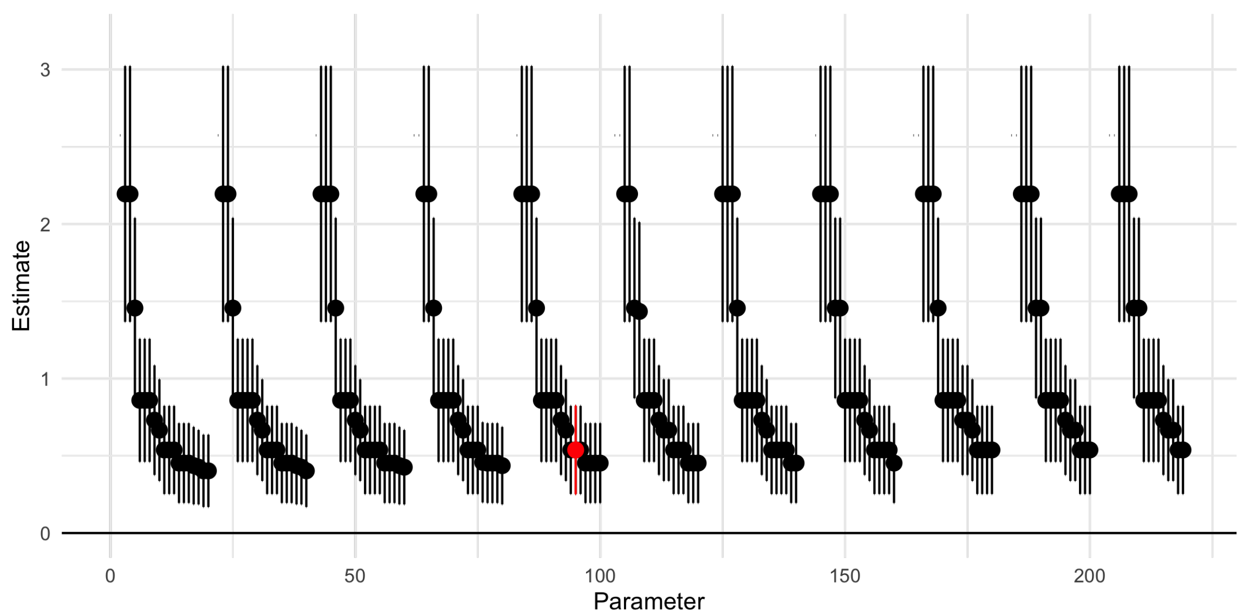


Figure C3: Sensitivity of estimates from logistic regression (main specification, with municipality fixed effects) to parameter choices. Vertical lines represent 95% confidence intervals. Estimate corresponding to the chosen parameter values ($k = 15,\ q = 0.4$) is marked in red.

D Descriptive Statistics

Table D2: Descriptive statistics for 1x1 km grid cells

Statistic	N	Mean	St. Dev.	Min	Max
Δ turbine	45,704	0.01	0.09	0	1
Δ approval	45,704	0.11	0.13	−0.69	0.81
Approval (pre-2007)	45,704	0.83	0.18	0.00	1.00
Average population 2007-2020	45,704	122.00	574.96	0.00	22,932.20
Elevation (m)	45,700	29.11	24.92	−6.94	159.45
Mean wind capacity	45,491	477.22	114.93	0.00	1,012.69
Hilliness	45,698	7.91	5.95	0.00	57.68
Distance to coast	45,704	9.55	9.67	0.0000	49.10

E Results in Tabular Form

	Model 1	Model 2	Model 3	Model 4
Approval (standardized)	0.834^{***}	0.550^{**}	0.377^{*}	0.343^{*}
	(0.238)	(0.194)	(0.147)	(0.163)
Elevation		-0.003	-0.008	-0.009
		(0.016)	(0.015)	(0.015)
Elevation, squared		-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)
Hilliness		-0.167^{***}	-0.211^{***}	-0.211^{***}
		(0.035)	(0.044)	(0.041)
Hilliness, squared		0.004^{***}	0.005^{***}	0.005^{***}
		(0.001)	(0.001)	(0.001)
Distance to coast		0.086	0.102^{*}	0.099^{*}
		(0.046)	(0.048)	(0.047)
Distance to coast, squared		-0.002	-0.002^{*}	-0.002^{*}
		(0.001)	(0.001)	(0.001)
Mean wind capacity		0.015^{*}	0.018^{**}	0.019^{**}
		(0.007)	(0.007)	(0.007)
Mean wind capacity, squared		-0.000^{*}	-0.000^{**}	-0.000^{**}
		(0.000)	(0.000)	(0.000)
Border distance 0-1 km				0.350
				(0.220)
Border distance 1-3 km				-0.147
				(0.215)
Border distance 3-5 km				-0.283
				(0.288)
Border distance 10+ km				0.298
				(0.253)
(Intercept)	-4.748^{***}	-9.080^{***}	-9.909^{***}	-9.971^{***}
	(0.157)	(2.454)	(2.306)	(2.335)
Municipal FE	No	No	Yes	Yes
AIC	5092.616	4890.941	4602.141	4589.066
BIC	5110.076	4978.193	5535.731	5557.556
Log Likelihood	-2544.308	-2435.471	-2194.070	-2183.533
Deviance	5088.616	4870.941	4388.141	4367.066
Num. obs.	45704	45485	45485	45485

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table E3: Effect of standard deviation increase in approval score on hosting a turbine (>80 m, cross-sectional logit model).

	Model 1	Model 2	Model 3	Model 4
Approval (standardized)	0.822^{***}	0.535^{**}	0.361^{***}	0.326^{**}
	(0.234)	(0.188)	(0.107)	(0.119)
Elevation		-0.004	-0.009	-0.010
		(0.016)	(0.013)	(0.013)
Elevation, squared		-0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
Hilliness		-0.169^{***}	-0.211^{***}	-0.210^{***}
		(0.035)	(0.038)	(0.036)
Hilliness, squared		0.004^{***}	0.005^{***}	0.005^{***}
		(0.001)	(0.001)	(0.001)
Distance to coast		0.085	0.101^{*}	0.098^{*}
		(0.046)	(0.044)	(0.043)
Distance to coast, squared		-0.002	-0.002^{*}	-0.002^{*}
		(0.001)	(0.001)	(0.001)
Mean wind capacity		0.015^{*}	0.018^{**}	0.018^{**}
		(0.007)	(0.006)	(0.006)
Mean wind capacity, squared		-0.000^{*}	-0.000^{**}	-0.000^{**}
		(0.000)	(0.000)	(0.000)
Border distance 0-1 km				0.354
				(0.201)
Border distance 1-3 km				-0.142
				(0.197)
Border distance 3-5 km				-0.278
				(0.265)
Border distance 10+ km				0.296
				(0.237)
(Intercept)	-4.743^{***}	-8.992^{***}	-9.730^{***}	-9.787^{***}
	(0.155)	(2.421)	(2.124)	(2.141)
Municipal FE	No	No	Yes	Yes
Deviance (Null)	5164.518	5150.896	5150.896	5150.896
df.null	45703	45484	45484	45484
Log Likelihood	-2544.314	-2435.571	-2214.021	-2203.626
AIC	5092.627	4891.141	4642.042	4629.251
BIC	5110.087	4978.393	5575.632	5597.741
Deviance	5088.627	4871.141	4428.042	4407.251
DF Resid.	45702	45475	45378	45374
nobs	45704	45485	45485	45485

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table E4: Effect of standard deviation increase in approval score on hosting a turbine (>80 m, cross-sectional Firth's logit model).

	Model 1	Model 2	Model 3	Model 4
Δ approval (standardized)	1.003^{**}	0.729^{*}	0.653^{*}	0.652^{*}
	(0.388)	(0.312)	(0.274)	(0.305)
Approval (pre-2007)	8.422^{**}	6.280^{**}	4.919^{**}	4.765^{*}
	(2.696)	(2.075)	(1.673)	(1.936)
Elevation		−0.014	−0.010	−0.011
		(0.015)	(0.015)	(0.015)
Elevation, squared		−0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
Hilliness		-0.166^{***}	-0.204^{***}	-0.204^{***}
		(0.043)	(0.056)	(0.053)
Hilliness, squared		0.003^{*}	0.004^{*}	0.004^{**}
		(0.001)	(0.002)	(0.002)
Distance to coast		0.063^{*}	0.105^{*}	0.104^{*}
		(0.026)	(0.054)	(0.050)
Distance to coast, squared		-0.002^{*}	−0.002	−0.002
		(0.001)	(0.001)	(0.001)
Mean wind capacity			0.017^{*}	0.017^{*}
			(0.007)	(0.007)
Mean wind capacity, squared			-0.000^{*}	-0.000^{*}
			(0.000)	(0.000)
Border distance 0-1 km				0.411
				(0.262)
Border distance 1-3 km				−0.102
				(0.240)
Border distance 3-5 km				−0.156
				(0.321)
Border distance 10+ km				0.459
				(0.237)
(Intercept)	-11.970^{***}	-9.273^{***}	-13.930^{***}	-13.977^{***}
	(2.281)	(1.776)	(2.379)	(2.525)
Municipal FE	No	No	Yes	Yes
AIC	4332.875	4179.240	3895.719	3883.458
BIC	4359.065	4257.807	4838.034	4860.673
Log Likelihood	−2163.437	−2080.620	−1839.860	−1829.729
Deviance	4326.875	4161.240	3679.719	3659.458
Num. obs.	45704	45694	45485	45485

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table E5: Effect of standardized change in approval score on gaining a turbine post-2007 (>80 m, first difference logit model).

	Model 1	Model 2	Model 3	Model 4
Δ approval (standardized)	0.980^{**}	0.636^{*}	0.612^{**}	0.611^{**}
	(0.377)	(0.310)	(0.191)	(0.213)
Approval (pre-2007)	8.235^{**}	5.468^{*}	4.625^{***}	4.465^{***}
	(2.615)	(2.128)	(1.092)	(1.299)
Elevation		-0.005	-0.011	-0.012
		(0.015)	(0.012)	(0.012)
Elevation, squared		-0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
Hilliness		-0.169^{***}	-0.208^{***}	-0.207^{***}
		(0.039)	(0.041)	(0.039)
Hilliness, squared		0.003^{***}	0.005^{***}	0.005^{***}
		(0.001)	(0.001)	(0.001)
Distance to coast		0.104^{*}	0.104^{*}	0.103^{*}
		(0.046)	(0.048)	(0.045)
Distance to coast, squared		-0.002^{*}	-0.002^{*}	-0.002^{*}
		(0.001)	(0.001)	(0.001)
Mean wind capacity		0.014^{*}	0.017^{**}	0.017^{**}
		(0.007)	(0.006)	(0.006)
Mean wind capacity, squared		-0.000	-0.000^{**}	-0.000^{**}
		(0.000)	(0.000)	(0.000)
Border distance 0-1 km				0.414
				(0.233)
Border distance 1-3 km				-0.097
				(0.213)
Border distance 3-5 km				-0.151
				(0.290)
Border distance 10+ km				0.457^{*}
				(0.220)
(Intercept)	-11.805^{***}	-13.417^{***}	-13.454^{***}	-13.486^{***}
	(2.209)	(2.849)	(2.030)	(2.137)
Municipal FE	No	No	Yes	Yes
Deviance (Null)	4406.618	4393.392	4393.392	4393.392
df.null	45703	45484	45484	45484
Log Likelihood	-2163.450	-2062.660	-1862.474	-1852.468
AIC	4332.900	4147.320	3940.947	3928.937
BIC	4359.089	4243.296	4883.262	4906.152
Deviance	4326.900	4125.320	3724.947	3704.937
DF Resid.	45701	45474	45377	45373
nobs	45704	45485	45485	45485

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table E6: Effect of standardized change in approval score on gaining a turbine post-2007 (>80 m, first difference Firth's logit model).

	Model 1	Model 2	Model 3
Δ approval (standardized)	0.698^{*}	0.423	0.419^{*}
	(0.338)	(0.273)	(0.189)
Approval (pre-2007)	6.398^{**}	4.154^{*}	3.500^{***}
	(2.291)	(1.822)	(1.061)
Elevation		-0.003	-0.010
		(0.014)	(0.012)
Elevation, squared		-0.000	0.000
		(0.000)	(0.000)
Hilliness		-0.169^{***}	-0.205^{***}
		(0.039)	(0.040)
Hilliness, squared		0.003^{**}	0.005^{***}
		(0.001)	(0.001)
Distance to coast		0.098^{*}	0.101^{*}
		(0.044)	(0.046)
Distance to coast, squared		-0.002^{*}	-0.002^{*}
		(0.001)	(0.001)
Mean wind capacity		0.012	0.015^{**}
		(0.007)	(0.006)
Mean wind capacity, squared		-0.000	-0.000^{**}
		(0.000)	(0.000)
(Intercept)	-10.202^{***}	-11.570^{***}	-11.804^{***}
	(1.916)	(2.628)	(1.913)
Municipal FE	No	No	Yes
Deviance (Null)	4501.931	4488.660	4488.660
df.null	45703	45484	45484
Log Likelihood	-2216.511	-2121.311	-1926.844
AIC	4439.021	4264.623	4069.688
BIC	4465.211	4360.599	5012.002
Deviance	4433.021	4242.623	3853.688
DF Resid.	45701	45474	45377
nobs	45704	45485	45485

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table E7: Effect of standardized change in approval score on gaining a turbine post-2007 (>60 m, first difference Firth's logit model).

	Model 1	Model 2	Model 3
Δ approval (standardized)	1.246^{**}	0.865^{*}	0.657^{***}
	(0.420)	(0.345)	(0.193)
Approval (pre-2007)	9.940^{***}	6.915^{**}	4.909^{***}
	(2.996)	(2.453)	(1.107)
Elevation		-0.006	-0.011
		(0.015)	(0.013)
Elevation, squared		-0.000	0.000
		(0.000)	(0.000)
Hilliness		-0.181^{***}	-0.226^{***}
		(0.037)	(0.041)
Hilliness, squared		0.004^{***}	0.005^{***}
		(0.001)	(0.001)
Distance to coast		0.090	0.089^{*}
		(0.046)	(0.045)
Distance to coast, squared		-0.002	-0.002
		(0.001)	(0.001)
Mean wind capacity		0.013	0.015^{**}
		(0.007)	(0.006)
Mean wind capacity, squared		-0.000	-0.000^{**}
		(0.000)	(0.000)
(Intercept)	-13.297^{***}	-14.261^{***}	-13.799^{***}
	(2.545)	(3.043)	(1.875)
Municipal FE	No	No	Yes
Deviance (Null)	4310.775	4297.592	4297.592
df.null	45703	45484	45484
Log Likelihood	-2111.537	-2009.693	-1805.952
AIC	4229.074	4041.387	3827.904
BIC	4255.264	4137.363	4770.218
Deviance	4223.074	4019.387	3611.904
DF Resid.	45701	45474	45377
nobs	45704	45485	45485

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table E8: Effect of standardized change in approval score on gaining a turbine post-2007 (>100 m, first difference Firth's logit model).

	Model 1	Model 2	Model 3	Model 4
Own density (logged, std.)	-0.534^{***}	-0.394^{***}	-0.323^{***}	-0.313^{***}
	(0.066)	(0.084)	(0.073)	(0.073)
Elevation		0.000	-0.005	-0.006
		(0.015)	(0.013)	(0.013)
Elevation, squared		-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)
Hilliness		-0.144^{***}	-0.183^{***}	-0.184^{***}
		(0.033)	(0.035)	(0.034)
Hilliness, squared		0.003^{***}	0.004^{***}	0.004^{***}
		(0.001)	(0.001)	(0.001)
Distance to coast		0.093^{*}	0.105^{*}	0.106^{*}
		(0.045)	(0.045)	(0.044)
Distance to coast, squared		-0.002^{*}	-0.002^{*}	-0.002^{*}
		(0.001)	(0.001)	(0.001)
Mean wind capacity		0.018^{*}	0.020^{**}	0.020^{**}
		(0.007)	(0.006)	(0.006)
Mean wind capacity, squared		-0.000^{*}	-0.000^{**}	-0.000^{**}
		(0.000)	(0.000)	(0.000)
Border distance 0-1 km				0.228
				(0.209)
Border distance 1-3 km				-0.159
				(0.198)
Border distance 3-5 km				-0.274
				(0.268)
Border distance 10+ km				0.305
				(0.261)
(Intercept)	-4.736^{***}	-9.759^{***}	-10.366^{***}	-10.316^{***}
	(0.157)	(2.390)	(2.194)	(2.186)
Municipal FE	No	No	Yes	Yes
Deviance (Null)	5164.518	5150.896	5150.896	5150.896
df.null	45703	45484	45484	45484
Log Likelihood	-2501.404	-2419.045	-2198.313	-2190.417
AIC	5006.808	4858.089	4612.627	4602.833
BIC	5024.267	4945.341	5554.942	5571.324
Deviance	5002.808	4838.089	4396.627	4380.833
DF Resid.	45702	45475	45377	45374
nobs	45704	45485	45485	45485

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table E9: Effect of own local population density (logged) on hosting a turbine (>80 m, cross-sectional Firth's logit model).

	Model 1	Model 2	Model 3	Model 4
Neighboring density (logged, std.)	0.026	0.141^{*}	0.218^{***}	0.104^{***}
	(0.062)	(0.060)	(0.056)	(0.073)
Elevation		-0.004	-0.010	-0.011
		(0.015)	(0.013)	(0.013)
Elevation, squared		-0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
Hilliness		-0.176^{***}	-0.216^{***}	-0.216^{***}
		(0.034)	(0.037)	(0.034)
Hilliness, squared		0.004^{***}	0.005^{***}	0.005^{***}
		(0.001)	(0.001)	(0.001)
Distance to coast		0.106^{*}	0.107^{*}	0.109^{*}
		(0.045)	(0.043)	(0.044)
Distance to coast, squared		-0.002^{*}	-0.002^{*}	-0.002^{*}
		(0.001)	(0.001)	(0.001)
Mean wind capacity		0.019^{**}	0.020^{***}	0.019^{**}
		(0.007)	(0.006)	(0.006)
Mean wind capacity, squared		-0.000^{*}	-0.000^{***}	-0.000^{**}
		(0.000)	(0.000)	(0.000)
Border distance 0-1 km				0.269
				(0.209)
Border distance 1-3 km				-0.090
				(0.198)
Border distance 3-5 km				-0.258
				(0.268)
Border distance 10+ km				0.278
				(0.261)
(Intercept)	-4.582^{***}	-10.254^{***}	-10.160^{***}	-10.081^{***}
	(0.164)	(2.313)	(2.078)	(2.186)
Municipal FE	No	No	Yes	Yes
Deviance (Null)	5164.518	5150.896	5150.896	5150.896
df.null	45703	45484	45484	45484
Log Likelihood	-2582.135	-2449.119	-2213.089	-2207.846
AIC	5168.270	4918.238	4640.179	4637.693
BIC	5185.730	5005.489	5573.769	5606.183
Deviance	5164.270	4898.238	4426.179	4415.693
DF Resid.	45702	45475	45378	45374
nobs	45704	45485	45485	45485

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table E10: Effect of neighboring local population density (logged) on hosting a turbine (>80 m, cross-sectional Firth's logit model).

F Placebo Test

As a placebo test, we use the same model as in Figure 10 to measure the effect of a change in the approval score on the location of a turbine before 2007. Figure F4 shows that the increase in the approval score of a grid cell after reform was not associated with its hosting of a turbine before the 2007 reform.

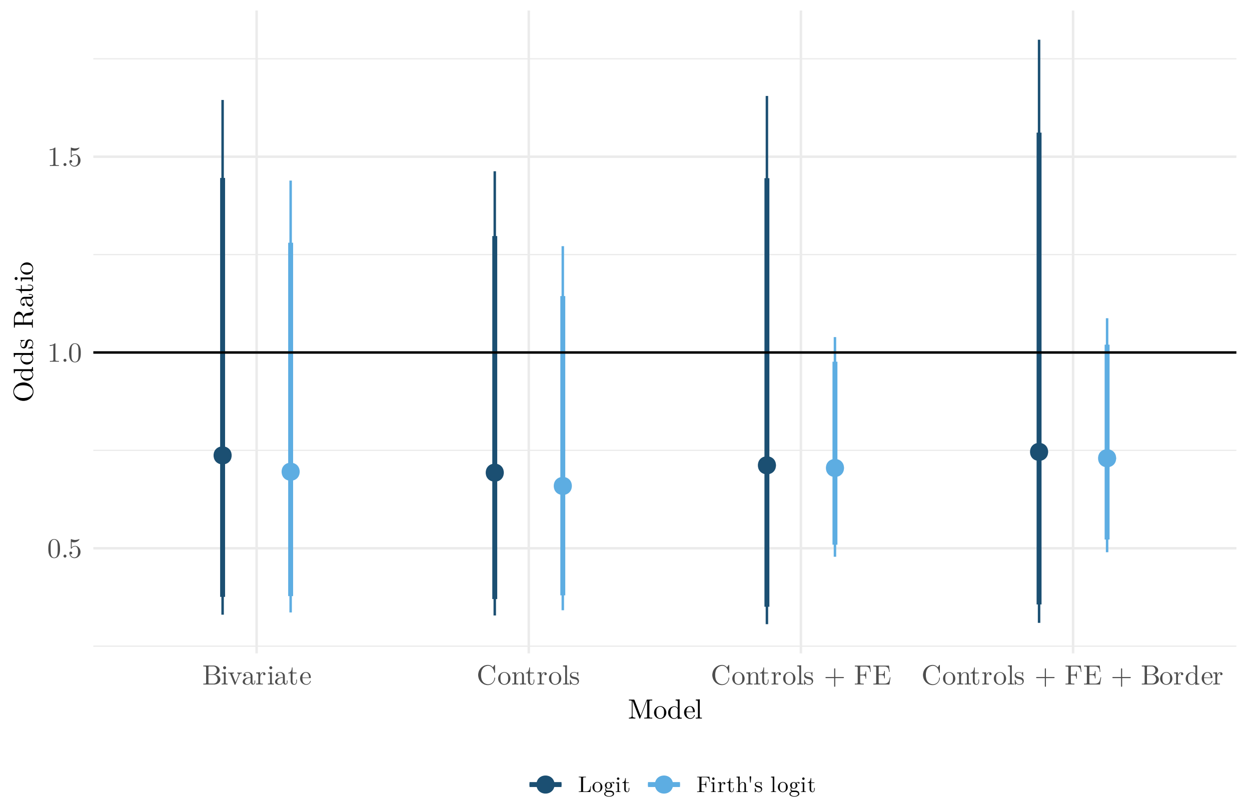


Figure F4: Effect of standardized change in approval score on binary indicator for gaining a turbine pre-2007, exponentiated coefficients. See Tables F11 and F12 for tabular form. (1 standard deviation ≈ 0.1.)

	Model 1	Model 2	Model 3	Model 4
Δ approval (standardized)	−0.305	−0.367	−0.340	−0.293
	(0.409)	(0.381)	(0.430)	(0.449)
Approval (pre-2007)	2.679	1.543	−0.357	−0.036
	(1.591)	(1.651)	(1.937)	(2.093)
Elevation		−0.000	−0.012	−0.014
		(0.030)	(0.024)	(0.025)
Elevation, squared		0.000	−0.000	0.000
		(0.000)	(0.000)	(0.000)
Hilliness		−0.127**	−0.194***	−0.194***
		(0.048)	(0.058)	(0.059)
Hilliness, squared		0.003**	0.005***	0.005***
		(0.001)	(0.001)	(0.001)
Distance to coast		0.021	0.082	0.084
		(0.076)	(0.088)	(0.091)
Distance to coast, squared		0.000	−0.002	−0.002
		(0.001)	(0.002)	(0.002)
Mean wind capacity		0.022	0.034*	0.034
		(0.014)	(0.017)	(0.017)
Mean wind capacity, squared		−0.000	−0.000*	−0.000
		(0.000)	(0.000)	(0.000)
Border distance 0-1 km				−0.153
				(0.485)
Border distance 1-3 km				−0.549
				(0.474)
Border distance 3-5 km				−0.593
				(0.473)
Border distance 10+ km				0.035
				(0.540)
(Intercept)	−8.565***	−13.783**	−14.744**	−14.729**
	(1.369)	(4.413)	(5.512)	(5.630)
Municipal FE	No	No	Yes	Yes
AIC	1379.456	1362.938	1377.564	1380.224
BIC	1405.646	1458.915	2319.878	2357.439
Log Likelihood	−686.728	−670.469	−580.782	−578.112
Deviance	1373.456	1340.938	1161.564	1156.224
Num. obs.	45704	45485	45485	45485

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table F11: Effect of standardized change in approval score on gaining a turbine pre-2007 (>80 m, first difference logit model, placebo).

	Model 1	Model 2	Model 3	Model 4
Δ approval (standardized)	-0.363	-0.417	-0.349	-0.315
	(0.371)	(0.335)	(0.198)	(0.203)
Approval (pre-2007)	2.181	1.073	-0.569	-0.332
	(1.319)	(1.374)	(0.743)	(0.791)
Elevation		-0.002	-0.014	-0.016
		(0.028)	(0.018)	(0.018)
Elevation, squared		0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
Hilliness		-0.129^{**}	-0.191^{***}	-0.191^{***}
		(0.045)	(0.039)	(0.039)
Hilliness, squared		0.003^{***}	0.005^{***}	0.005^{***}
		(0.001)	(0.001)	(0.001)
Distance to coast		0.021	0.079	0.080
		(0.072)	(0.063)	(0.064)
Distance to coast, squared		0.000	-0.002	-0.002
		(0.001)	(0.001)	(0.001)
Mean wind capacity		0.021	0.032^{**}	0.032^{**}
		(0.013)	(0.011)	(0.011)
Mean wind capacity, squared		-0.000	-0.000^{**}	-0.000^{**}
		(0.000)	(0.000)	(0.000)
Border distance 0-1 km				-0.115
				(0.323)
Border distance 1-3 km				-0.516
				(0.321)
Border distance 3-5 km				-0.561
				(0.326)
Border distance 10+ km				0.045
				(0.385)
(Intercept)	-8.122^{***}	-12.970^{**}	-13.801^{***}	-13.678^{***}
	(1.132)	(4.079)	(3.723)	(3.691)
Municipal FE	No	No	Yes	Yes
Deviance (Null)	1400.207	1399.265	1399.265	1399.265
df.null	45703	45484	45484	45484
Log Likelihood	-686.798	-670.835	-611.551	-610.436
AIC	1379.596	1363.670	1439.103	1444.872
BIC	1405.786	1459.647	2381.418	2422.087
Deviance	1373.596	1341.670	1223.103	1220.872
DF Resid.	45701	45474	45377	45373
nobs	45704	45485	45485	45485

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table F12: Effect of standardized change in approval score on gaining a turbine pre-2007 (>80 m, first difference Firth's logit model, placebo).

G Modeling Count Data

To model the effect of a change in approval scores on the number of turbines constructed, we need to account for both the skew of our data and the high number of cells without turbines (count zero). Testing for dispersions shows that our data are better suited for a negative binomial rather than a Poisson model. To handle the concentration of zeros, we use a hurdle model. The "Zero model" results help identify the factors related to the presence or absence of turbines in a given cell. The results of the "Count model" show the factors influencing the number of turbines in a grid cell, conditional on nonzero counts.

We use the same change in approval score design of our analysis, measuring the relationship between change in approval scores from pre- to post-municipal reform on the number of post-2007 turbines, controlling for pre-2007 approval score. Because our dependent variable is now the number of turbines post-2007 (rather than a change in the number of turbines), we include a control for the number of turbines in a cell before 2007. We use only linear definitions of our control variables, as the regression is unable to estimate values for the quadratic definitions when using this functional form. However, results on our parameter of interest (Approval) are substantively the same regardless of whether linear or quadratic controls are included. We use robust standard errors clustered at the municipal-level.

As shown in Table G13, a standard deviation change in approval score post-2007 reform is associated with a 119% increase in the odds of hosting any turbines post-2007.[8] In contrast, a standard deviation change in approval score is not associated with a statistically significant change in the odds of hosting an additional turbine conditional on hosting any at all.

That the main effect of approval score is on whether to host any turbines—rather than an additional turbine—is not surprising given the unobserved variation that can occur in the number of turbines sited in a grid cell. For example, larger turbines need more space between them in order to maximize their energy efficiency. Therefore, it is unclear whether two 80-meter turbines are a more intense outcome compared to one 120-meter turbine. Alternative approaches, such as the cumulative turbine height in a given cell, require strong assumptions about the linear additive effects of turbine height. Instead, we believe that political conflict occurs most closely at the point of deciding to site new turbines, rather than the number of turbines.

[8] $(e^{0.784} - 1) \times 100 = 119\%$

	Model 1	Model 2
Count model: (Intercept)	-2.337	-1.835
	(1.240)	(1.176)
Count model: Δ approval (standardized)	0.258	0.216
	(0.212)	(0.196)
Count model: Approval (pre-2007)	3.090^{*}	2.626^{*}
	(1.432)	(1.317)
Count model: Num. turbines (pre-2007)	0.221^{***}	0.210^{***}
	(0.027)	(0.025)
Zero model: (Intercept)	-11.613^{***}	-9.889^{***}
	(1.520)	(1.277)
Zero model: Δ approval (standardized)	0.964^{***}	0.784^{***}
	(0.272)	(0.232)
Zero model: Approval (pre-2007)	7.963^{***}	6.266^{***}
	(1.768)	(1.484)
Zero model: Num. turbines (pre-2007)	8.907^{***}	9.556^{***}
	(1.070)	(1.369)
Count model: Elevation		0.001
		(0.003)
Count model: Hilliness		-0.042^{***}
		(0.013)
Count model: Distance to coast		-0.002
		(0.006)
Count model: Mean wind capacity		0.000
		(0.000)
Zero model: Elevation		-0.013^{***}
		(0.004)
Zero model: Hilliness		-0.108^{***}
		(0.017)
Zero model: Distance to coast		0.022^{**}
		(0.007)
Zero model: Mean wind capacity		0.001^{*}
		(0.001)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table G13: Effect of increase in approval score on gaining a turbine post-2007 (>80 m, first difference negative binomial hurdle model).