Spinning Stories: Wind Turbines and Local Narrative Landscapes in Germany

Erika Christie Berle and Tom Broekel

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Erika Christie Berle[1] and Tom Broekel[2]

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Abstract

The successful transition toward renewable energies requires public support in areas where their expansion may cause adverse effects. In this context, narratives are crucial as they shape people's perceptions. This article examines the relationship between onshore wind power and related narratives in regions across Germany.

We run a series of spatial regression models on regional newspaper data, and our findings suggest that wind-related topics are more prominent and more neutrally (less angrily) framed in regions with more wind turbines. Public attitudes supporting wind energy expansion correlate with the prominence of related topics in regions' narrative landscapes. In contrast, support for anti-wind protests does not seem to correlate with the prominence of wind-energy-related topics in regions with higher wind turbine densities.

Keywords: narrative landscapes, wind turbines, regional analysis, regional news, narratives, Germany

JEL: R10, R12, R52, Q28, Q48, Q50

[1] Department of Economics and Finance, University of Stavanger Business School, University of Stavanger, Norway.
e-mail: erika.c.berle@uis.no, *telephone: +47 98864690*
correspondence to University of Stavanger UiS Business School N-4036 Stavanger Norway

[2] Department of Innovation, Management and Marketing, University of Stavanger Business School, University of Stavanger, Norway. e-mail: *tom.brokel@uis.no*

1. Introduction

Transforming our energy systems is crucial to becoming carbon neutral by 2050 and limiting the global temperature increase to a maximum of 1.5 degrees Celsius (IPCC, 2018). While the technologies necessary for this transition are widely available, achieving the energy transition still requires substantially increasing renewable energy production.

The importance of wind turbines for transitioning towards more environmentally friendly energy production is unquestioned. However, the spatial footprint needed for such infrastructure causes local externalities, laying the groundwork for opposing local negative impacts (Zerrahn, 2017). Expanding wind farm development required to reach carbon neutrality will fuel such conflicts. Many factors, including the functioning of national and local institutions, the availability of technological solutions, and public attitudes toward wind turbines, shape the intensity and outcomes of these conflicts. These attitudes may determine the success or failure of the transformation, even when other requirements, such as economic and technological factors, are in place (Rohe & Chlebna, 2021; Tuitjer et al., 2022). A crucial factor shaping these attitudes is narratives.

This paper explores the relationship between wind turbine density and the narratives surrounding wind energy, which shape public attitudes. Narratives as an influence on economic development and the energy transition are receiving increasing attention (see, e.g., Shiller, 2017; Esposito et al., 2023; Gehring & Grigoletto, 2023; Jambrina-Canseco, 2023). This paper contributes to this discussion by examining how prominently and with what framing wind energy is featured in a location's narrative landscapes moderated by the presence of wind turbines in nearby locations. We introduce regional news data as an additional novelty to empirically describe these narrative landscapes.

The empirical study utilizes the comprehensive collection of news in the RegNeS database (Ozgun & Broekel, 2021) and detailed information on the locations of all wind turbines in Germany. Our analysis finds that wind energy-related topics are less angry but more prominently featured in the narrative landscapes of regions with many turbines. To a certain degree, existing public attitudes mediate these relationships, with significant differences between urban and rural regions.

The paper develops the central hypotheses in the subsequent section. Section 3 introduces the employed data and empirical approach before presenting the results in Section 4. Section 5 concludes the paper.

2. Wind energy and narrative landscapes

2.1. From narratives to narrative landscapes

In this paper, we are interested in how local conditions - specifically, the number of wind turbines – relate to local narratives. Specifically, whether frequent exposure to wind turbines relates to how prominently related topics feature and are framed in local narratives.

While Merriam-Webster-lexicon defines narratives as "*a way of presenting or understanding a situation or series of events that reflects and promotes a particular point of view or set of values*", there is no commonly accepted definition in the academic literature. Definitions differ widely and vary in the considered and emphasized constitutional elements of narratives. This includes the central events, the relationship between events and actors, relationships between actors, the choice of language, and the arguments (Dennison, 2021). The complexity of the concept is elevated by the fact that individual narratives rarely exist in isolation. On the contrary, they are characterized by substantial interrelatedness across multiple dimensions. This is certainly the case for wind-energy-related narratives deeply interwoven with narratives related to renewable energies, energy prices, land use, and many more.

The interrelatedness, complexity, and multi-dimensionality of narratives represent significant challenges for identifying, quantifying, and analyzing multiple locations. These issues are evident in wind-energy-related narratives, which are highly location- and situation-specific and intertwined with many other narratives. For example, narratives about the first wind turbine in a region differ from those about expanding an existing wind park. Environmental groups might oppose installations locally to preserve nature while generally supporting wind energy. Wildlife might be seen as either a victim of turbine blades or saved by reduced pollution. Political parties, corporations, and energy collectives may vary in their involvement and influence across different areas.

Given this paper's focus on the relationship between narratives and local wind turbine installations across multiple (all) regions of a country, we introduce the concept of "narrative landscape" to empirically study narratives. A region's narrative landscape is the aggregate of all its narratives. It can be considered a multidimensional space where each dimension represents an attribute of narratives, such as political orientation, number of involved actors, and, crucial for this paper, prominence and framing. An individual narrative can be described as a vector in this space, with each element representing its projection along one of these dimensions.

Shifting the focus from individual narratives to the narrative landscape acknowledges that single narratives rarely shape collective behavior, but rather how a specific topic is featured in this landscape and how it "scores" along multiple relevant dimensions. Put differently, it is not single narratives about wind turbines and birds that shape perceptions but the weighted sum of all supporting and opposing narratives.[3] Depending on the context, different dimensions of the landscape are relevant. However, we argue that prominence and framing matter in all settings. Prominence relates to how widely a topic spreads across local narratives and how frequently people encounter it. It captures how often a topic comes to mind (Sheafer, 2007). Framing pertains to how a topic is presented, including the tone and direction of related narratives. That is, framing addresses how people perceive a topic (Rössler, 2001; Chuan et al., 2019), while prominence focuses on the frequency of these thoughts. The joint influence of prominence and framing determines how narratives related to a specific topic, e.g., wind energy, will affect people's behavior.

2.2. Wind energy and narratives

Levi et al. (2023) recently mapped public attitudes toward wind turbines in Germany, revealing a non-random spatial distribution of these attitudes. Their findings suggest a link between the increasing number of wind turbines and rising public acceptance despite various negative externalities associated with wind turbines leading to perceptions of "spatial injustice" (Devine-Wright, 2005; Zerrahn, 2017) and "energy privileges" (Stokes et al. 2023). This counterintuitive trend is attributed to "acclimatization," where prolonged exposure to wind turbines leads to a shift in individual perceptions, softening negative attitudes and sometimes turning them neutral or positive (Devine-Wright, 2005; Dong et al., 2023; Levi et al., 2023; Russell & Firestone, 2021; Wilson & Dyke, 2016).

[3] Note that "narrative landscapes" and public discourse intersect but are not the same. Narrative landscapes offer a structured approach to understanding the collective impact of interconnected narratives within a location, while public discourse is the dynamic process of exchanging and debating ideas within the public sphere.

We propose that the presence of wind turbines is associated with the framing of wind-energy-related topics in local narrative landscapes. Specifically, we anticipate that due to the acclimatization effect, frequent exposure to wind turbines is reflected in the narrative landscapes, which are likely to be more accepting of wind energy.

H1: *In regions with many wind turbines, wind energy-related topics tend to be more positively or at least less negatively framed in local narrative landscapes than in regions with fewer turbines.*

Regarding the possibility of a reverse causal relationship from narratives to wind turbines, while this is conceivable, it appears less likely. Gardt et al. (2021) demonstrate that even the most visible forms of anti-wind energy sentiments, such as local anti-wind turbine initiatives, have had only a marginal impact on the probability of wind turbine installations in Germany. Consequently, there is little evidence that local narratives significantly influenced these decisions, primarily driven by the availability of suitable space and wind speed. This does not imply that these narratives are irrelevant. Initially, wind turbines were installed in smaller numbers and more remote locations, resulting in fewer noticeable externalities. Recently, as new wind turbine locations are closer to settlements and other conflicting land uses, narratives will likely become more relevant. Additionally, the influence of narratives is more indirect, for instance, by contributing to the formation of anti-wind turbine initiatives and shaping local political discussions.

Concerning prominence, a dual relationship is plausible. The acclimatization effect, where wind turbines become commonplace over time, may reduce the novelty and interest in wind energy narratives (Berger & Milkman, 2012). Yet, it can also strengthen these narratives when turbines become part of a location's identity (Swidler, 1986), further increasing their circulation. Our second hypothesis encapsulates these expectations.

H2: *Wind-energy-related topics are more prominent in local narrative landscapes with many wind turbines.*

Levi et al. (2023) note regional variations in attitudes toward wind turbines due to cultural, historical, and geographical factors. These attitudes interact with and influence narratives. Concerning predominantly negative public attitudes towards wind energy, it amplifies the prominence of negative narratives. Various factors might explain this. For instance, local news media, aiming to satisfy their audience, can reinforce such framing (Carroll & McCombs, 2003). Additionally, word of mouth can significantly reinforce these narratives, as individuals tend to trust information from personal contacts more than from impersonal sources (Kimmel, 2010). Social media platforms can amplify these narratives by creating echo chambers where similar viewpoints are shared and reinforced (Sunstein, 2001). Confirmation bias, where people favor narratives aligning with their beliefs, also plays a role (Nickerson, 1998). Suppose limited support for wind energy arises from the abundance of existing turbines; perceptions of spatial injustice and insufficient positive impacts fuel negative narratives. This forms our third hypothesis.

H3: *In locations with negative public attitudes on wind energy, wind-energy-related topics are more prominently and negatively featured in local narrative landscapes.*

Existing regional attitudes don't just directly influence wind energy narratives; they can also moderate how local wind turbines affect these narratives. For instance, in regions with generally low support for wind energy, a new wind turbine or large wind turbine numbers are more likely to stimulate new (negative) narratives than in regions where people are more neutral. Consequently, the number of wind turbines in an area can influence public attitudes and the prominence and framing of wind-energy-related narratives.

H4: *The relationship between public attitudes and the prominence and framing of wind energy-related topics in local narrative landscapes are moderated by the density of wind turbines in a region.*

Lastly, structural differences between places can influence these relationships. For instance, urban residents may encounter many wind turbines but find them less intrusive than rural ones because turbines are less noticeable in dense urban environments. In urban settings, wind energy topics compete with a broader array of topics for attention and hence, might be less prominently featured in local narrative landscapes (Wang, 2020).

Obtaining insights into these matters is crucial not just for understanding how variations emerge in narrative landscapes at the subnational level concerning a specific topic. Tuitjer et al. (2022) emphasized that more research is needed on place-specific factors shaping public attitudes about climate-change-related topics. These authors call for comparative studies at the sub-national level addressing questions such as "What exactly is it that matters about a place to become significant in CCO [Climate Change Opinions] formation (physical geographic features, exposure to climate change)?" (p. 7). As these authors point out, spatial (sub-national) heterogeneities in climate change attitudes and narratives are anything but well understood. By focusing on a specific subtopic in this debate, the present study contributes by quantifying the spatial heterogeneity in the prominence of related topics and their framing in local narrative landscapes.

3. Data and Empirical Approach

3.1.News Data and the Narrative Landscape

We rely on regional news data to study how wind-energy-related topics feature in local narratives, as traditional surveys often lack this information over time and across regions (Weber et al., 2017; Levi et al., 2023). Media plays a significant role in shaping the presentation of topics, sometimes even fulfilling an 'agenda-setting' function (McComb & Shaw, 1972). While media exhibits selectivity and a tendency toward negative presentation, biases vary depending on outlets, topics, and timeframes (DellaVigna & Kaplan, 2007; Ozgun & Broekel, 2021, 2022).

The media is embedded in its geographical context, forming a mutually reinforcing relationship with locations (Ozgun & Broekel, 2021a, 2022a). Over time, this alignment between media and how it presents specific topics is strengthened due to its need to serve its audience and its ability to choose among media outlets (Garz, 2018; Dehler-Holland et al., 2021, 2022). Although capturing all news data would ideally provide a more comprehensive insight into the local narrative landscape, our study focuses on newspapers with high readership and relevance in Germany (Allcott & Gentzkow, 2017; Deephouse et al., 2017; Hölig et al., 2022).

While newspapers may not capture the entirety of a location's narrative landscape, they significantly reflect the narratives most relevant to the study context. The absence of certain topics in local newspapers implies that journalists do not consider these issues significant to their readership. Similar applies to the way and framing of topics' presentation. This editorial decision is critical; a persistent disconnect between the content offered and the audience's interests can lead to a decline in readership and financial sustainability (Hoffman, 2016; Boczkowski, 2010).

Examining the frequency and sentiments of topics in newspapers provides valuable insights into the community priorities and the local narrative landscape. However, these insights depend on the representativeness of the newspaper data used. Our study utilizes a comprehensive data source encompassing the majority of newspapers circulating in the country, ensuring a broad and representative overview of prevailing narratives.

3.2.Newspaper Data

We rely on the Regional News Syndicate (RegNeS) database (Ozgun & Broekel, 2021). This database holds daily collections of German-language newspaper headlines and snippets. Stretching from July 2019 to the end of 2021, it covers over 300 print and online news sources in the German-speaking world, with the majority being newspapers. The database also features a regionalization of the news based on readership information and the targeted audiences of outlets.

For our empirical analysis, we refined a dataset of over 14 million news items, focusing on those linked to Germany with at least 11 characters, resulting in 11,882,990 unique items. A news item represents a unique headline published by a news source at a specific time. We excluded extremely early and recent observations, removing data before August 1, 2019. Our focus was on newspapers, excluding other sources for consistency. Following Ozgun & Broekel (2021), we excluded newspapers with fewer than 400 articles during the sample period. After cleaning, our sample consisted of 10,410,328 unique news items from 293 newspapers. Some items were published by multiple sources, increasing the observation count.

Working with regional newspaper data at the regional level is complex, requiring precise readership data for all sources. The RegNeS database provides such data, though some are approximations (see discussion in Ozgun & Broekel, 2021). Another challenge involves using smaller spatial units than newspaper distribution areas, leading to similar data values when newspapers serve adjacent regions. To address these challenges, we worked at the level of newspaper regions. A newspaper region consists of all Nomenclature of Territorial Units for Statistics (NUTS3) regions for which the RegNeS database reports a non-zero readership for a specific newspaper. We aggregate news item values to the level of these newspapers and their corresponding newspaper regions.

All non-news-related variables are based on NUTS3-level information. These are aggregated to the level of newspaper regions weighted by the NUTS3 region's population share within the newspaper region. This approach implies an interdependence among our observations because newspaper regions can overlap when serving the same NUTS3 regions. Furthermore, many newspapers share a significant portion of their news items, primarily if they source from the same provider, such as the German Press Agency (DPA), transfer ownership, or have joint editorial offices. This aspect needs consideration in our empirical analysis.

There are 293 newspapers in our sample. Some of these newspapers have substantial regional sections that qualify as “independent” units of analysis. In the RegNeS database, such sections are characterized as unique news “channels,” which share the newspaper name with other “channels.” Whenever the share of news items indistinct to a “channel” in the total number of news items associated with a newspaper exceeds 50%, this channel is considered a (quasi-) individual newspaper in the following. On this basis, our set of newspapers increased to 356.

3.3.News Coverage of Wind Turbines

To identify news items covering topics related to wind energy, we conducted a regular expression search for tokens containing the following strings: “Windkraft” (wind power), “Windenergie” (wind energy), “Windkraftanlage” (wind turbine), “Windrad” (wind wheel), “Windräder” (wind wheels), and “Windpark” (wind park). These are the keywords commonly used in this context. Table 1 provides the number of detected news items for each search token. Note the potential for double counting because multiple tokens might appear in the same news item. We identify 19 726 unique news items mentioning the search terms. Figure 1 illustrates their summed occurrence for each week during the considered period (Supplementary Material A provides more details).

Table 1 Number of times search terms are found in news items

#	*Word*	*Frequency*
1	*Windkraft (wind power)*	*9 279*
2	*Windräder (wind wheel)*	*6 061*
3	*Windpark (wind park)*	*5 326*
4	*Windenergie (wind energy)*	*3 226*
5	*Windrad (wind wheel)*	*2 532*
Sum		***26 424***

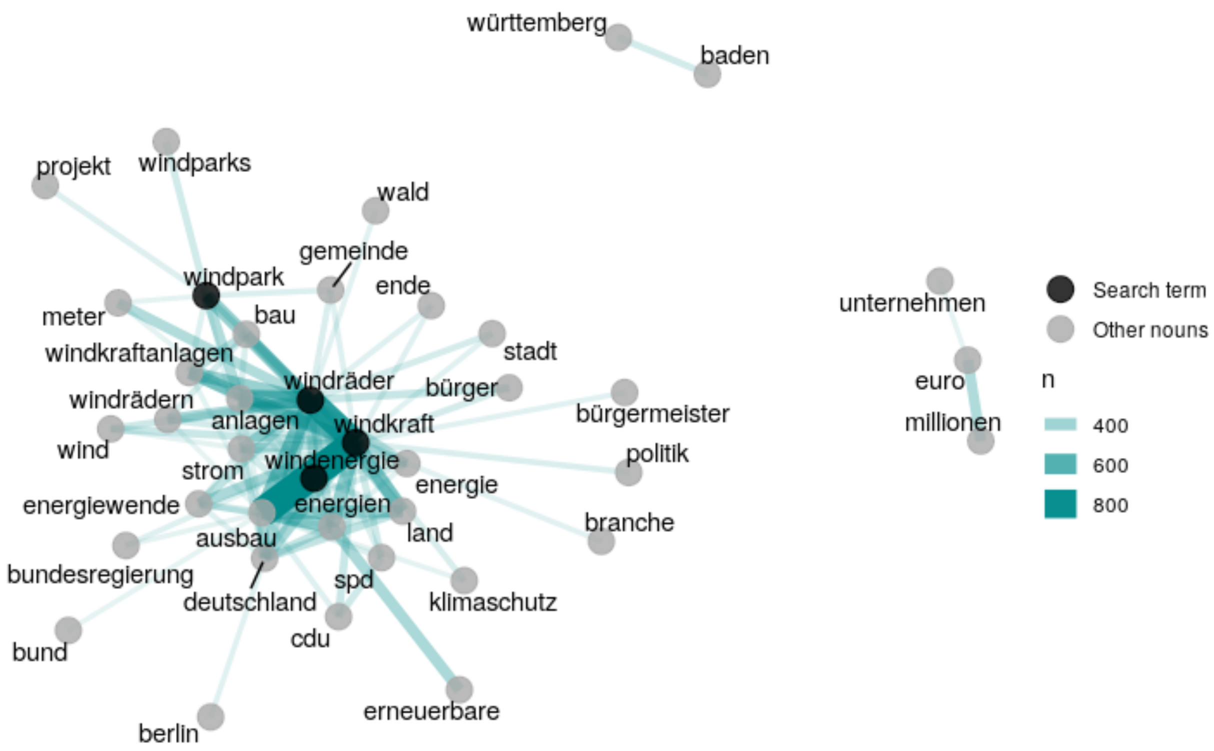


Figure 1: Network of the most frequent tokens in wind-related news

We extract the terms most frequently co-occurring with our selected keywords to evaluate our selection of search tokens. The resulting network of co-occurrences is presented in Figure 1. It features very general tokens, such as “Wind” (wind), “Anlage” (facility), and “Bau”/“Ausbau” (construction/expansion), that link to wind energy. The co-occurrence frequencies underline the close connection between wind energy and the transition towards renewable energies, as evidenced by high values for tokens like “Energiewende” (energy transition), “erneuerbare” (renewable), and “Klimaschutz” (climate protection). The political dimension of wind energy becomes visible in tokens related to policy, such as “Bundesregierung” (federal government), “Bürgermeister” (mayor), “Bürger” (citizens), “Politik” (politics), and political parties (“SPD”, “CDU”), which obtain high co-occurrence values. Similarly, spatial features are firmly connected, such as “Land” (country), “Stadt” (city), “Wald” (forest), and “Gemeinde” (municipality), referring to the local nature of many topics related to wind turbines.

The co-occurrence analysis reveals that there are no additional tokens frequently co-occurring with wind turbines that could improve the identification of wind turbine-related items, giving us confidence in having minimized the chances of a “false negative” bias. Moreover, most topics of the identified items appear closely related to wind turbine construction, suggesting a low potential for a “false positive” bias.

The first variable (NUM.WIND) captures the frequency with which newspapers refer to wind energy. This variable represents the number of news items published by a newspaper featuring at least one of the search tokens listed in Table 1. This frequency approximates the prominence of wind energy-related topics in local narrative landscapes.

3.4.Sentiment Analysis

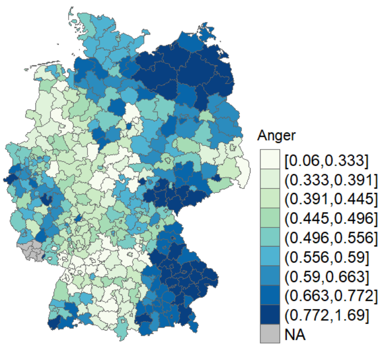
In addition to prominence, we seek to capture the framing of narratives by analyzing one of its dimensions: the sentiments of the presentation. We use tools that allow for more nuanced text analysis (Meier et al., 2018). Anger is frequently mentioned in association with wind power and is ranked among the most impactful emotions related to wind energy (McLaren Loring, 2007; Devine-Wright & Howes, 2010; Fast, 2015; Olson-Hazboun et al., 2016; Russell & Firestone, 2021). Following these studies, we focus on the "anger" emotion to describe the sentiment/emotionality dimension of narratives' framing. Our data is characterized by a time lag of 2.5 years between the observation of wind turbines and the news collection, implying that the acclimation effect is likely to have toned down narratives.

To quantify emotions, we use the German version of the Linguistic Inquiry and Word Count (LIWC) tool (Meier et al., 2018). LIWC differs from other tools by considering stopwords and low-content words (articles, pronouns, prepositions, negations, and numbers) when extracting subtle sentiments (Pennebaker, 2011; Pennebaker et al., 2014). In this paper, we focus on the value of the emotion variable ANGER returned by the LIWC tool, which we calculate for the subset of news items featuring at least one token associated with wind turbines, denoted as ANGER.WIND. Its values approximate (one dimension of) the framing of wind-energy-related topics in local narrative landscapes. Figure 2 panel a) gives a rough impression of its regional distribution at the level of NUTS3 regions, whereby a larger score indicates higher sentiment. Interestingly, except for North-East Germany, higher levels of anger seem to concentrate in locations with fewer wind turbines (see Figure 2 panel a).

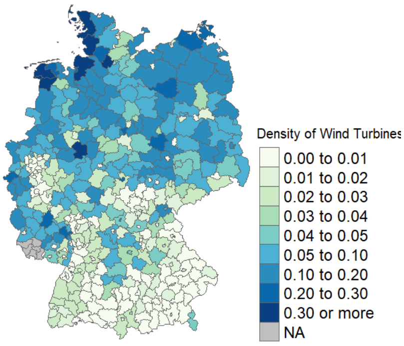
3.5.Information on Wind Turbines

We merge two registers, one before 2016 and the other after, with the latest entry in 2017, to obtain data on onshore wind turbines, providing geolocations for each turbine (total: 27,974, close to the "official" count of 28,978 by Deutsche WindGuard GmbH (2021). While potential selection biases cannot be tested without an official dataset, we have no indications of such biases. Figure 2b displays their distribution across NUTS3 regions.

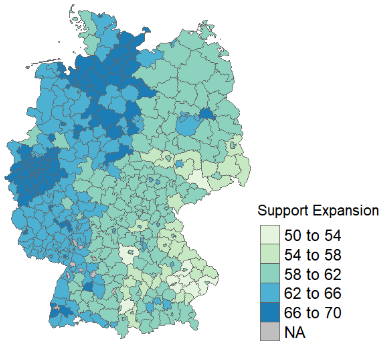
Based on this information, we straightforwardly construct the variable WIND.DENS. We identify newspaper regions as all NUTS3 regions where a newspaper has a readership according to the RegNeS database. We count the number of wind turbines in these regions and divide this by the combined area in square kilometers. Using the density instead of the total number of wind turbines controls for the heterogeneity in regions' geographical sizes. It can also be interpreted as the likelihood of observing a wind turbine at a random location within this area.



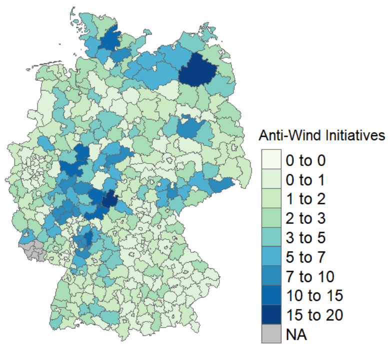
a) Average Anger



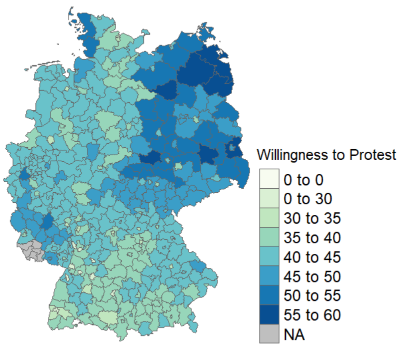
b) Density of wind turbines



c) Support Expansion



d) Anti-wind initiatives



e) Willingness to Protest

Figure 2 Geographical distribution of key variables at a NUTS3 level

3.6. Information on Public Opinion

We use Levi, Wolf, and Sommer (2023) data to capture existing public opinion on wind energy. They provide two representative panel studies conducted in Germany between 2017 and 2021. Using detailed census data, multilevel regression with post-stratification methods, and machine learning, the data is aggregated to the level of NUTS3 regions (for details, see Renn et al., 2020; Wolf et al., 2021; Frondel et al., 2022). The variable most directly related to the context of this paper is the item "Zustimmung zum Ausbau von Windenergie an Land" (support for expanding onshore wind energy), which closely approximates public attitudes about wind turbines. This variable, SUPPORT.EXPANSION, measures the population's share supporting the general expansion of onshore wind turbines, as displayed in Figure c).

The second factor we use to capture public attitudes toward wind turbines, which connect to local wind turbine numbers, is the extent to which people support anti-wind-energy protests. This is measured by the item “Protestbereitschaft gegen lokale Windkraftanlagen” (willingness to protest local wind turbines), and is therefore considered the variable SUPPORT.PROTEST. Both variables, SUPPORT.PROTEST and SUPPORT.EXPANSION, are calculated as the population-weighted average of the relevant item values from Levi et al. (2023) across all NUTS3 regions within a focal newspaper region, with the distribution illustrated in Figure 2 panel d).

We complement these survey-based variables with an indirect measure of public attitudes towards wind energy: the presence of anti-wind turbine initiatives, indicating local opposition (Gardt et al., 2021). These initiatives oppose wind-energy projects for various reasons (Reusswig et al., 2016; Weber et al., 2017) and emerge in reaction to nearby turbine construction (Gardt et al., 2021). While not directly reflecting average local attitudes, they signify a substantial group with opposing views, representing a non-actor-based power. Data on these initiatives is sourced from Gardt et al. (2021), featuring 817 initiatives within the last ten years. We tally the initiatives within each newspaper region's territory, creating the variable ANTI.WIND. Figure 2c illustrates their spatial distribution at the NUTS3 level.

3.7. Control Variables

We consider several control variables to isolate the relationship between our main explanatory variables and wind-energy-related topics in regional narrative landscapes (NUM.WIND, ANGER.WIND). Most importantly, we account for general characteristics of newspapers, including the total number of news items (NUM.NEWS), the average length of news items (NUM.WORDS), and the total number of newspapers in a region (NUM.PAPERS), all collected from the RegNes database. Complementing these newspaper-data-based variables, we add control variables capturing important socioeconomic characteristics. A spatial lag of wind density (LAG.WIND) accounts for potential neighborhood effects, i.e., local wind turbines might not exclusively influence the narrative landscape but also wind turbines in neighboring regions. We consider the GDP per capita (GDP), as wind turbines may impact economic developments (Bednarz & Broekel, 2020; Guo et al., 2015), which can shape sentiments. For the same reason, we include unemployment (UNEMP), which is closely related to regional news sentiments (Ozgun & Broekel, 2021). Population density (POP.DEN) is added to capture how some externalities of wind turbines, such as noise and flickering, are perceived differently in densely populated areas (Zerrahn, 2017).

The dummy variable EAST has a value of one if the region covers a former part of the GDR, as those regions are characterized by distinct journalistic activities (Ozgun & Broekel, 2021). We also consider the share of doctors (DOCTORS), the share of academics (ACADEMICS), the availability of broadband internet access (INTERNET), and the share of highly skilled individuals (HIGHSKILL), as these characteristics are known to influence views on energy transition (Molnarova et al., 2012; Rohe & Chlebna, 2021). The quality of the physical landscape is accounted for through the variable NATURE, which summarizes how much of a region's area remains in a natural (unaltered) condition. Touristic demand for a region is approximated by the number of overnight stays (TOURIST). Both aspects are associated with acceptance levels of wind turbines (Zerrahn, 2017). All variables describing regional characteristics are obtained from the statistical offices of the German federal states and sourced from the INKAR database's latest update in 2018 (Bundesamt für Bauwesen und Raumordnung, 2017).

In contrast to the newspaper-data-based variables, these socioeconomic variables are rather time-invariant. Consequently, they do not lose explanatory power even when past values are used. As with all the other variables above, we aggregate them to the level of newspaper regions, weighted by population or area shares. Table 2 provides summary statistics for all dependent and independent variables.

Table 2: Summary statistics

		n	*mean*	*sd*	*median*	*min*	*max*	*se*
Depende	NUM.WIND	356	48.32	75.42	16.50	0.00	456.00	4.00
	ANGER. WIND	356	0.49	0.72	0.30	0.00	6.25	0.04
Newspaper	NUM. NEWS	356	29 373.83	43 427.62	12 131.00	2.00	311 105.00	2 301.66
	AVG.ANGER	356	0.56	0.34	0.48	0.00	2.41	0.02
	WORD.WIND	356	64.91	185.28	30.79	0.00	2709.11	9.82
	AVG.WORD	356	52.19	97.95	31.33	5.35	1138.09	5.19
	NUM.PAPERS	356	20.73	5.73	19.15	9.00	37.00	0.30
Region	UNEMP	356	5.63	2.13	5.70	1.50	13.00	0.11
	GDP	356	39.36	14.61	37.32	18.80	172.40	0.77
	POP.DEN	356	784.15	835.99	436.83	36.00	4 790.00	44.31
	EAST	356	0.20	0.39	0.00	0.00	1.00	0.02
	DOCTORS	356	61.55	17.47	57.91	18.00	134.00	0.93
	ACADEMICS	356	15.06	6.34	13.65	6.00	38.40	0.34

TOURIST	356	5.37	5.00	4.16	0.00	49.50	0.27
NATURE	356	231.12	298.43	122.70	6.40	2 376.60	15.82
HIGHSKILL	356	13.83	5.37	12.91	5.90	32.90	0.28
INTERNET	356	79.18	12.73	82.36	27.40	99.20	0.67
WIND.DENS	356	0.06	0.07	0.05	0.00	0.5	0.00
LAG.WND	365	0.05	0.04	0.06	0.00	0.19	0.00
ANTI WIND	356	0.86	1.22	0.49	0.00	8.52	0.06
SUPPORT.EXPANSIO N	356	0.61	0.09	0.63	0.00	0.70	0.00
SUPPORT.PROTEST	365	0.41	0.07	0.41	0.00	0.57	0.00

See Supplementary Material B for correlation table and C for descriptions.

4. Empirical Method

Our dependent variables are continuous, and our data have a cross-sectional nature. Using spatial error regression, we consider the complex dependency structures between our observations. Spatial lag models are an extension of the OLS regression and consider potential dependencies in the error term. In our case, these dependencies are approximated by a (spatial) weight matrix. In contrast to the usual construction of such a weight matrix that utilizes information on spatial neighborhoods or distances, we follow Ozgun and Broekel (2021) and consider the primary source of dependence in this context: the degree of overlap in the newspaper data. For each pair of newspaper regions, we calculate the share of news that they share, either because the newspapers are sections of the same overarching news outlet, use the same news provider, or utilize the same editorial offices (see Supplementary Material D). The resulting weight matrix W_{ij} is a row-standardized version of these shares (Fischer & Wang, 2011).[4]

We use the most common specification of the spatial error model as given in Fischer & Wang (2011):

$$\epsilon_i = \lambda \sum_{j=1}^{n} W_{ij}\epsilon_j + u_i \qquad 1)$$

Where λ is the autoregressive parameter, u_i is a random, i.i.d., error term. In a matrix form, and assuming that $|\lambda| < 1$, yields:

[4] Using this weight matrix, we can also test the degree of autocorrelation in our model using a Moran's I test (See Supplementary Material E). None of the models are significant at a 10% level suggesting that the overlap between newspaper-regions is limited.

$$\epsilon = (I - \lambda W)^{-1} u \tag{2)}$$

The spatial error model is a combination of equations 1) and 2):

$$y = X\beta + (I - \lambda W)^{-1} u \tag{3)}$$

We run the models in three distinct setups. In the first, *NUM.WIND* is the dependent variable, and the second is the dependent variable *ANGER.WIND*. To explore the moderating effect of local wind turbines on the relationship between public attitudes and narratives, we employ interaction effects involving anti-wind turbine initiatives (*ANTI.WIND*), public attitude concerning wind energy expansion *(SUPPORT.EXPANSION)*, public support for anti-wind protests (*SUPPORT.PROTESTS*), and the density of wind turbines in a region (*WIND.DENS*). Lastly, we explore potential heterogeneity concerning the region type and complement the primary models with separate estimations for rural regions. We define newspaper regions as rural when less than 50% of its population resides within NUTS3 regions classified as "Rural" by the Federal Office for Building and Regional Planning (Bundesamt für Bauwesen und Raumordnung, 2017). 303 (85%) newspaper regions are rural. The remaining 15% of regions are "Urban."

We improve the model fit substantially by log-transforming all variables except those that are binary.

5. Results and Discussion

5.1. The framing of wind-energy-related topics in narrative landscapes

Table 3 presents the regression results with the framing of news items related to wind energy (ANGER.WIND) being the dependent variable, including two control variable levels. Columns 1 to 3 include controls based solely on newspaper data, while columns 4 to 6 incorporate regional control variables. The regressions are conducted on two subsamples: "rural," and the entire sample[5].

Among the control variables, there is a positive relationship between the dummy variable for regions in the east (EAST, i.e., regions in the former GDR) and ANGER.WIND stands out. This is likely due to these regions' distinct socioeconomic and industrial structures (Rohe & Chlebna, 2021). This peculiarity persists even when controlling for the higher density of wind

[5] Regression results from the urban subsample is placed in Supplementary Material F.

turbines in East Germany (panel (a) in Figure 2) and the generally angrier framing of topics in local narrative landscapes (AVG.ANGER) in these areas. Therefore, wind turbine-related topics in East Germany tend to score higher on ANGER.WIND compared to West Germany.

The regressions are used to test the first hypothesis (**H1**), which explores the relationship between wind turbines, captured by WIND.DENS, and the framing of wind-related topics in the local narrative landscape. WIND.DENS has a significantly negative coefficient when regional control variables are excluded, but its significance drops to 0.1 when these controls are included. While this supports hypothesis **H1**, it suggests that regional characteristics moderate the relationship between wind turbines and the emotional framing of topics in local narrative landscapes. Specifically, the correlation between a region located in East Germany (EAST), wind turbine density, and the anger in framing wind turbine-related topics is notable.

There are several reasons for the less angry (more neutral) framing of wind energy-related topics in regions with more turbines. Residents living near larger numbers of turbines may have acclimated to them (Firestone & Kirk, 2019; Russell & Firestone, 2021). A less negative attitude toward local wind turbines is also observed when the local community is involved in the decision-making process or acts as an investor through local energy cooperatives (Mulvaney et al., 2013; Punt et al., 2022), which typically indicates the presence of existing wind turbines. In summary, hypothesis **H1** is confirmed at the 0.1 level.

Table 3 Spatial Error Regression – Framing of wind-energy-related news

	Log(ANGER.WIND)			
	All	*Rural*	*All*	*Rural*
	(1)	(2)	(4)	(5)
log(WORD.WIND)	0.051***	0.051***	0.049***	0.048***
	(0.013)	(0.014)	(0.013)	(0.014)
log(AVG.ANGER)	0.640***	0.504***	0.607***	0.461***
	(0.103)	(0.113)	(0.114)	(0.121)
log(WIND.DENS)	-0.696**	-0.498*	-0.604*	-0.568
	(0.292)	(0.296)	(0.357)	(0.356)
log(LAG.WIND)	0.796	0.8	0.766	0.763
	(0.544)	(0.527)	(0.566)	(0.547)
log(NUM.PAPERS)			0.047	-0.008
			(0.095)	(0.103)
log(POP.DENS)			-0.005	0.006
			(0.036)	(0.037)
log(UNEMP)			-0.056	-0.022
			(0.073)	(0.074)
log(GDP)			0.046	0.17
			(0.098)	(0.113)
log(DOCTORS)			-0.002	0.054
			(0.113)	(0.118)
log(ACADEMICS)			0.053	0.013

			(0.162)	(0.180)
log(TOURIST)			0.023	-0.026
			(0.035)	(0.036)
log(NATURE)			-0.011	0.032
			(0.029)	(0.030)
log(HIGHSKILL)			-0.109	-0.139
			(0.192)	(0.204)
log(INTERNET)			0.16	0.282*
			(0.148)	(0.153)
EAST			0.185***	0.163**
			(0.066)	(0.066)
Intercept			Yes	Yes
Spatial adj. SE			Yes	Yes
Num. obs.	356	303	356	303
Log Likelihood	-83.865	-78.577	-49.680	-17.052
AIC	181.73	124.935	193.154	135.359
Note:			*p<0.1; **p<0.05; ***p<0.01	

5.2.The prominence of wind-energy-related topics in narrative landscapes

Table 4 summarizes the results of our second hypothesis (**H2**), which examines the relationship between wind turbines in a place and the prominence of wind energy-related topics in local narrative landscapes. The density of wind turbines (WIND.DENS) obtains a significantly positive coefficient in all models (0.01 level), while its spatial lag (LAG.WIND) is insignificant. This indicates that only local (nearby) wind turbines within the same region are correlated with the prominence of wind-energy-related topics in local narrative landscapes. We ran an instrument variable regression using wind speed as an instrument for the number of wind turbines, yielding similar results with a significant coefficient, strengthening the finding. See Supplementary Material G.

For the rural subsample, the coefficient is slightly smaller, suggesting that wind turbine-related topics are featured less prominently in rural narrative landscapes than in urban areas (see Supplementary Material F).

Several control variable results stand out. Contrary to our expectations, touristic demand (TOURIST) does not appear to be related to the prominence of wind energy-related topics, despite research generally confirming a close link between wind turbines and tourism developments (Broekel & Alfken, 2015; Kipperberg et al., 2019). Similarly, proximity to untouched areas (NATURE) is also insignificant. In line with our expectations, wind-energy-related topics are less frequent in the narrative landscapes of areas with higher population densities (POP.DENS). Conversely, they are more prominent in areas with higher shares of academics (ACADEMICS). The control variables derived from newspaper data exhibit the expected patterns. Specifically, we tend to find more mentions of wind-energy-related topics when there are more news items (NUM.NEWS) and when these news items are longer (NUM.WORDS).

Table 4 Spatial Error Regression – Prominence of wind-energy-related narratives

	Log(NUM.WIND)			
	All	*Rural*	*All*	*Rural*
	(1)	(2)	(4)	(5)
log(NUM.NEWS)	0.834***	0.813***	0.839***	0.821***
	(0.033)	(0.035)	(0.033)	(0.035)
log(NUM.WORDS)	0.313***	0.235***	0.330***	0.253***
	(0.080)	(0.084)	(0.075)	(0.081)
log(WIND.DENS)	5.568***	4.913***	5.120***	4.456***
	(0.855)	(0.904)	(0.993)	(1.058)
log(LAG.WIND)	1.171	2.442	1.909	1.874
	(1.684)	(1.641)	(1.675)	(1.684)
log(NUM.PAPERS)			0.013	-0.139
			(0.265)	(0.304)
log(POP.DENS)			-0.229**	-0.204*
			(0.101)	(0.110)
log(UNEMP)			-0.224	-0.078
			(0.203)	(0.222)
log(GDP)			0.08	0.193
			(0.267)	(0.331)
log(DOCTORS)			0.458	0.239
			(0.310)	(0.346)
log(ACADEMICS)			1.308***	0.990*
			(0.442)	(0.527)
log(TOURIST)			0.155	0.153
			(0.096)	(0.106)
log(NATURE)			0.113	0.09
			(0.081)	(0.091)
log(HIGHSKILL)			-0.954*	-0.775
			(0.525)	(0.599)
log(INTERNET)			-0.254	-0.028
			(0.411)	(0.453)
EAST			-0.148	-0.163
			(0.189)	(0.198)
Intercept	Yes	Yes	Yes	Yes
Spatial adj. SE	Yes	Yes	Yes	Yes
Num. obs.	356	303	356	303
Log Likelihood	-461.476	-389.373	-439.527	-377.457
AIC	914.361	913.158	787.913	141.989
Note:				**p<0.1; **p<0.05; ***p<0.01*

5.3.Public attitudes and the prominence of wind-energy-related narratives

Hypothesis H3 examines how public attitudes influence the prominence of wind-energy-related topics in local narrative landscapes (see Table 5) and their framing (see Supplementary Material H). In rural areas, evidence supports a link between public attitudes and the prominence of wind-energy-related news — specifically, ANTI-WIND and SUPPORT.EXPANSION exhibit statistically significant positive coefficients at the 0.1 and 0.05 levels. The results suggest that more supportive public attitudes in rural regions are positively associated with a greater prominence of wind-energy-related topics in the local narrative landscapes. The higher relative impact (visually, economically, environmentally) of wind turbines in rural areas, compared to urban ones (Supplementary Material F), is likely to give the topic greater relevance. Furthermore, public opinion is not neutral regarding turbines; it involves either supportive or rejecting narratives. Our analysis suggests that the virality-stimulating effect of more positive public attitudes dominates that of rejecting attitudes. We find no direct association between public attitudes and the framing of topics in narrative landscapes (Supplementary Material H).

Table 5 Spatial Error Regression – Public attitudes and prominence of narratives

	Log(NUM.WIND)					
		All			*Rural*	
	(1)	(2)	(3)	(4)	(5)	(6)
log(ANTI.WIND)	0.183			0.217*		
	(0.113)			(0.124)		
log(SUPPORT.PROTEST)		0.732			2.052	
		(1.195)			(1.541)	
log(SUPPORT.EXPANSION)			0.995			2.151**
			(0.780)			(1.010)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Spatial adj. SE	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	356	356	356	303	303	303
Log Likelihood	-438.232	-439.342	-438.715	-375.952	-376.582	-375.206
AIC	914.464	916.684	915.431	789.905	791.165	788.412
Note:						**p<0.1; **p<0.05; ***p<0.01*

5.4.The moderating effect of wind turbine density

Hypothesis **H4** proposes that the number of locally existing wind turbines moderates the relationship between public attitudes and wind-energy-related topics in narrative landscapes. Table 6 provides the results with NUM.WIND as the dependent variable. We observe a moderating effect for SUPPORT.PROTEST. This variable obtains a significant positive coefficient in the subsample of rural regions (column 5). The interaction effect between SUPPORT.PROTEST*WIND.DENS is significantly negative for all samples. The negative coefficient of the interaction effect indicates that when wind density (WIND.DENS) and support for protests (SUPPORT.PROTEST) increase, wind-energy-related topics tend to be less frequent. Their combined effect on the relationship is stronger than any of the individual main effects.

Table 3 Spatial Error Regression – Public attitudes, mediation and the prominence of narratives

	Log(NUM.WIND)					
	All			*Rural*		
	(1)	(2)	(3)	(4)	(5)	(6)
log(ANTI.WIND)* log(WIND.DENS)	-0.477			-0.692		
	(1.714)			(1.844)		
log(ANTI.WIND)	0.21			0.253		
	(0.150)			(0.162)		
log(SUPPORT.PROTEST) *log(WIND.DENS)		-60.046***			-61.473***	
		(21.191)			(23.011)	
log(SUPPORT.PROTEST)		1.951			3.829**	
		(1.263)			(1.642)	
log(SUPPORT.EXPANSION) *log(WIND.DENS)			42.086			26.125
			(36.667)			(40.373)
log(SUPPORT.EXPANSION)			0.293			1.768
			(0.990)			(1.233)
log(WIND.DENS)	5.303***	26.867***	-15.382	4.851***	26.905***	-8.196
	(1.334)	(7.731)	(17.922)	(1.458)	(8.446)	(19.680)
log(LAG.WIND)	1.673	1.635	1.721	1.494	0.985	1.224
	(1.690)	(1.652)	(1.672)	(1.700)	(1.686)	(1.695)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Spatial adj. SE	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	356	356	356	303	303	303
Log Likelihood	-438.193	-435.4	-438.058	-377.636	-374.586	-376.574
AIC	916.386	910.8	916.116	795.272	789.171	793.148
Note:				**p<0.1; **p<0.05; ***p<0.01*		

There are multiple potential explanations for these findings. Firstly, it could be attributed to the acclimatization effect. Higher wind turbine density often means they have been in place longer, making people accustomed to their presence. Reduced attention to wind energy as a topic can occur even when wind turbines are still disapproved of. Secondly, if higher wind turbine density indicates an extended presence in a region, the times of intensive discourse and

Table 7 Spatial Error Regression – Public attitudes, mediation and framing of narratives

	Log(ANGER.WIND)					
		All			*Rural*	
	(1)	(2)	(3)	(4)	(5)	(6)
log(ANTI.WIND)* log(WIND.DENS)	0.263			0.204		
	(0.632)			(0.620)		
log(ANTI.WIND)	-0.050			-0.042		
	(0.054)			(0.054)		
log(SUPPORT.PROTEST) *log(WIND.DENS)		15.839**			15.611**	
		(7.654)			(7.645)	
log(SUPPORT.PROTEST)		-0.412			0.255	
		(0.460)			(0.550)	
log(SUPPORT.EXPANSIO N)*log(WIND.DENS)			-10.399			-11.76
			(13.374)			(13.533)
			0.013			0.578
log(SUPPORT.EXPANSIO N)			(0.363)			(0.413)
log(WIND.DENS)	-0.729	-6.317**	4.473	-0.761	-6.303**	5.086
	(0.485)	(2.782)	(6.540)	(0.486)	(2.799)	(6.599)
log(LAG.WIND)	0.806	0.808	0.802	0.757	0.754	0.687
	(0.573)	(0.563)	(0.567)	(0.546)	(0.541)	(0.546)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Spatial adj. SE	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	356	356	356	303	303	303
Log Likelihood	-78.117	-76.434	-78.112	-45.736	-43.181	-45.087
AIC	196.233	192.868	196.224	131.473	126.362	130.174

Note: **p<0.1; **p<0.05; ***p<0.01*

virality of wind-energy-related narratives may already be over. The most intensive discussions about wind turbines usually occur when they are new to a place. Thirdly, these topics' framing in local narrative landscapes is not considered at this stage. With more turbines, both opposing and supportive narratives may lose virality, potentially decreasing the overall prominence of wind-turbine-related narratives. We explore this in the subsequent analysis.

5.5.Public attitudes and the framing of wind-energy-related narratives

Continuing with hypothesis **H4**, we investigate whether the density of wind turbines moderates the association between public attitudes and the framing of wind-energy-related topics in local narrative landscapes. None of the central variables (ANTI.WIND, SUPPORT.PROTEST, and SUPPORT.EXPANSION) become significant except when the interaction effects with

WIND.DENS are included (see Table 7 and Supplementary Material I). Even then, only the interaction of SUPPORT.PROTEST*WIND.DENS becomes significantly positive for the complete sample (0.5 level) and the rural region sub-samples (0.1 level). Accordingly, wind energy-related topics are framed more angrily in regions with greater support for anti-wind protests and a high density of wind turbines. In regions with higher wind density, an increase in support for protests is associated with a steeper increase in angrier framing than in regions with lower wind density. However, the negative coefficient for WIND.DENS (columns 2 and 5) indicates that the framing becomes more neutral in tone when the interaction effect is not triggered, aligning with our results in Table 3. This supports hypothesis H4, indicating that a more wind-energy-opposing public attitude combined with strong triggers (many wind turbines) tends to produce an angrier framing of wind energy-related topics in local narrative landscapes.

Considering the previous results of wind energy-related topics being less prominent in these regions' narrative landscapes, this finding indicates that when narratives go viral in these regions, they are accompanied by higher levels of anger. This relatively complex pattern aligns with the literature on sentiments and wind turbines (Zerrahn, 2017). However, it does not support the idea of a strong acclimatization effect, according to which people should become more neutral toward wind turbines over time when exposed to them more. This puts our previous discussions on the acclimatization effect somewhat into perspective. It is important to remember that we are examining average associations across regional populations, suggesting potential individual-level heterogeneity. Some groups may be significantly influenced by the acclimatization effect, while others may not. Further individual-level research is required to explore this aspect.

In sum, the finding adds further evidence supporting hypothesis H4, implying that the regional density of wind turbines moderates the relationship between public attitudes and their framing in local narrative landscapes.

6. Conclusion and Policy Implications

The public's attitude toward renewable energy infrastructure influences the pace of the transition to a low-carbon society. As a prominent example of such infrastructure, wind turbines require local acceptance for effective renewable energy adaptation (Zerrahn, 2017). Local narratives play a crucial role in this context, as they convey and disseminate information and opinions about this and other topics, forming expectations that potentially shape agency, economic dynamics, and policy designs (Shiller, 2017; Jambrina-Canseco, 2023).

Despite the growing attention to narratives in economic development, few studies have explored the sub-national geography of narratives and the factors contributing to their prominence and framing (Hannemann et al., 2023; Jambrina-Canseco, 2023). This article introduces the concept of local narrative landscapes, defined as the aggregate of narratives within a locality. It presents a multidimensional space where each dimension reflects various narrative attributes, particularly prominence and framing. The article further examines how wind turbines are represented in these landscapes across Germany. Using news data to approximate the prominence and framing of wind energy-related topics in local narrative landscapes, we show that these topics are more prominent in locations where wind turbines are common. In the same locations, wind energy-related topics are also framed less angrily. Conversely, areas with lower wind turbine density tend to feature angrier framing of wind energy-related topics in their narrative landscapes.

Public attitudes towards wind energy correlate with the prominence of the topic. Greater support for rural wind turbine expansion is associated with a higher prominence of wind-energy-related topics in local narrative landscapes. Except when high levels of local support for expansion coincide with a high density of turbines, the negative relationship with prominence outweighs the generally positive association between turbines and the prominence of wind-energy-related topics. When high support for anti-wind turbine protests coincides with abundant turbines, the framing of wind-energy-related topics becomes angrier in local narrative landscapes. This pattern is primarily observed in rural regions and does not apply to urban areas (Supplementary Material F), highlighting a significant rural-urban divide in the factors shaping narrative landscapes regarding wind energy. Observing a rural-urban divide underlying the complex spatial patterns of public acceptance of wind turbines supports existing studies (e.g., Zerrahn, 2017).

The study has specificities and limitations to consider. It relies on the assumption that regional news validly gives representative insights into narrative landscapes despite potential political bias and underrepresentation of minorities in news reporting (Walmsley, 1980; Gentzkow & Shapiro, 2006; DellaVigna & Kaplan, 2007). Minorities are often underrepresented or misrepresented (Khoo et al., 2012). However, we argue that by focusing on cross-regional variations, such biases are neutralized if they have a systematic subnational dimension that correlates with the subject of our investigation. By constructing overlapping newspaper regions (circulation areas) and including several controls at the newspaper level, we are confident that this assumption is valid in our case.

Our multivariate regression models reveal a connection between public attitudes and the prominence and framing dimensions in local narrative landscapes concerning the topic of wind energy (Supplementary Material B). This link isn't apparent in bivariate correlations. Two potential explanations warrant further exploration. Firstly, narrative landscapes may differ from public attitudes; the former are fluid and influenced by factors like interest groups, event timing, and a mix of competing narratives, while the latter is more stable and latent. Controlling for confounders is essential to unveil these underlying relationships. Secondly, using news data to approximate dimensions of local narrative landscapes might be biased due to news also reporting about events outside the focal region. This is due to our geolocation method, which is based on readership rather than event locations. However, the frequency and sentiments of such reporting should still align with the local audience's preferences. Again, we are confident that the reliance on a broad spectrum of news outlets minimizes the likelihood of such biases. Our study includes a time gap between the establishment of wind turbines and the observed narrative landscapes based on news data. We significantly capture narrative landscapes after most turbines have been put into place. We, therefore, may miss how these landscapes evolve with changes in turbine numbers if cross-sectional differences don't align with these conditions. Future research should consider longer data periods to validate our findings. Crucially, our empirical findings are relative. Therefore, a negative relation between wind turbine density and wind energy topics being framed angrier does not imply increased positivity. Rather, it indicates that narratives are more neutral in regions with a higher density of wind turbines.

Our findings have important implications for policymakers and stakeholders involved in the energy transition. Narratives about renewable energies influence the acceptance and support of these technologies and, eventually, the political and economic decisions related to their deployment and regulation. Recognizing regional narrative variations aids in adapting the introduction and presentation of new wind turbine projects. Specifically, public information campaigns and addressing inaccurate and biased information bases can counter viral narratives and help prepare local narrative landscapes for future wind turbine expansions. Addressing inaccurate or biased information on renewable energy impacts is a vital challenge.

Another interesting observation is that there are notable differences between East and West Germany. Wind energy-related topics are framed angrier in East Germany's narrative landscapes, whereas wind-energy-related narratives are equally prominent. This adds further quantitative empirical evidence to the two parts of Germany, showing systematic differences in narrative landscapes that may be related to cultural differences (Blum, 2004) or media activities (Haller, 2012; Ozgun & Broekel, 2021).

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Supplementary Material

A. Word Frequency and Term Frequency

B. Correlation Plot

C. Description of variables

D. Density plot identifying overlapping news items between regions

E. Moran's I test

F. Spatial regressions: the impact of opposition on wind-related news and anger

G. Interaction effects

H. Positive Emotions in Wind-Related News and The Density of Wind Turbines

I. Instrument Variable Regression

A. *Word Frequency and Term Frequency – Inverse Document Frequency*

Our sample has 26 424 unique wind-related news observations. To understand what these articles contain beyond the employed search term, we investigate the 20 most frequent tokens in these articles, including the search terms listed in Table 2.

Table A1 The most frequent terms found in the news containing the search terms

#	*Word*	*Frequency*
1	*windkraft*	*4938*
2	*windräder*	*4725*
3	*windpark*	*3485*
4	*euro*	*2335*
5	*windenergie*	*2321*
6	*windkraftanlagen*	*2194*
7	*ausbau*	*2193*
8	*stadt*	*2059*
9	*windrad*	*1990*
10	*anlagen*	*1876*
11	*brandenburg*	*1856*
12	*land*	*1831*
13	*deutschland*	*1793*
14	*strom*	*1658*
15	*spd*	*1642*
16	*cdu*	*1578*
17	*corona*	*1539*
18	*energie*	*1519*
19	*bau*	*1453*
20	*energien*	*1433*

Each search term captures a slightly different aspect related to wind energy. For example, “windenergie” captures words related to procedural conflicts such as plan figures (planzahlen), bickering (zank), approval documents (genehmigungsunterlagen), and court (buhlen). While “Windräder” appears to capture habitat and recreational concerns, as it associates with forest districs (waldviertel), ornithologists (vogelkundler), hiking trails (wanderwege), and wheel guard (wheelguard). Noticeably, the regional aspect of wind energy is frequently related to all search words referencing specific locations, such as Kallenwald, Salzburg, Sillerup, Südsachsen, Geiselbach, Pinzgau, and Sassendorfer, to name a few.

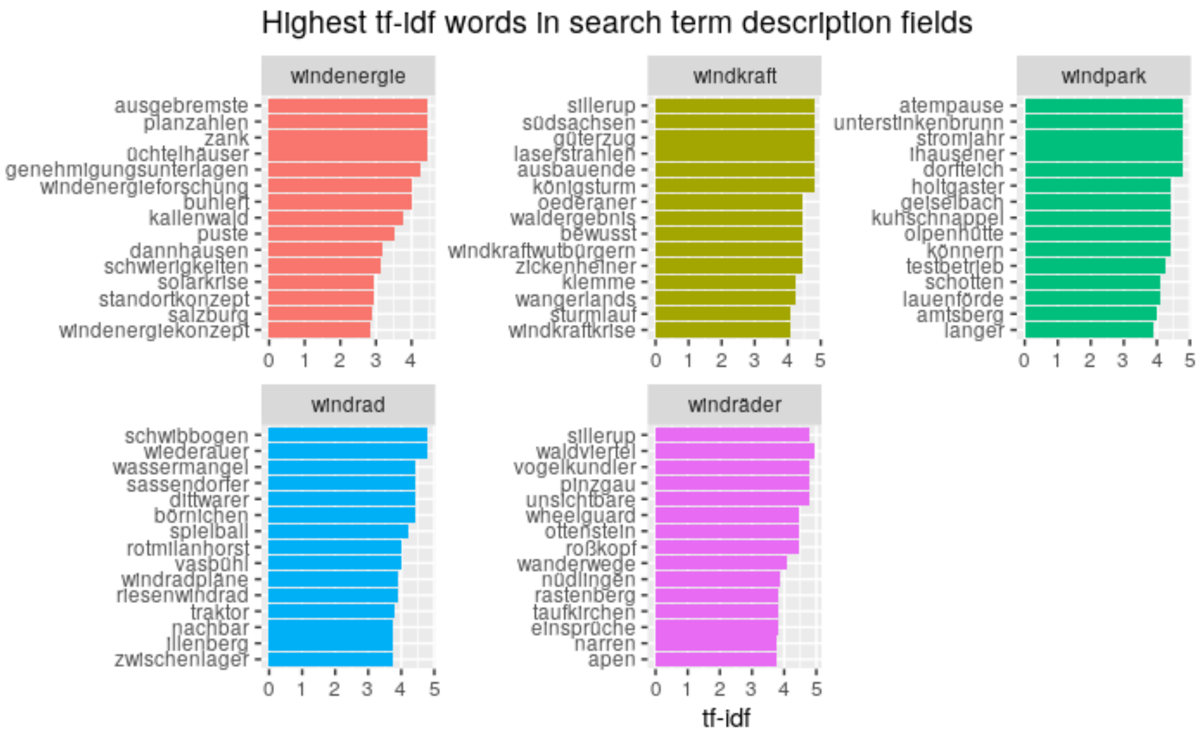


Figure A1 TF-IDF analysis

Visualization of the strongest associated words for each search term.

B. *Correlation Plot*

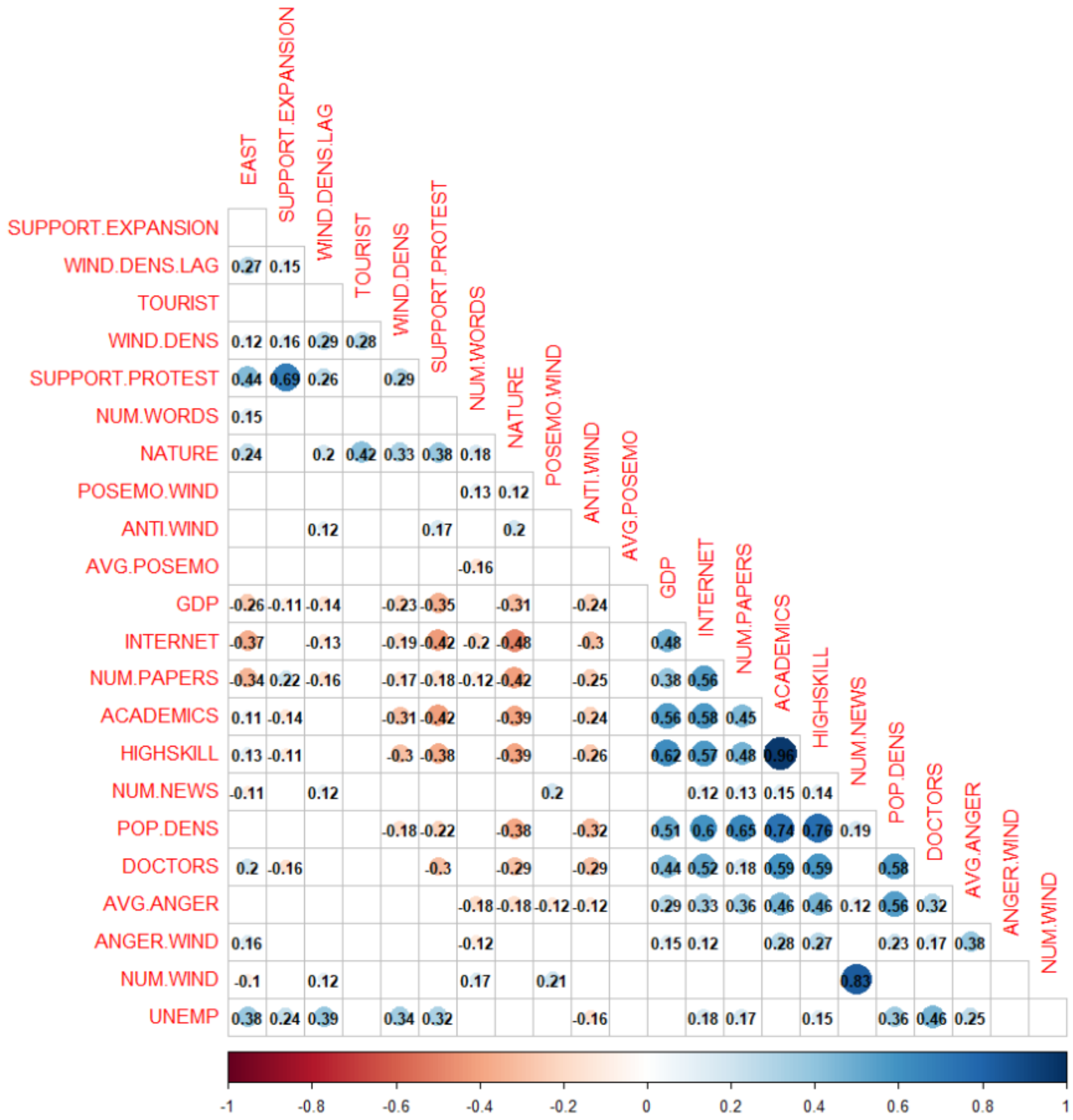


Figure B1 Correlation plot

The figure illustrates the significant correlation. Small circles illustrate 90% significance level, medium circles 95% and large circles 99%. The color visualizes the correlation strength, whereas deep red indicates a strong negative correlation and deep blue illustrates a strong positive correlation.

C. *Description of variables*

Table C1 Descriptions of variables

		Description
Dependent	NUM.WIND	Sum of wind related news in a newspaper.
	POSEMO.WIND	Average positive emotion in wind energy related news measured using LIWC.
	ANGER. WIND	Average anger in wind energy related news measured using LIWC.
Newspaper	NUM. NEWS	Number of news in a newspaper.
	AVG.ANGER	Average anger in all news for the newspaper measured using LIWC, measured in percentage. A score of 6% would imply that 6% of words in a news item is viewed as angry.
	AVG. POSEMO	Average positive emotions in all news for the newspaper measured using LIWC.
	WORD.WIND	Average number of words in news items related to wind related news.
	AVG.WORD	Average number of words in a news item.
	NUM.PAPERS	Number of papers in a newspaper region.
Region	UNEMP	Unemployment in the newspaper region scaled by readership.
	GDP	GDP in the newspaper region scaled by readership.
	POP.DEN	Population density in the newspaper region scaled by population share.
	EAST	Dummy variable taking the value of 1 if the region covers parts of previously East Germany.
	DOCTORS	Percentage of doctors scaled by population share in a newspaper region.
	ACADEMICS	Percentage of academics scaled by population share in a newspaper region.
	TOURIST	Number of overnight stays scaled by population share in a newspaper region.
	NATURE	Percentage of preserved nature in a newspaper region scaled by readership.
	HIGHSKILL	Percentage of highly skilled people scaled by population share in a newspaper region.
	INTERNET	Percentage of internet coverage in a newspaper region scaled by population share.
	WIND.DENS	The number of wind turbines divided by the total area in the newspaper region
	ANTI WIND**	Number of anti-wind initiatives divided by the total population in the newspaper region and scaled by 100 000.
	SUPPORT.EXPANSION	Population supporting expansion divided by total population in a newspaper region.
	SUPPORT.PROTEST	Population supporting protest divided by total population in a newspaper region.

D. *Density plot identifying overlapping news items between regions*

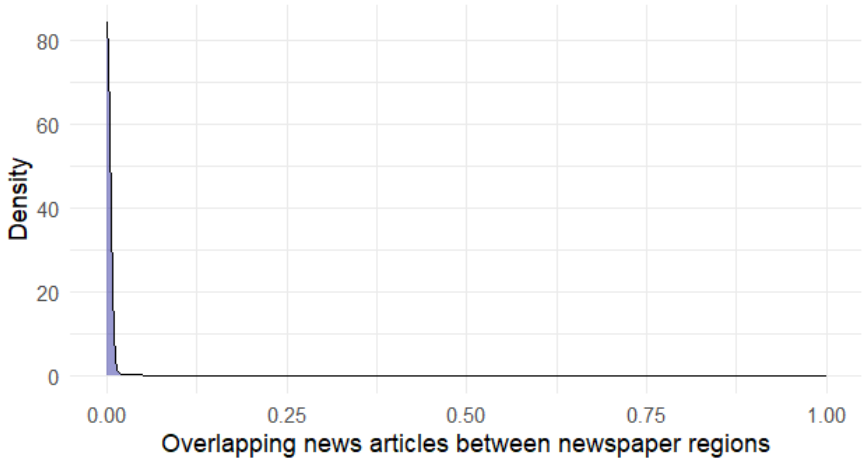


Figure D1 Density plot identifying overlapping news items between the newspaper regions

E. *Moran's I test*

The Moran's I test is applied to check for spatial autocorrelation in the regular regression model. Spatial correlations are common in spatial research and correct for spatial lag models and spatial error dependence models (Fischer & Wang, 2011). The null hypothesis is that there is no autocorrelation. The p-values from Moran's I test displayed in Table E1 are significantly different from the null hypothesis, and models correcting for spatial autocorrelations appear appropriate.

	WIND.DENS		ANTI.WIND	ANTI.WIND* WIND.DENS		SUPPORT.PROTEST	SUPPORT.PROTEST* WIND.DENS		SUPPORT:EXPANSION		SUPPORT.EXPANSION* WIND:DENS
	ANGER.WIND	NUM.WIND	NUM.WIND	NUM.WIND	ANGER.WIND	NUM.WIND	NUM.WIND	ANGER.WIND	NUM.WIND	NUM.WIND	ANGER.WIND
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$RS_{nr} > 0$											
p-value	0.073	0.000	0.000	0.003	0.082	0.000	0.001	0.074	0.000	0.000	0.067
Moran I	0.042	0.143	0.0111	0.086	0.042	0.109	0.110	0.044	0.109	1.109	0.045

F. *Rural subsample spatial regression analysis*

Table F1 displays the results from Table 3 (Table F1 columns 1 and 2) and Table 4 (Table F1 columns 3 and 4) for the *urban* subsample. Comparing the results to Tables 3 and 4, we find that in areas where a minority of people live in urban areas, we find no impact on the framing (column 2). The investigation of the prominence of news narratives suggests that wind turbine-related topics are featured less prominently in the narrative landscapes of rural areas than in urban areas.

We also observe a negative relationship between NATURE and ANGER.WIND. This suggests that the availability of untouched areas nearby is associated with anger in framing wind turbine-related topics (column 2). These areas either have a lower probability of further wind turbine installations, or offer compensation for potential expansions, such as a well-developed urban infrastructure. Additionally, in urban areas with greater touristic demand (TOURIST), wind-related topics are framed more angrily in regional narrative landscapes, consistent with other studies on local wind energy and tourism (Broekel & Alfken, 2015; Kipperberg et al., 2019; Riddington et al., 2010).

Table F1: Spatial regressions: the impact of opposition on wind-related news and anger

	Log(ANGER.WIND)		*Log(NUM.WIND)*	
	(1)	(2)	(3)	(4)
log(WIND.DENS)	-2.478***	0.398	6.228***	12.666***
	(0.941)	(1.472)	(2.367)	(2.630)
log(LAG.WIND)	0.021	1.414	-3.822	0.374
	(1.091)	(1.161)	(2.768)	(2.268)
log(WORD.WIND)	0.061**	0.026		
	(0.030)	(0.031)		
log(AVG.ANGER)	1.229***	0.783**		
	(0.208)	(0.346)		
log(NUM.NEWS)			0.979***	1.035***
			(0.083)	(0.069)
log(NUM.WORDS)			0.652***	0.748***
			(0.147)	(0.135)
log(NUM.PAPERS)		0.447		-0.297
		(0.280)		(0.638)
log(POP.DENS)		-0.006		0.01
		(0.158)		(0.278)
log(UNEMP)		-0.236		-1.353***
		(0.238)		(0.460)
log(GDP)		-0.008		0.447
		(0.256)		(0.481)
log(DOCTORS)		-0.009		1.215*
		(0.382)		(0.663)
log(ACADEMICS)		-0.078		1.232
		(0.414)		(0.771)

log(TOURIST)		0.299**	0.191
		(0.145)	(0.231)
log(NATURE)		-0.213**	-0.162
		(0.096)	(0.166)
log(HIGHSKILL)		-0.413	-1.626
		(0.656)	(1.192)
log(INTERNET)		0.189	-2.052**
		(0.472)	(0.926)
EAST		0.737**	0.538
		(0.352)	(0.648)
Intercept		Yes	Yes
Spatial adj. SE		Yes	Yes
Num. obs.	53	53	53
Log Likelihood	-55.468	-9.544	-46.185
AIC	48.104	55.088	143.714
Note:			**p<0.1; **p<0.05; ***p<0.01*

Table F2 display the urban subsample analysis complementing Table 5. The results align with the findings from the overall sample (Table 5, columns 1 to 3), finding no direct association between public attitudes and the framing of topics.

Table F2 Spatial Error Regression – Public attitudes and prominence of narratives

	Log(NUM.WIND)		
	(1)	(2)	(3)
log(ANTI.WIND)	0.009		
	(0.284)		
log(SUPPORT.PROTEST)		-2.092	
		(1.521)	
log(SUPPORT.EXPANSION)			-0.7
			(0.990)
Intercept	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Spatial adj. SE	Yes	Yes	Yes
Num. obs.	53	53	53
Log Likelihood	-46.184	-45.274	-45.941
AIC	130.368	128.547	129.883
Note:			**p<0.1; **p<0.05; ***p<0.01*

The *urban* subsample analysis complementing Table 6 is displayed in Table F3. SUPPORT.EXPANSION obtains a negative coefficient and a positive significant interaction coefficient SUPPORT.EXPANSION. This implies that wind-energy-related topics are more prominent in local narrative landscapes when there is more support for wind turbine expansion and a high density of turbines. Again, the effect size outweighs the negative association between SUPPORT.PROTEST and prominence by itself in urban areas.

Table F3 Spatial Error Regression – Public attitudes, mediation and the prominence of narratives

	Log(NUM.WIND)		
	(1)	(2)	(3)
log(ANTI.WIND)*log(WIND.DENS)	8.134		
	(5.250)		
log(ANTI.WIND)	-0.532		
	(0.406)		
log(SUPPORT.PROTEST) *log(WIND.DENS)		-205.462***	
		(69.002)	
log(SUPPORT.PROTEST)		0.476	
		(1.745)	
log(SUPPORT.EXPANSION)*log(WIND.DENS)			207.018**
			(86.132)
log(SUPPORT.EXPANSION)			-3.751**
			(1.532)
log(WIND.DENS)	9.101***	81.615***	-91.512**
	(3.074)	(23.867)	(42.936)
log(LAG.WIND)	-1.773	-1.378	-1.156
	(2.501)	(2.247)	(2.303)
Intercept	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Spatial adj. SE	Yes	Yes	Yes
Num. obs.	53	53	53
Log Likelihood	-44.832	-41.262	-43.065
AIC	129.664	122.523	126.131
Note:			**p<0.1; **p<0.05; ***p<0.01*

Table F4 investigate whether the density of wind turbines moderates the association between public attitudes and the framing of narratives for the urban subsample, finding a weak negative correlation between framing and the support for expansion.

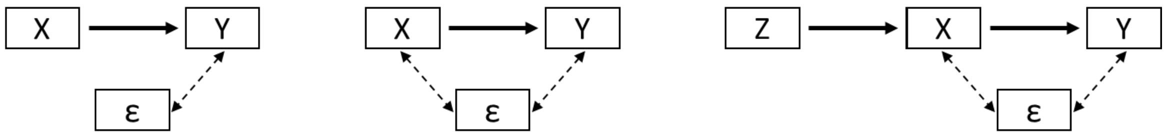
Table F4 Spatial Error Regression – Public attitudes, mediation and framing of narratives

	Log(ANGER.WIND)		
	(1)	(2)	(3)
log(ANTI.WIND)* log(WIND.DENS)	0.699		
	(2.543)		
log(ANTI.WIND)	-0.027		
	(0.202)		
log(SUPPORT.PROTEST) *log(WIND.DENS)		17.995	
		(36.925)	
log(SUPPORT.PROTEST)		-1.426	
		(1.007)	
log(SUPPORT.EXPANSION)*log(WIND.DENS)			49.824
			(41.566)
log(SUPPORT.EXPANSION)			-1.514*
			(0.794)

log(WIND.DENS)	-0.794	-6.624	-25.097
	(1.572)	(12.643)	(20.741)
log(LAG.WIND)	2.765**	3.051***	3.295***
	(1.148)	(1.138)	(1.132)
Intercept	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Spatial adj. SE	Yes	Yes	Yes
Num. obs.	53	53	53
Log Likelihood	-5.92	-4.868	-4.205
AIC	51.84	49.737	48.411
Note:			**p<0.1; **p<0.05; ***p<0.01*

G. *Instrument Variable Regression*

We also applied an instrument variable regression approach using wind speed as an instrument variable (IV) for wind turbines. In observational studies, IV controls for confounding and measurement errors to identify causal relationships.



a) Valid measurement of causal relationship

b) Biased measurement of causal relationship

c) Instrument measurement of causal relationship

Figure J1 Measurements of causal relationships

We seek to examine how wind turbines (X) affect the prominence and framing of narratives related to wind energy (Y). Figure J1 a) shows a valid measurement of the direct effect of X on Y, where the error term is not correlated with either variable. However, problems arise if the error term is correlated with both X and Y, as shown in b). For instance, a political situation could reduce the residents' influence, affecting both the number of turbines and the amount and framing of wind-related narratives. Wind turbines obviously depend on wind, and wind speed could be a good instrument Z for wind turbines, as it likely influences X. To be a good instrument, wind speed should not be related to Y except through X. It is hard to imagine that wind speed directly affects the narratives on wind energy except through the wind development plans – but we may have overlooked some issue here. We estimate IV estimators using a two-stage simultaneous equation model. The first-stage regression looks the following:

$$Num\ \widehat{wind\ turbiness_i} = \pi_0 + \pi_1 Max\ wind\ speed_i + \delta' \boldsymbol{np}_{ia} + \gamma' \boldsymbol{pl}_i + v_i \qquad i)$$

The first stage, displayed in Function i) decomposes *X* , the number of wind turbines, into a problem-free component explained by *Z* (maximum wind speed in a region), and a problematic component *v* that correlates with the error term ε – that correlates with both *Y* and *X*. For the second stage, we use the predicted values of X (density of wind turbines$_i$) to estimate:

$$Num\ wind\ related\ news_i = \Psi_0 + \Psi_1 Num\ \widehat{wind\ turbiness_i} + \delta' \boldsymbol{np}_{ia} + \gamma' \boldsymbol{pl}_i + v_i \qquad ii)$$

The IV regression using max wind speed as an instrument for the number of turbines yields non-significant results for anger and significant results for the number of wind news, see Table G1. The Durbin – Wu – Hausman test results suggest that wind turbine density might be exogenous in the proposed model. The Durbin – Wu – Hausman test evaluates whether the two-stage 'regression's endogenous regressor (wind turbines) is truly endogenous. We conclude that the spatial error model used in the article provides valid results.

Table G1 IV regression: max windspeed as an instrument for the number of turbines

	log(ANGER.WIND)	log(NUM.WIND)
log(WIND.DENS)	-1.917	8.032**
	(1.692)	(3.891)
Intercept	Yes	Yes
Newspaper control	Yes	Yes
Regional control	Yes	Yes
Adj. R2	0.212	0.715
Num. obs.	356	356
Wu-Hausman	0.072	0.806
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

H. *Spatial regressions: the impact of opposition on wind-related news and anger*

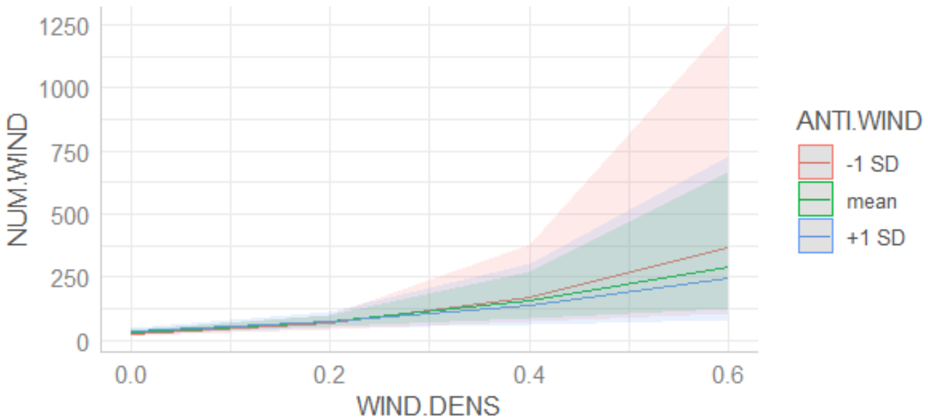
We run the regressions in Table 7 without any interaction effects. Table H1 summarizes the estimation for the number of wind-related news. We find no significant effect when we exclude the interaction effects.

Table H1 Spatial Error Regression – Framing of narratives

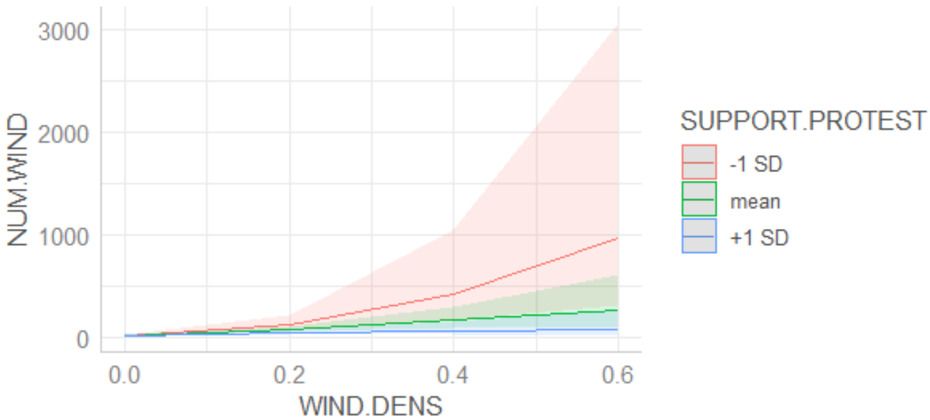
	Log(ANGER.WIND)								
	All			*Rural*			*Urban*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(ANTI.WIND)	-0.035			-0.027			0.055		
	(0.041)			(0.042)			(0.146)		
log(SUPPORT.PROTEST)		-0.074			0.501			-0.806	
		(0.433)			(0.521)			(0.884)	
log(SUPPORT.EXPANSION)			-0.163			0.356			-0.709
			(0.284)			(0.343)			(0.552)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial adj. SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	356	356	356	303	303	303	53	53	53
Log Likelihood	-78.204	-78.562	-78.414	-49.472	-49.219	-49.143	-9.474	-9.132	-8.747
AIC	194.407	195.125	194.828	136.945	136.438	136.286	56.947	56.264	55.495
Note:							*p<0.1; **p<0.05; ***p<0.01		

I. *Interaction effects*

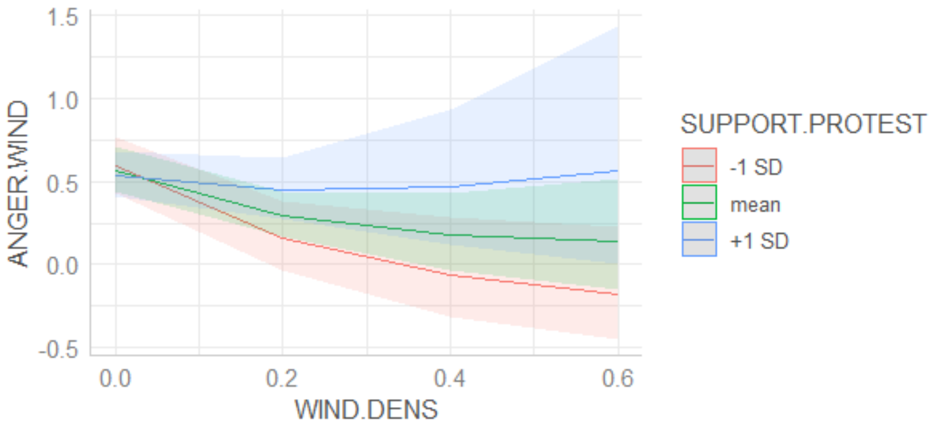
An interaction effect implies that the effect of one variable depends on another variable. Figure I1 shows the significant interaction effects in Tables 6 and 7. Since both coefficients are continuous, we split the plot into mean and +/- one standard deviation. Panel a) shows that ANTI.WIND is positively related to NUM.WIND. However, when the wind density increases from around .4, newspaper regions with fewer anti-wind turbine initiatives (-1SD, red line) seem to have a stronger increase in wind-related news than regions with the highest number of anti-wind turbine initiatives, although all react positively. Similarly, for SUPPORT PROTEST, newspaper regions with less support have a stronger positive reaction to WIND.DENS than newspaper regions that are more supportive in estimating NUM.NEWS. For ANGER, we find that areas with high support for protest and high density of wind turbines are positively correlated with ANGER.NEWS, consistent with our interpretation of Table 7. Regions with mean or lower support levels experience a decrease in anger when WIND.DENS increases, with the regions with lower support levels having the strongest negative reaction.



a) *Estimated interaction effect (Table 6), WIND.DENS*ANTI.WIND predicting NUM.WIND*



b) *Estimated interaction effect (Table 6), WIND.DENS*SUPPORT.PROTEST predicting NUM.WIND*



c) *Estimated interaction effect (Table 7), WIND.DENS*SUPPORT.PROTEST predicting ANGER.WIND*

Figure I1 Interaction effects

J. *Positive Emotions in Wind-Related News and the Density of Wind Turbines*

A decrease in negative emotions does not imply an increase in positive emotions. We measure positive emotion using the German version of Linguistic Inquiry and Word Count (LIWC), and re-run our spatial regression to understand how increasing the density of turbines impacts the level of positive emotions (POS.WIND) in wind-related news. Summary statistics are found in Table J1. The results are displayed in Table J2. We find evidence that a higher density of turbines is associated with less positive emotions in wind-related news. For urban areas, we find that a higher density of turbines in neighboring areas negatively impacts the level of positive emotions in wind-related news. The results align with our expectations in J2: narratives are less prominent in areas with a higher density of turbines. We find no impact of public attitudes with (Table J4) or without (Table J3) interaction effects.

Table J1 Summary Statistics

	n	*mean*	*sd*	*median*	*min*	*max*	*se*
AVG. POSEMO	356	2.42	0.45	2.39	0.74	4.45	0.02
POSEMO.WIND	356	1.57	1.1	1.72	0.00	8.00	0.06

Table J2 Spatial Error Regression – Positive emotions in wind news

	log(POS.WIND)		
	All	*Rural*	*Urban*
	(1)	(2)	(3)
log(WIND.DENS)	-0.923**	-1.103**	1.444
	(0.424)	(0.455)	(1.521)
log(LAG.WIND)	0.662	0.575	-3.306**
	(0.712)	(0.708)	(1.428)
Intercept	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Spatial adj. SE	Yes	Yes	Yes
Num. obs.	356	303	53
AIC	313.599	282.645	56.875
Note:			*p<0.1; **p<0.05; ***p<0.01

Table J3 Spatial Error Regression – Framing of narratives

	Log(POSEMO.WIND)								
	All			*Rural*			*Urban*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(ANTI.WIND)	-0.002			0.003			-0.232*		
	-0.049			-0.054			-0.135		
log(SUPPORT.PROTEST)		0.172			0.193			-0.149	
		-0.512			-0.666			-0.758	
log(SUPPORT.EXPANSION)			0.347			0.373			0.224
			-0.333			-0.437			-0.498
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial adj. SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	356	356	356	303	303	303	53	53	53
Log Likelihood	-78.204	-78.562	-78.414	-49.472	-49.219	-49.143	-9.474	-9.132	-8.747
AIC	194.407	195.125	194.828	136.945	136.438	136.286	56.947	56.264	55.495
Note:						*p<0.1; **p<0.05; ***p<0.01			

Table J4 Spatial Error Regression – Mediating effect framing of narratives

	Log(POSEMO.WIND)								
		All			*Rural*			*Urban*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(ANTI.WIND)* log(WIND DENS)	0.082			0.463			-2.947		
	(0.736)			(0.789)			(2.834)		
log(ANTI.WIND)	-0.007			-0.039			-0.021		
	(0.064)			(0.069)			(0.221)		
log(SUPPORT.PROTEST) * log(WIND DENS)		-4.69			-5.052			-11.162	
		(6.205)			(6.756)			(24.654)	
log(SUPPORT.PROTEST)		0.185			0.096			0.714	
		(0.371)			(0.485)			(0.677)	
log(SUPPORT.EXPANSION)* log(WIND*DENS)			-1.982			-5.021			-6.566
			(10.695)			(11.855)			(31.542)
log(SUPPORT.EXPANSION)			0.244			0.285			0.505
			(0.289)			(0.362)			(0.574)
log(WIND.DENS)	-0.965*	1.065	0.343	-1.343**	1.085	1.699	2.052	4.106	3.493
	(0.577)	(2.261)	(5.228)	(0.625)	(2.476)	(5.780)	(1.831)	(8.418)	(15.783)
log(LAG.WIND)	0.657	0.308	0.302	0.436	0.191	0.192	-2.272	-1.977**	-1.927**
	(0.719)	(0.480)	(0.480)	(0.712)	(0.484)	(0.483)	(1.504)	(0.976)	(0.941)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial adj. SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	356	356	356	303	303	303	53	53	53
Log Likelihood	-138.793	-0.948	-0.817	-120.898	-5.71	-5.682	-13.654	8.311	8.394
AIC	317.585	41.896	41.634	281.795	51.421	51.365	67.309	23.378	23.212
Note:									*p<0.1; **p<0.05; ***p<0.01

K.