Flooding Feeds: Elite Issue Attention and Competition after a Natural Disaster

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Abstract

Two rhetorical strategies dominate the party issue competition literature: issue ownership and wave-riding. Relaxing the assumption of parties as unitary actors, I theorize and empirically assess the extent to which candidates use these strategies following a salience shock. Rather than treat the two strategies as mutually exclusive, for candidates I argue they are synergistic. Concerns about opportunism *both* between and within parties suggest that increases in issue attention are driven by issue-owning candidates representing affected constituents. Using original candidate communication data from the 2021 German election, I leverage longitudinal and geographic variation in exposure to a natural disaster as a shock to climate salience to assess this conditional wave-riding hypothesis. Using an event study, I find that flood-affected Green candidates increase their climate issue attention compared to their unaffected partisans. Considering electoral returns to rhetoric, I find that increased climate attention was a vote-winning strategy for Green candidates.

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Laying out its four critical tasks for the next German government ahead of the 2021 election, the mainstream center-left party, the SPD, listed a climate-neutral Germany as its first priority in its manifesto.[1] Likewise, in its introduction, the center-right CDU stated: "We want a modern Germany that thinks about tomorrow, acts today and lets great things continue to grow together: economic strength, consistent climate protection and social security," before establishing its carbon-neutral target for 2045.[2] Statements like these in mainstream party manifestos present a challenge to the traditional issue owner, the Green party, as growing issue salience makes it untenable for these parties to ignore climate change.[3] This increased programmatic competition over a once niche issue is symptomatic of a broader trend in party competition: issue overlap.

Understanding parties' strategic engagement with issues is an enduring question in party competition research (Stokes, 1963; Budge and Farlie, 1983; Petrocik, 1996; Sagarzazu and Klüver, 2017; Green-Pedersen, 2019). Prominent accounts stress issue ownership, or the competency with which a party is viewed over a given issue, as important in shaping a party's issue engagement (Petrocik, 1996; Bélanger and Meguid, 2008; Abou-Chadi, 2014; Wagner and Meyer, 2014; Seeberg, 2016). Alternatively, others suggest that parties "ride the wave," or follow what is salient in the moment, as the failure to do so may lead them to being seen as out of touch with the

[1](Sozialdemokratische Partei Deutschlands, 2021)

[2](Christlich Demokratische Union Deutschlands, 2021, p. 4) Author's translation.

[3]See survey data from Forschungsgruppe Wahlen E.V. (2021) on the most salient issue in Germany. Climate change was the most important issue for much of the summer. Furthermore, recent research considers this apparent consensus as the basis for the radical right's politicization of and therefore engagement with climate change (Dickson and Hobolt, 2024).

electorate (Ansolabehere and Iyengar, 1994; Klüver and Spoon, 2016; Klüver and Sagarzazu, 2016). This fear of being perceived as out of touch induces parties to overlap on issues, even those they prefer to ignore (Green-Pedersen and Mortensen, 2010; Green-Pedersen, 2019; Grossman and Guinaudeau, 2021). Regardless of the issue strategy, parties focus their attention in an effort to gain votes by appearing more credible or persuasive on a set of issues (Ansolabehere and Iyengar, 1994). Recent developments in the literature have diversified the medium of communication away from the manifesto, for example using press releases (Klüver and Sagarzazu, 2016; Seeberg, 2020*a*), legislative questions (Green-Pedersen and Mortensen, 2010; Meyer and Wagner, 2021), or media coverage (Meyer, Haselmeyer and Markus, 2020) with mixed support for both arguments.

Although theories of issue attention are applicable to both parties and politicians, the empirical literature to date has largely focused on the former. The issues garnering political actors' attention, and thereby shaping the contours of political conflict and debate, are essential components of the agenda setting and policy process (Kingdon, 1995) and ultimately democratic representation (Przeworski, Stokes and Manin, 1999). Given that most democracies feature some type of decentralized representation (either through federated party lists or more intensively via majoritarian districts), institutional conditions often provide the opportunity for individual politicians to contribute *independently* to this debate and with their constituents. Our understanding of representation, agenda setting, and the policy process rests on shaky foundations absent some understanding of candidate issue attention dynamics. While centralized party channels may overlap and compete over issues (Green-

Pedersen, 2019; Grossman and Guinaudeau, 2021), it is an open question whether this tendency trickles down to the rank and file and how individual issue priorities translate into unified partisan appeals. Hence this paper asks the following question: does issue ownership or wave-riding better characterize candidate issue attention following a salience shock?

Climate change, a niche issue once dominated by Green parties, but now highly salient among the general public and party system, presents an ideal issue to start to study issue competition dynamics at the candidate level. The tension between an issue owned by one party, the Greens, but also relevant to the electorate, presents non-owning candidates with a trade-off: focus on an issue for which they may lack expertise or *competency* or risk being seen as out of touch. While in line with theories of issue ownership, which stress concerns about perceived opportunism between parties as important in shaping issue engagement, the shift to candidates reveals opportunism concerns are likewise present *within* the issue-owning party; rather than arising from a lack of expertise however, the opportunism concerns afflicting issue owners are representational in nature. Despite having the expertise to adeptly discuss the issue (Egan, 2013), issue-owning candidates representing constituents less affected by the salience shock risk coming across as prioritizing far-flung events at the expense of parochial concerns, reducing the incentive to *increase* their issue attention.

Strong sanctioning methods may allow parties to better keep their candidates on brand, suggesting a more uniform wave-riding phenomena in the wake of a salience shock, yet common models of candidate recruitment in practice lack these mechanisms (Rahat and Hazan, 2001). This independence shapes the response between and within parties by candidates. Absent such sanctioning mechanisms, I argue that candidate issue attention following a salience shock is more likely to be characterized by conditional wave-riding: increases in issue attention by candidates from the issue-owning party, but *only* those candidates representing affected constituents given the opportunism concerns above. By studying candidates, I am able to both theorize and empirically assess intra-party heterogeneity in issue attention rather than assuming a unitary actor status (Adams, 2012). Rather than issue-ownership and wave-riding being mutually exclusive states of issue competition as they are at the party-level, the shift to the candidate-level reveals a synergy between the two frameworks.

To assess this argument, I study candidate communication on Twitter in the lead-up to the 2021 German Federal Election as its close proximity to a natural disaster lets me leverage temporal and spatial variation to a plausibly exogenous issue salience shock. Similar to other work using Twitter as a source of political communication data (Barberá et al., 2019), I use candidate tweets as a proxy for issue attention. I estimate a series of structural topic models (STMs) to measure the different issues that characterized the 2021 campaign. Labeling the topics as issues, I leverage the "once in 400 year" floods to examine how candidates' rhetoric changed on an issue deemed critical in all but the far-right's platform (Eddy and Erlanger, 2021). Furthermore, the close timing of the floods to the election in Germany permits an analysis of the electoral returns to climate issue attention strategies.

As a first cut at the data, I show that Green candidates increased their climate issue attention by 60 percentage points, whereas other parties candidates barring the far-left Die Linke (4 p.p.) did not change their issue attention. This finding goes directly against generalized wave-riding, in which all candidates follow the relevant issue, while providing some support for an issue-ownership logic. Next, I leverage the spatial variation in flooding in an event study design. I find that this increase in issue attention is driving almost entirely by affected Green candidates. Compared to their unaffected peers, affected Green candidates posted five times as many additional tweets discussing climate change per week. Rather than *all* issue-owning candidates talking more about climate change, the response was strong but limited to a small portion of the party. This intra-party variation evidence refutes a pure issue-ownership logic. The 2021 election marked a historic return for the Greens, its highest ever, moreover the electoral analysis finds that increased climate attention is associated with a roughly 2 percentage point vote share increase in affected districts. Given that the Greens gained 6 p.p. on average this is a substantial. Rather than natural disasters presenting common shocks, these findings suggest that local elite mediation shapes popular response. This suggests an alternative strategy to policy benefits available to non-incumbents (Bechtel and Hainmueller, 2011) and providing issue-owners a means of demonstrating competence to handle locally-relevant issues (Ashworth, Bueno de Mesquita and Friedenberg, 2018). This candidate level data differs from other more centralized sources such as the manifesto or press release coverage of the issue over the same period.[4]

An extension to members of parliament in Belgium, also affected by the floods, generalizes these issue attention findings across contexts. Using the same dictionary

[4]See Figure 3 and Appendix E.

measure of climate issue attention in both countries, I find only Green MPs increase their climate rhetoric following the floods. Among the Greens, I find again that this increase is driven by MPs in affected districts. These findings are consistent with a conditional logic of wave-riding in which issue-owning candidates representing affected constituents are more likely to increase their issue attention following a shock.

This article makes several contributions to the study of politics. First, by examining candidate rather than party communication I provide theory and evidence for when prominent party-level strategies are used by candidates. Rather than considering issue ownership or wave-riding as substitutes, I consider and provide evidence consistent with opportunism concerns influencing candidate issue attention dynamics between and within parties, letting them function as complements. Climate and environmental issue dominance by Green parties is often considered a prototypical example of issue ownership, yet even with clear ownership I demonstrate that most Green candidates did not increase their issue attention. This finding, alongside my argument focusing on the opportunistic concerns and resource constraints of candidates provides a starting point for more general explanations of candidate issue attention beyond this case. Furthermore, the shift to the candidate level allows me to test in a more credible fashion the electoral underpinnings of canonical arguments in the party competition literature. In doing so, I respond to a call for scholars of party competition to move beyond the unitary actor assumption (Adams, 2012).[5]

The geographic variation in climate disaster exposure permits not only a consid-

[5]For other work that considers individualized communication see Meyer and Wagner (2021) on legislative questioning.

eration of inta-party heterogeneity in issue attention, but also extends earlier work on politicians on social media with evidence on how they respond to salience shocks (Barberá et al., 2019). Lastly, while a large body of work studies the impacts of climate change at the level of mass politics, our knowledge about how elites respond to and mediate the connection between climate change and electoral politics is nascent (Birch, 2023; Wappenhans et al., 2024). The results demonstrate that even in a context in which the climate is highly salient and political parties have nominally embraced the issue, candidates by and large do not focus on it even in the midst of climate disaster, consistent with the trade-offs identified above. Strategic considerations may lead candidates to dismiss the issue, rather than hand an advantage to their competitors in a similar fashion to parties (Hobolt and de Vries, 2015) or appear opportunistic even when they enjoy the benefit of being issue-owners. This slippage between party and candidate issue attention is arguably positive when considering representation and democratic accountability (Przeworski, Stokes and Manin, 1999).

1 Issue Competition

Considering competition over issues rather than positions, a large body of research in political science has studied the ways in which political parties struggle to set the electoral issue agenda (Stokes, 1963; Petrocik, 1996; Green-Pedersen, 2007). Issue competition is the process by which political parties attempt to highlight issues they want to center debate in electoral competition (Green-Pedersen, 2007, p.609). As noted above, prominent partisan strategies in the literature consider either ownership or salience.

Accounts adhering to the former school suggest that parties try to push issues over which they enjoy ownership in an effort to raise public awareness for their preferred topics (Petrocik, 1996). This perspective suggests the issue agenda is elite-led or top-down. If issue ownership is relatively exclusive, then parties can develop distinct profiles or brands (Budge and Farlie, 1983; Carmines and Stimson, 1989; Roberson, 1976), which can be recognized and rewarded by voters (Bélanger and Meguid, 2008; Seeberg, 2017). Issue ownership has often been studied in tandem with niche parties–small parties formed around a specific policy domain–forgoing a broad platform typical of mainstream parties (Abou-Chadi, 2014; Meguid, 2005; Spoon, Hobolt and de Vries, 2014). This is most evident in the emergence of Green parties in Western Europe (Kitschelt, 1989).[6]

Alternatively, rather than parties focusing on issues they own, they may follow the public and "ride the wave" of issue salience (Ansolabehere and Iyengar, 1994). Here, a party's issue strategy follows some other actor. By connecting with potential voters on issues deemed important, parties avoid the risk of being perceived as out of touch with the electorate or losing the opportunity to frame the issue favorably (Green-Pedersen and Mortensen, 2010). An issue's salience may come from the party system (Green-Pedersen, 2019; Grossman and Guinaudeau, 2021), issue entrepreneurs (Hobolt and de Vries, 2015) or the public often via the media (Barberá et al., 2019). Evidence of wave-riding at the party level has been demonstrated with press releases (Klüver and Sagarzazu, 2016) and manifestos (Wagner and Meyer,

[6]Note that recent work questions the extent to nicheness is a permanent characteristic of parties (Bischof, 2017; Spoon and Williams, 2021).

2014; Grossman and Guinaudeau, 2021).

Yet the trade-off related to following salient issues or competently discussing core issues faced by parties is less challenging than those faced by candidates, largely because of the unitary actor assumption. Parties are composed of a diverse set of individuals who can pool resources, making following and responding to salience shocks in a *credible* fashion easier. Individual candidates, by and large, lack these resources to competently respond to the same extent as parties. While better resourced parties may be better able to deploy wave-riding strategies (Wagner and Meyer, 2014), it is unlikely that individual candidates can do the same. Here, by considering parties as single actors, theories of wave-riding largely neglect the capacity threshold needed to actually engage in wave-riding.

In terms of following salient issues, parties face only the temporal trade-off as issue attention is centralized (i.e., a single message source), whereas candidates face both cross-sectional (i.e., party and candidate messaging) and temporal dimensions. Given its representation of an entire country, a party's scope of attention must be broader for fear of missing out (Green-Pedersen, 2019; Grossman and Guinaudeau, 2021). Candidates often represent smaller areas diminishing their incentives to address *non-local* salient issues. The more binding nature of these trade-offs for candidates suggests that wave-riding is unlikely to characterize candidate issue attention generally despite its prevalence among parties. At the same time, issue ownership explanations are too static (Budge and Farlie, 1983; Lupu, 2014), providing little in terms of an explanation of variation in issue attention over time. Hence, for candidates these strategies are more likely to be complements rather than substitutes as they often seen at the party-level.

2 Argument

In this section, I take the party competition literature as a starting point to develop an explanation of *candidate* issue attention dynamics. By issue attention, I mean the amount of resources or emphasis a political actor dedicates to a given issue, not a specific event.[7] I begin at the party-level given that certain aspects, namely the concern over credibility, competence, and opportunism, are shared by both parties and candidates as strategic actors. Candidates desire to credibly convey their competence to voters in attempt to gain office. Wave-riding theories suggest political actors achieve this by following the salient issues of interest to voters, diminishing the importance of expertise or ownership. Here, competence is conveyed via the responsiveness of candidates to their constituents' concerns, reaffirming the representational linkage. In contrast, issue ownership suggests competence is developed through continued attention to a given issue, developing expertise and therefore credibility. The differing emphasis on expertise and its influence on credibility pits them as mutually exclusive issue attention strategies at the party level.

My main contention is that they are synergistic at the candidate-level. Whereas perceived opportunism is a concern for non-issue-owners at the party-level, shifting to candidates introduces similar opportunism concerns *within* the issue-owning party,

[7] For example, a natural disaster, such as a hurricane or forest fire can be a salient event for climate change, but discussion of the hurricane or forest fire alone is not paying greater attention to the issue of climate change. There must be an rhetorical connection between the two.

albeit in terms of representation not expertise. Rather than *all* candidates from the issue-owning party increasing attention following a salience shock, candidates whose constituents are unaffected by the shock risk being seen as opportunistic in a similar fashion to their competitors. Using a far-off event to focus on their preferred issue risks coming across as negligent towards local priorities. Absent strict sanctioning mechanisms, which would in effect reduce parties to unitary actors by enforcing mass compliance across candidates and eliminating their communicative independence, we should expect candidates to engage in conditional wave-riding, in which candidates (1) from the issue-owning party and (2) representing constituents affected by the salient issue are more likely to increase their issue attention.

As discussed above the party competition literature theorizes two prominent strategies by which parties compete over issues. At the party-level these strategies are mutually exclusive. If only the issue-owning party focuses on the salient issue, we cannot simultaneously observe wave-riding, or a general increase in attention. As noted above, wave-riding theories downplay the potential role of variation in expertise between parties, expecting only temporal variation in issue attention. [8] If formulated at the candidate level, a wave-riding argument would suggest the following:

[8] To elaborate the hypotheses, I directly translate the party-level expectation to candidates, ignoring momentarily the spatial variation in exposure to the salience shock to emphasize the difference between party- and candidate-level expectations. At the party-level, given the unified actor, only H1 and H2 are possible. Devolving to smaller subnational units and relaxing this assumption of a unified partisan actor is a necessary condition for H3 and H4. Exposed provinces may differ from unexposed ones. In Appendix E, I provide evidence of such geographic spillovers using alternative treatment definitions.

H1. *General Wave-Riding*: Candidates, regardless of party, increase their issue attention following a shock to its salience.

That is, we should expect all candidates to increase their attention to the issue after a salience shock. Yet, as scholars of issue ownership have noted, parties are able to develop reputations or brands visible to voters (Lupu, 2014; Seeberg, 2017) and potential recruits (Egan, 2013). The process of selection draws in candidates interested in and knowledgeable of the core issue. This provides candidates with varying capacities to adeptly address the salient issue, with less risk of appearing opportunistic to their competitors. Expertise, according to an issue ownership logic, confers greater credibility to issue-owning candidates, improving the signal of their quality to voters. Candidates from non-issue-owning parties risk being perceived as opportunistic, whereas issue-owning candidates face no such misperception. Hence, carrying an issue ownership argument from the party- to candidate-level suggests the following:

H2. *Issue Ownership*: Candidates, only those of the issue-owning party, increase their issue attention following a shock to its salience.

Both the above strategies assume no variation in issue attention strategy *within* the party. Furthermore, there is an implicit assumption of a homogeneous shock to issue salience. That is, the change in issue salience is uniform across the entire voting population. This assumption is understandable at the party-level: Most parties represent the national territory and ideally should respond to issue shocks, even localized ones at times that are of great importance. Shifting to candidates, however, it is less likely that issue shocks impact the entire country in an equal fashion.

Relaxing this assumption and building from the wave-riding logic above suggests that candidates representing constituents more affected by the salience shock should pay greater attention. The concern over perceived opportunism that confronts the national party may be diminished for these candidates: the constituents they seek to represent are affected by the issue. Hence, party-level issue ownership might mask more constituent-specific or localized wave-riding among candidates. Furthermore, for parties that do not address the issue, due to concerns over opportunism for example, an absence of sanctioning mechanisms to ensure uniformity of message, provides candidates with a window to address the issue. Put differently, under conditions of communication independence on the part of candidates, we might expect non-owners to respond to localized shocks. This suggests:

H3. *Localized Wave-Riding*: Candidates, only those representing more affected constituents, increase their issue attention following a shock to its salience.

Similar to the generalized wave-riding hypothesis above, its localized variant downplays the strategic concerns related to the competence of candidates to speak on a given issue. Considering both variation in spatial exposure and in issue expertise across candidates suggests two types of risks they must consider. First, as was the case between issue- and non-owning parties, the concern over competence remains. Second, however, is the concern over representation, or focusing on a salient issue, but one that is of less importance to a given candidate's constituents. I elaborate each in turn to arrive at an expectation of conditional wave-riding following shocks to issue salience.

Concerns related to issue competence may occur by two means. In both cases a non-owning candidate by engaging with the issue risks exposing their relative incompetence compared to the owner. This may directly benefit the issue-owning candidate, or, alternatively, other non-owning candidates may stand to benefit. The former scenario is more likely when the electoral threat of the issue owner is higher, whereas the latter is more likely when the issue owner presents less of a threat. Regardless, the mere presence of an issue owner by presenting non-owning candidates with a knowledgeable competitor with whom voters can compare generates these concerns. Whereas parties can pool the resources of many individuals and perhaps overcome competence concerns, individual candidates typically lack such resources.[9] This suggests that in affected districts non-owning candidates are less likely to increase their issue attention following a salience shock, rather than engage, they may try to reframe the issue, increasingly focusing on a local dimension or depoliticize it (Hobolt and de Vries, 2015).

Stopping here suggests a similar expectation as the second hypothesis, however this neglects representational dynamics within the issue-owning party. While issue-owning candidates have the capability to respond to the salient issue in a more credible fashion, spatial or geographic concerns of opportunism emerge for candidates representing constituents unaffected by the shock. Riding the wave of an issue of

[9]This line of reasoning suggests that candidates with more resources may be able to increase their issue attention more compared to their peers. Opportunism still remains a concern, however. I present suggestive evidence in line with this argument in Table 2, however this does not disaggregate between affected and unaffected candidates. An additional dimension of difference in the event study design is underpowered, and therefore the hypothesis is not readily testable. I leave this for future research.

less relevance to one's constituents is likely to come off as opportunistic behavior, *irrespective of issue-ownership*, hence increases in issue attention should be localized *within* the issue-owning party to those candidates most affected. Put differently, increasingly talking about an issue of no greater importance to one's constituents regardless of one's ability to address the issue risks coming across as prioritizing far-flung events over more parochial concerns. The absence of a local shock to respond to places issue-owning candidates in a similar trade off between chasing salience and sticking to core interests; in the present context, however, the concern arises from the spatial mismatch between where the shock occurs and the legislative connection. They may talk about the issue at the same rate but they are unlikely to increase their attention substantially. This suggests the following hypothesis:

H4. *Conditional Wave-Riding*: Candidates, only those from the issue-owning party and representing more affected constituents, increase their issue attention following a shock to its salience.

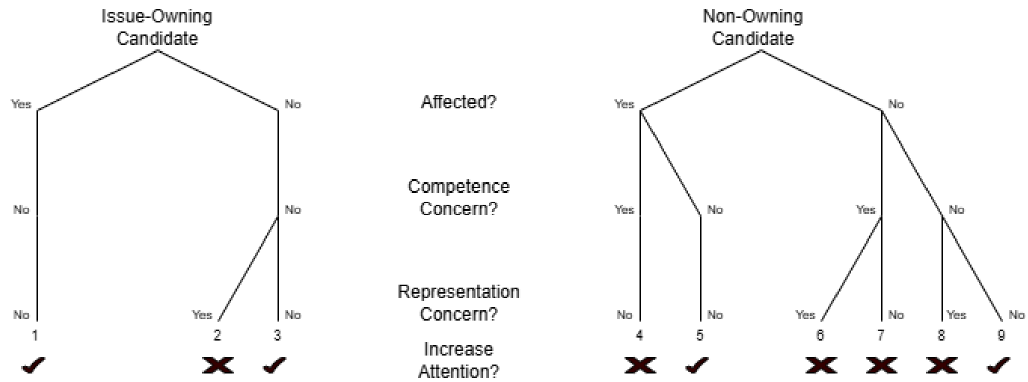
Whereas party-level arguments treat these strategies as mutually exclusive, conditional wave-riding highlights a complementarity between the two. Rather than expecting all affected candidates to talk about the issue or all issue-owning candidates to increase attention, it is the combination of the two that leads to a more granular increase in attention. Alone, issue ownership theory assumes no variation within the party in response to salience shocks. In contrast, wave-riding alone suggests no variation between parties. Taken together, a conditional logic of wave-riding due to issue ownership suggests variation both within and between parties in response to salience shocks. In either framework, the issue attention strategy is predicated on a goal of maximizing votes primarily via a fear of perceived opportunism and voter backlash diminishing incentives to engage the issue.

To summarize the decisions faced by candidates considering whether to respond to a salience shock, Figure 1 visualizes the decision tree faced by issue-owning and non-owning candidates respectively, before summarizing the combination of decisions by different groups of candidates to arrive at the hypotheses outlined above. To streamline the visualization and in line with the theory above, I assume that issue-owning candidates face no competence concern and candidates in affected districts face no representation concern. This results in nine branches. For a candidate to increase their issue engagement they must jointly not perceive a competence or representation concern. Issue-owning candidates in affected areas never face these concerns and hence always compose a part of the set of candidates increasing their issue attention (Node 1). In contrast, depending on whether we consider issue competence and local representation binding, non-owning candidates more often than not do not increase their issue attention (Node 9, but not Nodes 6-8).

3 Context

This article studies candidate issue attention in the lead-up to the 2021 German Federal election. The constitutionally mandated election date for late September alongside the occurrence of a natural disaster in mid-July permits an ideal setting for considering how candidates respond to an issue salience shock. Furthermore, the close proximity to the election date lets me consider whether candidates who engaged

Figure 1: Candidate Decision Tree



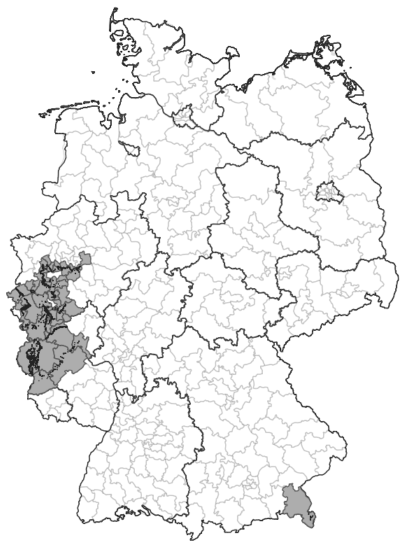
Hypothesis	Cells
1. General Wave-Riding	1,3,5,9
2. Issue Ownership	1,3,4,6,7,8
3. Localized Wave-Riding	1,2,5,6,7,8
4. Conditional Wave-Riding	1,2,4,6,7,8

with the prominent issue performed better at the ballot box. Figure 2 maps the extent of flooding. The majority of flooding was concentrated in Western Germany, a motivating factor in Hilbig and Riaz's (2024) study of the electoral consequences of flooding in North Rhineland-Westphalia and Rhineland-Palatinate alone. While direct exposure to flooding was geographically clustered, the disaster was covered widely at the national and international level, therefore the issue attention analysis below considers all candidates.[10]

The emerging literature that studies the electoral implications of natural disasters in the German context often focuses on the "second vote" or party-list vote in Ger-

[10]In Appendix A, I provide additional evidence on the connection between climate change and the intensity of the floods in the German press. In Appendix D, I demonstrate that the findings also exist focusing on the narrower subset of affected states.

Figure 2: Map of Germany with flooded districts and flooded areas in grey and black respectively.



many's mixed-member legislative system (Bechtel and Hainmueller, 2011; Garside and Zhai, 2022; Hilbig and Riaz, 2024). Due to my focus on candidates, I consider the first vote, that is for candidates running to win the seat in a single-member district, rather than the party allocation at the state level. Given that the center-left and -right parties have dominated these latter votes traditionally, with the remaining parties winning seats via proportional allocation, the incentives for candidates may differ along party lines. For mainstream candidates, the electoral threat of the Greens may be indirect in most cases, therefore the candidates from the two parties that have dominated the first vote elections may fear electoral reprisal to a lesser extent, yet the mere presence of a Green candidate provides voters with an informed or competent comparison regardless.[11]

[11] To address concerns that the results are unique to electoral competition in Ger-

While most candidates barring those from the SPD or CDU will only make it into government via list placement, empirically the vast majority of candidates (85%) in the data is cross-listed, that is they are simultaneously running on the state list and as a party's candidate in a district. Therefore an incentive exists to demonstrate their party's competence following salience shocks, even if the benefit is only indirectly to themselves. If cross-listing diminishes the individual concern for votes, this would bias against finding evidence for the conditional wave-riding logic above as candidates may simply seek to appease party superiors and focus on the core issue.[12] In either case, candidates are trying to maximize votes either for themselves and/or the party, hence I consider all parties present in the Bundestag in the preceding legislative period in the empirical analysis.[13]

In the German context, methods of candidate selection are similar across each of the major parties: decentralized selection at the state-level with little by way of primaries, rather candidates are selected by local elites in what are called "coronations" (Detterbeck, 2016). Sanctioning potential by the central elites in such a decentralized system is rather low (Rahat and Hazan, 2001). This suggests that candidates are at minimum partially independent and not strictly regurgitating the party message.[14]

many, I extend the analysis to Belgium below.

[12]If candidates did not care about their own profile as a candidate at all, we would expect no variation in issue attention among Green candidates within affected states, as the list is set at the state level. I show in Appendix Table E3 that this is not the case. Results mirror the main results, barring two weeks that are just below conventional significance levels. The absence of a clear attenuation effect in these coefficients compared with the main results, suggests this is due to a lack of power.

[13]These include the AfD, the CDU (CSU), Die Linke, the FDP, the Greens, and the SPD.

[14]Empirically, I find that almost two-thirds of tweets are not retweets and therefore

Furthermore, one party is the clear issue owner of climate change: the Green party.

Together ,this suggests that in the German context both spatial and expertise trade-offs are present for candidates, hence I expect Green candidates to engage more with the climate issue following the floods, with this result driven by an increase in issue attention by candidates in affected districts. Yet, as noted above, climate policy is a central issue to the German electorate writ large and other parties. Both mainstream parties, the center-left, SPD, and center-right, CDU, placed climate policy as a core tenant of their manifestos. Likewise, all remaining parties represented in the legislature barring the far-right AfD embrace robust climate action and dedicate substantial space in their manifestos to the issue.[15] At the party level, the parties appear to compete over the issue as it has remained highly salient among the German public, and these manifestos provide candidates with an array of policy details or information that they *could* access.[16] Furthermore, Figure 3 presents trends in environmental press releases over the period of study using data from Ivanusch (2024). The Green party does not appear to respond to floods in its press releases nor is it dominating the issue attention space.[17] These party-level data

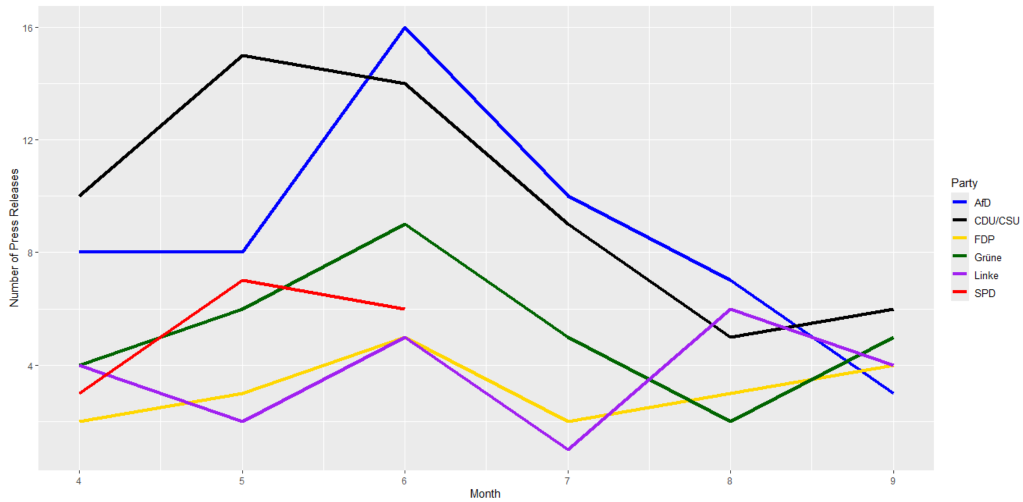
are unique to the candidate.

[15]In Appendix A, I provide a deeper overview of the policy positions, its centrality of climate change in each of the parties' manifestos, as well as media coverage of the flood and its connection to climate change.

[16]In Appendix C, I document the usage of climate rhetoric by non-Green parties through two close readings. By and large, candidates from other parties weakly engaged with the issue, oftentimes simply regurgitating the party's one line climate slogan.

[17]The absence of increase at the party-level could be explained by the party's emphasis on diversifying its message (Spoon and Williams, 2021). Alternatively, the binary classification strategy employed by Ivanusch (2024) differs from both the topic model and dictionary approach in that press releases can only discuss one issue.

Figure 3: Count of Party Press Releases on the Environment



highlight that non-Green candidates do not lack material to use if they wanted to regurgitate party-level communications, nor are their party organizations ignoring climate change, aside from the far-right.

4 Research Design

To assess contours in candidate issue attention following a salience shock, I analyze Twitter commentary from direct candidates for office using a list of candidates compiled by Sältzer et al. (2021) as the basis for a scrape of posts in the months preceding the election. This candidate list likewise provides me with the gender, incumbency status, and party affiliation for all candidates. A benefit of using Twitter to measure candidate issue attention is the equal access to the platform for the population of

Several party press releases mentioning the flood were classified as pertaining to the Welfare State, for example.

interest as recent research in Italy finds incumbents receive more media exposure following disasters than primary challengers (Masiero and Santarossa, 2021). Furthermore, these accounts are arguably a useful proxy of politician issue attention, as Bauer et al. (2023) find in a survey of sitting German politicians in 2020 that 89% of politicians operate their accounts alone or with some assistance from staff. Given their lack of resources, it is likely that the number of candidates solely operating their accounts in the present sample is higher. It is certainly true that more established politicians are better able to reach constituents than a new challenger even on Twitter, however this coverage bias would also be present with other sources of political communication such as press conferences or news media. Finally, Twitter is a relatively cheap form of communication–there are few restrictions on how much or about what they can post. These characteristics make it an appealing proxy measure of candidate issue attention.

With these accounts, I collected a panel of tweets from all account-holding direct candidates.[18] I focus on the month preceding and following the first day of flooding: July 13, 2021. In total, the sample consists of roughly 100,000 tweets from between 800-900 candidates out of 1784 direct candidates depending on the measurement strategy used. Accounts that had no tweets (or set to private) in either period were dropped from the dataset. As a robustness, I collected tweets from the Belgian lower

[18]For all subsequent analyses, I focus on candidates running in the first-vote in Germany's two-vote system. That is, the election for candidates to directly represent districts for office rather than state-level lists. Candidates can be cross-listed, eligible as a list and direct candidate for office. I focus on these candidates because candidates that are strictly on list are elected at the state-level and hence do not have as direct a linkage to flooded areas as district candidates.

house for the issue attention analyses. Further details on this sample and general sample statistics for the German sample can be found in Appendix B with empirical results in Appendices C & D. The German sample is largely representative of the population of candidates, barring a higher level of incumbents.

To measure climate issue attention, I use two strategies. In the first, I leverage structural topic models (Roberts, Stewart and Tingley, 2019). This allows me to consider issue attention writ large across the entire corpus of documents, mirroring work on issue attention on Twitter in American politics (Barberá et al., 2019). Each month-long collection of tweets is modeled as being composed of one or more topics. Using the top 30 predictive words as well as a sample of the most representative documents, I classified all 15 topics in the primary model.[19] The climate topic proportion for a given document i in month m is the first operationalization of climate issue attention.[20]

Second, I generate a count variable for the number of tweets in a given time period, *Climate Mention*, that takes a value of 1 if climate, climate change, or the energy transition is mentioned in a given tweet.[21] I aggregate this measure at either

[19]In Appendix B, I provide more details on STM estimation as well as the general contours of issue attention across the entire election cycle.

[20]I further validate the presence of climate rhetoric in the text with two close readings of a random sample of accounts from the Green Party, and the two mainstream parties. Second, I read all tweets from flooded districts. Further details can be found in Appendix C.

[21]German: Klima, Klimawandel, Energiewende. I omit *Flut*, *Hochwasser*, and *Überschwemmung*, German words that may refer to the floods, given that barring Green candidates, few other candidates linked the floods with climate change, hence flood mentions should not be equated with climate issue attention. In Appendix D, I provide more details on these close readings and validation exercises of the topic model analysis.

the month or week level. By utilizing an unsupervised machine learning approach alongside a dictionary measure, the design balances concerns about a lack of internal validity in the text analysis with a transparent, albeit narrow, measure of climate issue attention. In the analyses related to issue attention, these two variables are my outcomes of interest.

The salience shock is measured by temporal and spatial exposure to flooding. I code a temporal variable, *Post-Period*, which takes a value of 1 for the month following the floods. I measure direct exposure to flooding with geospatial data from the Copernicus Emergency Management Service to code a binary measure at the district level.[22] Overall, 36 out of 299 districts were affected. Documented flooding occurred primarily in two states in western Germany: North-Rhine Westphalia and Rhineland Palatinate.

As a first cut at the data, I ignore spatial variation in exposure to consider whether support exists for the generalized wave-riding or issue ownership hypotheses. I estimate a series of two-way fixed effects models (candidate-month) to assess the relationship between climate issue attention, measured as the document climate topic proportion in month i, and time and partisanship.[23] In Equation 1, the *Post-Period* variable is captured by the time fixed-effect γ_t. Given that a candidate's partisanship

[22]EMSR Report 517 contains a series of various shape files by administrative unit, which I combined to generate a single layer to code affected status. An overview can be found at: https://emergency.copernicus.eu/mapping/list-of-components/EMSR517.

[23]I eschew a more causal interpretation of this estimation strategy given the lack of sufficient pre-periods to assess potential violations of parallel trends by partisan affiliation. Furthermore, the alternative measurement strategies for the issue attention outcome present analysis provides a validation exercise.

is time-invariant, the variable is interacted with the *Post-Period* indicator to assess differential response by party. Lastly, I include the remaining individual covariates interacted with the time trend.

$$Y_{it} = \alpha_i + \gamma_t + \beta_1(PostPeriod_t \times Party_i) + \beta_2(PostPeriod_t \times X_i) + \epsilon_{it} \qquad (1)$$

Given that not all districts were affected by flooding, I introduce an additional dimension of difference into the above equation–the flooding status of a candidate's district–and estimate a triple difference specification using just the dictionary measure of issue attention aggregated at the week to test the localized versus conditional wave-riding hypotheses. Given the greater frequency of measurement, I employ an event-study design, considering the shift in issue attention at weekly intervals pre- and post-flooding.

$$Y_{iw} = \alpha_i + \gamma_w + \sum_{w=-3}^{4} (\beta_w Flooded_i \times Party_i \times \mathbf{1}_{w=k}) + \lambda_w X_i + \epsilon_{iw} \qquad (2)$$

In Equation 2, Y_{iw} is a candidate's issue attention in week w, α and γ are candidate and week fixed effects and the λ term captures individual covariates interacted in an analogous event study. β_w measures the shift in climate issue attention from a baseline of the week prior to flooding. By interacting partisan affiliation and flooded status, the coefficient captures the shift in issue attention between candidates in affected versus unaffected districts for a given party. This design lets me assess whether localized or conditional wave-riding better characterizes candidate issue attention once we relax the assumption of a uniform salience shock (i.e., via spatial variation in flood exposure).

Given the use of weekly data rather than monthly data, I am able to test for potential violations to the parallel trends assumption needed for causal identification in the difference-in-differences framework. Violations of said assumption would take the form of divergences in climate issue attention in the weeks prior to the flood among candidates of the same party, but differing in their direct exposure to flooding. I provide visual evidence of the absence of such divergences in the pre-period in Figure 4. Across all analyses that consider issue attention as the outcome, I cluster standard errors at the individual and district levels.

Table 1 provides an overview of the theoretical arguments and the corresponding evidentiary requirements and design specifications. I briefly summarize this below to provide the intuition behind the set of analyses described above.

General wave-riding would take the form of increased attention by all candidates following the floods. I test this first by assessing shifts in climate issue attention by month before and after the floods using the STM design elaborated above, and as a robustness I replicate the analysis using the same dictionary from the event study. If candidates, irrespective of partisanship or affected status, increased their climate issue attention, this would be evidence in favor of general wave-riding. This requires that any positive shift in climate rhetoric be *consistent* across candidate parties. This would take the form of a positive coefficient on the *Post-Period* variable and an absence of positive coefficients on the interactions between partisanship and time.

In contrast, issue ownership would predict increased climate attention by issue-owning candidates only. The interaction between partisanship and flooding in Equation 1, also a test for generalized wave-riding, lets me assess whether there was shift following the floods by partisanship. Increased climate issue attention by Green candidates would be consistent with this logic.

To strengthen confidence in a pure or homogeneous issue ownership result, I relax the uniform salience shock assumption by introducing variation in exposure with the *Flooded* variable. If pure issue ownership explains candidate reactions, then we would observe similar increases in rhetoric among Green candidates, irrespective of whether they aim to represent a district directly affected by flooding. In contrast, if *conditional* wave-riding is taking place we should see that most of the increased climate rhetoric is concentrated among Green candidates in affected districts. That is, we observe variation within the issue-owning party in the shift in climate attention before and after the flood split along flooded status. The triple difference in the event study, by interacting flooded status, an indicator for week, and partisanship, measures this. Evidence in favor of *conditional* wave-riding would consist of positive coefficients for the β coefficients in Equation 2 that represent affected Green candidates in the weeks after the floods.

The event study design lets me simultaneously consider evidence consistent with localized wave-riding. This would take the form of similar increases in climate issue attention by affected candidates from the remaining parties. This effect might be masked in the more aggregated data, if the shift in issue attention is smaller among non-Green candidates in affected versus unaffected areas. Similar to how we cannot simultaneously observe wave-riding or issue ownership at the party level, localized and conditional wave-riding cannot both be present in the data. Likewise, evidence in favor of localized or conditional wave-riding would weaken any evidence supporting the party-level variants assessed by Equation 1. Taken together, the twin designs, by sequentially adding dimensions of difference let me assess the strength of each of the various theories in multiple ways.

5 Results

5.1 Issue Competition–Assuming a uniform salience shock

Table 2 presents the results from the regression analysis using the topic model measure of issue attention. In column 1, I only include the *Post-Period* variable to assess for generalized wave-riding. This variable is positive and statistically significant. Columns 2 through 7 progressively include an interaction with partisanship and additional candidate level covariates to further probe the result. In column 2, I contrast Green candidates against all others. The size of the *Post-Period* coefficient, while remaining significant is substantially smaller, whereas the shift among Green candidates is much larger. Disaggregating further reveals a similar trend across the remaining columns. Whereas the interaction between the indicator for the month following the floods and partisan affiliation is substantively smaller and insignificant, barring modest increases by candidates from the far-left Die Linke, Green candidates increased their rhetoric by a large margin. The omitted baseline in these regressions is the far-right AfD, a party which denies the link between human activity and climate change. Lastly, Column 7 replicates the analysis, albeit with the climate topic

Table 1: Overview of Theoretical Arguments, Evidentiary Requirements and Empirical Design

Argument	Hypothesis	Evidence Needed	Design
General Wave-Riding	Candidates, regardless of party, increase their issue attention following a shock to its salience.	1. Post-Period > 0 2. Post-Period $\times$ Party $= 0$	Equation 1
Issue Ownership	Candidates, only those of the issue-owning party, increase their issue attention following a shock to its salience.	1. Post-Period $\times$ Green Party > 0 2. Post-Period $\times$ Non-Green Party $= 0$	Equation 1
Localized Wave-Riding	Candidates, only those representing more affected constituents, increase their issue attention following a shock to its salience.	1. Post-Period $\times$ Flooded > 0 2. Post-Period $\times$ Flooded $\times$ Party $= 0$	Equation 2
Conditional Wave-Riding	Candidates, only those from the issue-owning party and representing more affected constituents, increase their issue attention following a shock to its salience.	1. Post-Period $\times$ Flooded $\times$ Green Party > 0 2. Post-Period $\times$ Flooded $\times$ Non-Green Party $= 0$	Equation 2

Table 2: Regression Results: Flooding and Climate Change Candidate Rhetoric

	Climate Topic Proportion						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Green Binary × PostPeriod		0.61***					
		(0.02)					
CDU × PostPeriod			0.00	0.00	0.00		−0.00
			(0.00)	(0.00)	(0.00)		(0.02)
Die Linke × PostPeriod			0.03***	0.04***	0.03***		0.03**
			(0.01)	(0.01)	(0.01)		(0.01)
FDP × PostPeriod			−0.00	−0.00	−0.00		0.02
			(0.00)	(0.00)	(0.00)		(0.01)
Green × PostPeriod			0.62***	0.63***			0.61***
			(0.02)	(0.03)			(0.03)
SPD × PostPeriod			0.00	0.01	0.01		0.02
			(0.00)	(0.01)	(0.00)		(0.02)
Incumbent × PostPeriod				0.03**	0.00	0.13**	0.04**
				(0.01)	(0.00)	(0.05)	(0.02)
Female × PostPeriod				−0.02	−0.01	−0.04	−0.01
				(0.02)	(0.01)	(0.05)	(0.02)
Only Direct × PostPeriod				−0.03	−0.01	−0.12	−0.01
				(0.02)	(0.01)	(0.10)	(0.02)
Post-Period	0.16***	0.01***	0.00	−0.01	0.00	0.62***	−0.01
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.04)	(0.01)
ID, Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Topics	15	15	15	15	15	15	10
N	1584	1584	1584	1584	1197	387	1584
R^2	0.56	0.87	0.87	0.87	0.53	0.82	0.84
Adj. R^2	0.11	0.73	0.73	0.73	0.05	0.63	0.68

CR2 Errors clustered at individual and district. The unit of analysis is the candidate-month. Model 5 omits Green candidates, whereas Model 6 omits all non-Green candidates. Post-Period is the month fixed effect, the marginal effect of partisanship is omitted as it is collinear with candidate fixed effects.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

from the 10-topic no-prior specified model, to demonstrate the results are not driven by model selection.

Across Columns 2 - 4 & 7, the interactive coefficients testing issue ownership are substantively large and very precisely estimated. Given that the outcome variable is the document topic proportion, which ranges from 0 to 1, the effect size can be interpreted directly: an increase of roughly 60 percentage points for Green candidates.

In other words, Green candidates almost exclusively focused on climate issues in the month after the flood. In contrast, the remaining parties' candidates, barring those from Die Linke which had a modest increase in climate rhetoric, did not reference climate issues at greater rates following the floods. This provides evidence in favor of issue ownership rather than generalized wave-riding.

In what way did Green candidates engage with the climate issue in their Twitter communication? Table 3 presents the top 20 most predictive words from the topic in English. The words display the diversity of the themes present within the climate change issue both in terms of the physical phenomena alongside policy responses. For example, both adaptation and mitigation (protection) are key predictors of the topic alongside ocean warming, forest fire, and extreme weather, that is manifestations of climate change.

Table 3: Top 20 words for Climate Change Topic

climate change, ocean warming, climate adaptation, climate confusion, risk provision, education offensive, immediate climate protection program, forest fire, standard of action, climate crisis, century task, extreme weather events, precaution, country, extreme weather, department, legal blockade, reason why, climate protection, Paris Agreement

In the validation exercises in Appendix C, a close reading of a random sample of tweets from mainstream and Green candidates shows a larger increase for the Greens than their competitors. This is likewise true among candidates in flooded districts (See Tables D2 & D4). Green candidates in these flooded districts increased their focus on both mitigation and adaptation, while also emphasizing that climate change is currently taking place and not a problem for the future. Furthermore, using the dictionary approach at the month-level, only Green candidates increased their climate change rhetoric after the shock (see Table D9). This is not to say other candidates never spoke about the issue, yet as the close readings demonstrate the baseline level of climate rhetoric in the month before the flood highlights a lack of issue attention writ large, despite the centrality of climate change in parties' manifestos (see Appendix A2). This is further evidenced by the general topic model analysis in Appendix Figure C2, Green partisanship clearly predicts climate issue attention across the entire electoral period. In other words, the shift in rhetoric by the Green candidates can be seen as an amplification of issue ownership, whereas the remaining parties' candidates largely failed to change their rhetoric towards climate change. Given that flooding did not increase the use of Twitter as a medium for campaign communication, as I demonstrate in Tables D13 and E9, this suggests Green candidates, and in particular affected ones, increasingly paid attention to the climate issue at the expense of others.

When did mainstream candidates talk about climate issues? Across both parties, candidates often shared similar messages about the central tenants of their platforms, typically as retweets from the party account. For example, center-left candidates often posted: "Affordable rents. Innovative climate protection. Stable pensions. A strong candidate for chancellor. A strong SPD."[24] Yet beyond these talking points about climate protection or policy in abstract, there was little by way of specifics or engagement with the issue beyond slogans. For the CDU, this contrasts sharply with the extensive plans for a carbon neutral economy and clean technology inno-

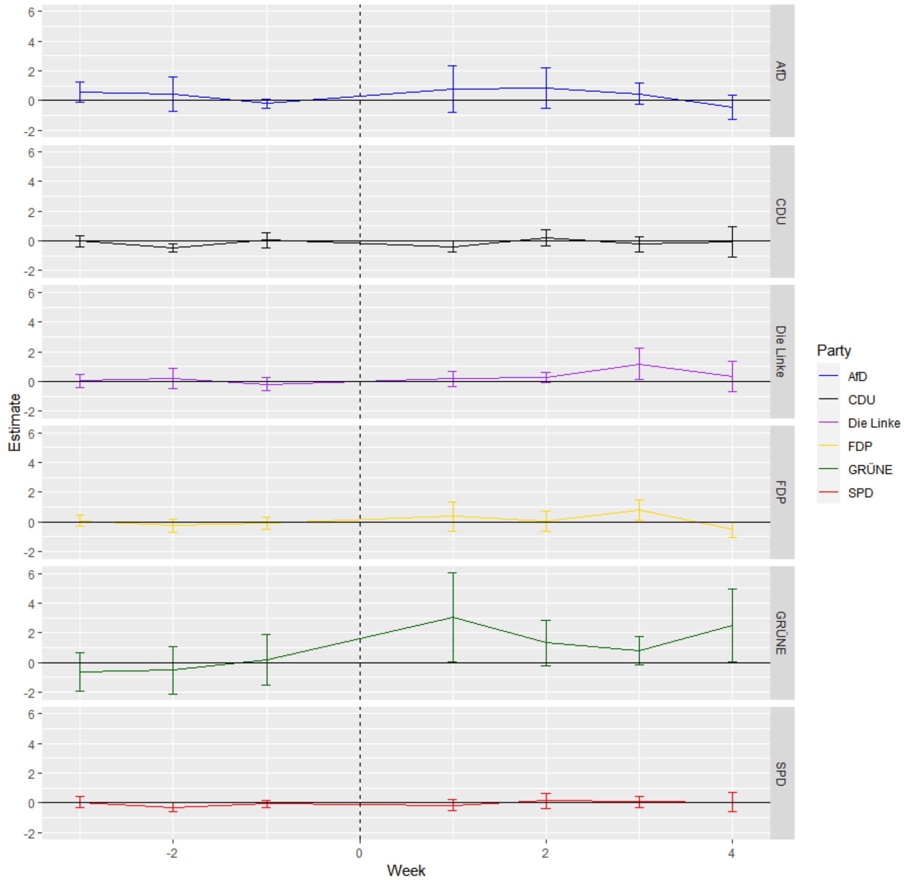
[24]Saskia Christina Esken, 4 August 2021. Original tweet barring emojis in German: Innovativen Klimaschutz stabile Renten starken Kanzlerkandidaten eine starke SPD.

vation championed in its manifesto as noted above. In Appendix D, I discuss this discrepancy in individual versus party rhetoric among mainstream parties in greater detail. Columns 4 through 7 in Table 2 present models including individual-level controls. Given that expertise might moderate the relationship between issue ownership and attention I consider how incumbency shapes climate engagement. The results suggest that only among Green candidates is this experience translated into greater issue attention. I now turn to the event study.

5.2 Issue Competition–Uneven disaster exposure

To assess potential intra-party variation in issue responsiveness, I leverage the dictionary approach and weekly-aggregated measure of climate issue attention. In a similar fashion to above, in Table 4 column 1 I first consider just the interaction between flooded and time, ignoring partisan differences. While there are positive coefficients on some of the weeks following the floods, further disaggregation in column 2 suggests once again these positive coefficients are likely driven by the affected Green candidates. Figure 4 presents the results of the event study described in Equation 2 for all parties. The absence of deviations in the pre-period suggests there is not a clear violation of the parallel trends assumption for each of the parties. First, the absence of consistent positive point estimates following the floods across the various parties is inconsistent with a localized wave-riding hypothesis. Second, comparing within parties between flooded and unaffected districts, only Green candidates paid

Figure 4: Triple Difference Event Study



Note: Appendix Tables E2 present the full results. Bars represent 95% confidence intervals.

greater attention to climate change.[25] Substantively, Green candidates in flooded districts posted roughly 3 additional tweets about climate change per week following the floods, whereas their unaffected partisans only posted 0.5 additional climate tweets. Given the average candidate posted roughly 11 tweets per week, this is a sizable increase.

[25]There is one positive coefficient statistically distinguishable from zero among Die Linke mirroring the result in Table 2.

To further probe the robustness of this result, in Appendix Table E3, I subset to consider only the two states that were affected by flooding: North-Rhine Westphalia and Rhineland-Palatinate. The results mirror those in Column 2 of Table 4, with the only exception being the reduction in power results in positive but insignificant results for the second and third week after the flood between Green candidates. In sum, the event study analysis presents evidence in support of the fourth hypothesis related to intra-party variation in issue attention, or conditional wave-riding. While these non-Green candidates in affected districts may have had a greater incentive to address climate change given media linkages between climate change and the flood's intensity, the increase in attention was confined to candidates from the party that has traditionally dominated the issue. Yet we do not observe a general issue ownership phenomena, increased attention was limited within the Green party: Candidates in affected districts increased their climate issue attention substantially more compared to their peers, consistent with the conditional wave-riding argument above.

Table 4: Regression Results: Flooding and Climate Change Campaign Rhetoric by Week

	Climate Count	
	Model 1	Model 2
Num. of Tweets	0.06^{***}	0.06^{***}
	(0.01)	(0.01)
Week -3 × Flood	−0.02	
	(0.16)	
Week -2 × Flood	−0.21	
	(0.19)	
Week -1 × Flood	−0.03	
	(0.17)	
Week 1 × Flood	0.64^{*}	

	Model 1	Model 2
	(0.35)	
Week 2 × Flood	0.44**	
	(0.18)	
Week 3 × Flood	0.47***	
	(0.17)	
Week 4 × Flood	0.34	
	(0.29)	
Week -3 × Flood × Green		−0.65
		(0.67)
Week -2 × Flood × Green		−0.50
		(0.82)
Week -1 × Flood × Green		0.18
		(0.88)
Week 1 × Flood × Green		3.04**
		(1.52)
Week 2 × Flood × Green		1.30*
		(0.78)
Week 3 × Flood × Green		0.78
		(0.48)
Week 4 × Flood × Green		2.52**
		(1.26)
ID and Week FE	Yes	Yes
N	7352	7352
R^2	0.70	0.71
Adj. R^2	0.66	0.66

CR2 Errors clustered at individual and district. The unit of analysis is the candidate-week. Column 1 does not disaggregate by party. Column 2 considers Green candidates against all other candidates grouped together. Flooded is a time-invariant indicator for ever being flooded and its marginal effect is omitted as it is collinear with the candidate fixed effects. Table E2 presents the full regression results of the triple differences by party visualized in Figure 4. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3 Robustness Section

In this section, I further probe the robustness of the above results through five different analyses. I demonstrate the robustness of the above findings to alternative topic model specifications, omitting retweets, alternative dictionary measures, geographic spillovers and lastly extend the analysis to Belgium to assess the external validity. I discuss each in turn.

5.3.1 Alternative Topic Models

In Appendix B, I provide additional details on the diagnostic tests used to select the parameters of the topic models presented in Table 2. These dignostic test suggest a model with between 10 to 15 topics is most appropriate for corpus of tweets. As detailed above, the primary model is the 15-topic model with a prior prevalence function specified. In Table 2, Column 7 I demonstrate that the finding of an increase in climate rhetoric by Green candidates following the floods is not unique to this model: a similar coefficient is observed in a 10 topic model that omits a prevalence function. Across the four classes of robustness models, I consistently find at least one topic discussing climate change. In Table C3, I find that across each type of topic model, the combination of Green partisanship and the month following the flood is a consistent predictor of the climate topic with coefficients ranging in magnitude between 0.59-0.77, yet it is not a consistent predictor other topics like the COVID-19 pandemic or immigration (see Tables D5 & D6). There is some evidence in these models of candidates from fellow left-wing parties likewise increasing their climate attention, notably among the far- and center-left candidates. While in line with research emphasizing issue ownership fungibility (Bischof, 2017; Spoon and Williams, 2021), these shifts in issue attention are an order of magnitude smaller compared to the Greens and inconsistent across specifications.

5.3.2 Omitting Retweets

The results above include retweets, communication that is reposted typically verbatim from another accouunt. Given that roughly 40% of tweets are retweets, understanding whether this copied content is fully driving the above results is central to our understanding of candidate issue attention. I assess the impact of retweets in two ways. First, I omit all retweets to gauge independent communication by candidates. Second, recognizing that candidates may retweet material as a means of demonstrating domain expertise, I only exclude retweets that come from the party accounts. Given the focus on candidate issue attention, this lets me assess the extent to which candidates adopt the party message. In Tables D11 and D12, I replicate the results in Table 2, finding that Green candidates increased their issue attention in the month following the floods. While the coefficient attenuates slightly, it is still consistently distinguishable from zero. I likewise find no evidence that candidates from other parties increased their own independent climate issue attention. Tables E4 and E5 provide analogous replications for the event study design, providing further evidence of conditional wave-riding by affected Green candidates.

5.3.3 Alternative Dictionary

Building on other work that studies climate issue attention, I test the robustness of the narrow dictionary measure to an alternative developed from European center-left and -right parties' climate issue attention in their manifestos (Schwörer, 2024). Given that the Green party was not used to generate the measure, it should favor rhetoric employed by center-left and -right. In Tables D11 and D12 I find no substantive difference in the point estimates for the monthly analysis. Likewise, in Tables E4 and E5 I again find no evidence contrasting with the results in Figure 4 for the event study.

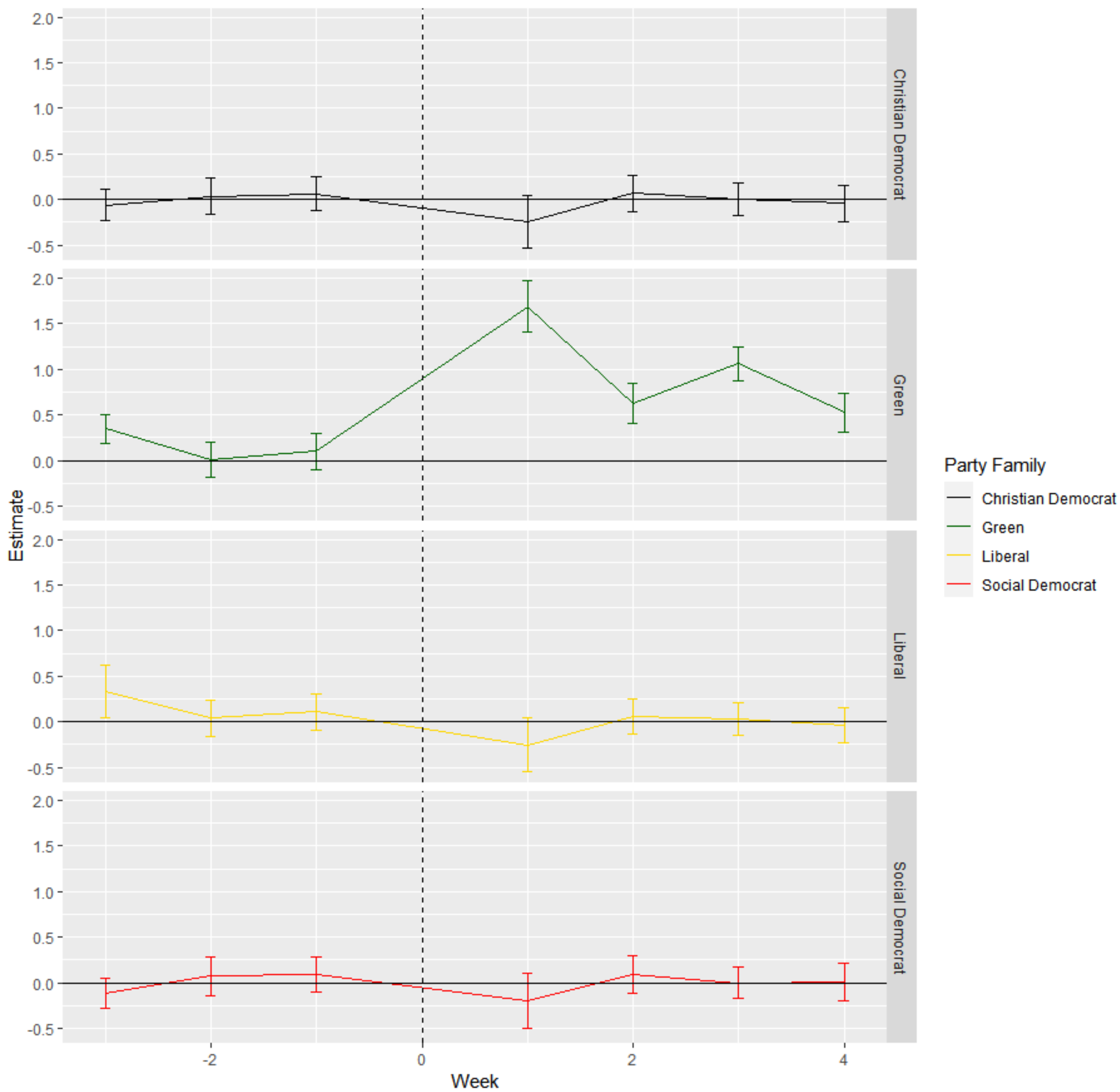
5.3.4 Geographic Spillovers

Given that individuals may work and spend leisure time in districts other than where they reside, the impact of flooding may spillover into adjacent districts, shaping the political response in these places. In Appendix E3, I consider such differences between affected, adjacent, and non-adjacent districts. I find that adjacent Green candidates inconsistently increased their climate issue attention, however it was to a lesser extent than fully affected ones. Furthermore, using these adjacent candidates as a a control group, I still find significant differences in the increase in climate issue attention by affected Green candidates.

5.3.5 Extension to Belgium

Given Germany's relatively unique electoral system, mixing both majoritarian and proportional dimensions, I assess the extent to which the findings generalize to a different institutional context. I focus on Belgium for several reasons. Belgium is a PR system in which lists are produced at the province level by each of the parties. While a small country, there are 11 constituencies, meaning that barring Brussels, the geographic scope of the constituencies is typically greater than in Germany, in which direct candidates compete in 299 constituencies. This geographic spread in a PR system suggests that the representational linkage is arguably weaker than in Germany. In terms of issue attention this should diminish the incentives for conditional wave-riding: MPs represent a broader set of interests, only a small fraction of which might have been impacted by flooding. Empirically, Belgium, in particular its southern provinces bordering Germany, was affected by the same flood event, permitting an assessment of issue attention shifts in an alternative context while holding constant features of the salience shock. Further details on data collection, monthly and weekly analyses can be found in Appendices C, D, and E respectively. The results for both monthly and weekly analyses corroborate the German findings: Greens increased their climate issue attention post-flood and this was driven by affected candidates within the Green party (see Figure 5). This generalizes support for conditional wave-riding outside of a majoritarian context, suggesting that the presence of issue owners is sufficient to generate such dynamics alongside some level of representational devolution, thereby allowing for representational concerns.

Figure 5: Triple Difference Event Study in Belgium



6 Electoral Extension

Both the wave-riding and issue ownership strategies are driven by a desire to win votes. Given the evidence above of conditional wave-riding, the analysis below probes the extent to which conditional wave-riding is a vote-winning strategy by considering issue attention as a moderating variable on the impact of flooding. Electoral data and time-varying district data comes from the German Federal Returning Office and the Federal Statistical Office respectively. The outcome in the electoral analyses is the district vote share for a given party.

To assess the electoral implications of issue attention, I use two empirical strategies. In the first, I subset the sample to only those districts in which a Green candidate is present in the Twitter data. Given evidence above that affected Green candidates increased their climate issue attention, this sample provides an assessment of whether the congruence between increased issue attention and natural disaster exposure is correlated with greater vote shares. The intuition behind this measurement strategy is that given that flooded Greens generally increased their rhetoric, the variable flooding is capturing this rhetoric shift indirectly. This is modeled implicitly, hence in the second strategy I include a third difference: whether a candidate's issue attention shift was above average compared to their party, thereby including an explicit measure of issue attention shift in the regression equation; a further interaction, however, reduces power, hence I present both.[26] This model is presented in Equation 3, where a positive coefficient on the β_1 would be evidence consistent with

[26] As an alternative, I compare within district shifts in issue attention in Table G6 with results similar to those in Table 5.

an electoral reward to increased issue attention. Substantively, this means that the difference in vote share is greater for candidates in flooded districts who shifted their issue attention above the party average compared to the analogous difference among green candidates in unaffected districts.

$$Y_{it} = \alpha_i + \gamma_t + \beta_1(DiD_{it} \times AttentionShift_i) + \beta_i X_{it} + \epsilon_{it} \tag{3}$$

To estimate the relationship between increased issue attention and electoral returns, I leverage a doubly-robust (DR) difference-in-differences design proposed by Callaway and Sant'Anna (2021) as it lets me include covariates in the estimation of treatment assignment likelihood and the outcome. In Appendix G, I provide further details on the empirical strategy and identifying assumptions.

Table 5 presents both traditional TWFE and DR estimates. Columns 1 and 3 present TWFE coefficients, whereas the even columns present analogous results using the DR estimator. In both cases, the results are substantively similar: among districts with candidates on Twitter, the Greens gained more at the ballot box in affected districts than in unaffected districts. This holds implicitly as the first two columns demonstrate, but likewise if candidates spoke more about climate change compared to the party average (*Rhetoric Shift*). Recall that 2021 was a historic result for the Green party, its best ever, hence while the 2 percentage point increase may seem small in magnitude, given the average increase of roughly 6 percentages points from 2017, the marginal effect size is substantial ($\approx$ 33%). The final two columns in Table 5 suggest these electoral gains were even larger for those candidates that

Table 5: Regression Results: Flooding, Rhetoric and Electoral Outcomes

	Green Vote Share Shift			
	TWFE	DR	TWFE	DR
DiD	0.02***	0.02***		
	(0.01)	(0.01)		
DiD × Rhetoric			0.01**	0.03***
Shift			(0.00)	(0.01)
District and Year FE	Yes	Yes	Yes	Yes
Num. obs.	577	567	574	567

CR2 errors clustered at state. The unit of analysis is the district-year. The sample only includes those districts with green candidates in the issue attention analysis. * p < 0.1, ** p < 0.05, *** p < 0.01.

increased their climate rhetoric above the party average.[27]

Existing work studying the electoral impact of the 2021 floods, finds mixed evidence in favor of the Greens gaining votes (e.g., (Hilbig and Riaz, 2024), (Garside and Zhai, 2022)). A key difference is the unit of analysis: municipalities versus districts.[28] Given that districts are composed of municipalities, intervening political variables such as campaigning operate at more aggregated units, producing spillovers thereby reducing any direct effect of flooding in, for example, adjacent municipalities. In Table G5, I demonstrate the robustness of the results by considering adjacent and directly flooded districts within the two most affected states, finding a similar positive impact for Green candidates. Taken together, the results suggest that wave-riding strategies *when* employed by the issue-owner may provide electoral rewards.

[27] In Appendix G, I demonstrate that neither the CDU nor the SPD performed better in these districts. Indeed, the latter saw its vote share decrease by about 1.5 percentage points.

[28] I discuss these design differences in further detail in Appendix G as well as Appendix E with respect to issue attention.

7 Discussion

In this article, I extend existing accounts of party competition to the candidate level to assess issue competition both across and within parties. Leveraging an exogenous shock to climate change salience, I find that wave-riding conditional on issue ownership is the dominant candidate rhetorical strategy. Rather than considering issue-ownership and salience theories as substitutes, the present results suggest they are better viewed as complements.

What are the implications of these findings for a more general explanation of candidate issue attention, that is what should we expect to characterize the norm? First, it appears unlikely that generalized wave-riding is the de facto strategy among candidates unless two conditions are met: (1) there is no strong issue owner of the salient topic, and (2) the salience shock is national. Barring shocks like these to the political system, we should observe candidate rhetoric largely characterized by a more steady issue ownership as most candidates lack the resources to effectively talk about a plethora of issues, in contrast to parties. I present suggestive evidence in line with this in Appendix D. Despite ample attention to climate change in party level communication mediums, non-Green candidates hardly mentioned the climate issue prior to the floods. Likewise, by considering how partisanship predicts the various topics that shaped the 2021 election, most issue are dominated by a single party, this suggests issue ownership rather than wave-riding. Shocks to the system, perhaps on issues less clearly linked to a single party such as the floods studied here, might induce localized wave-riding. Absent a clear owner, candidates and politicians representing communities heavily affected by an issue may face less concerns related to competence. Exploring the validity of these arguments is an area for future research.

By considering parties as organizations composed of actors with varied incentives, these results suggest that issue attention slippage–discrepancies in issue attention across communication channels and/or actors–is prevalent, yet its consequences, if any, are unclear. In the present case, the lack of any sustained attention to climate change by non-Green candidates is surprising given the focus it received in the manifestos and press releases, in particular for CDU candidates. Absent sanctioning methods to present a unified message, it is unlikely that central party elites can engender a mimicry of the manifesto in more atomized communication channels. Yet, even for the Green party, its candidates in non-affected areas likewise did not present a unified front. This variation in issue attention within the Green party following the floods is arguable a positive form of slippage: rather than engaging with the parties core issue, candidates did not ride the wave of a non-local issue.

While parties have increasingly paid attention to climate change in their manifestos, the dominance of Green candidates in general and in response to the floods begs the question of the sincerity of these appeals. By and large, local non-Green candidates do not engage with the climate issue despite its prominent position in centralized communication. This tenuous issue consistency across communication channels hints at the weakness of the mainstream consensus, a frailty which the radical right has exploited in recent years (Dickson and Hobolt, 2024). Not only are a sizable portion of voters in many parties climate skeptics as Dickson and Hobolt (2024) find, but the findings here highlight that many candidates fail to pay the slightest of lip service to climate change. Focusing on candidates, I complement a large literature that studies the impacts of climate change at the level of mass politics, while contributing to a small but growing literature on elite reactions to climate change (Birch, 2023; Wappenhans et al., 2024).

By studying a natural disaster in close proximity to an election, I provide evidence related to the electoral returns of issue attention strategies. I show that within the Green party candidates in affected districts, who spoke above average on climate change, performed better at the polls than their peers. Assessing the impact of issue attention strategies on electoral outcomes has been challenging given the frequency and unit of data used in existing research. The present results probe the viability candidates' issue attention strategies in shaping their electoral outcomes. Leveraging both individual-level issue attention data and shocks to issue salience provide a more credible means of testing the micro-foundations of the party competition literature in other settings and issue areas.

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Appendix

Table of Contents

A Additional Context

A.1 July 2021 Floods

The floods affecting much of north-western Europe in July 2021 occurred over a three day period beginning July 12th. With more than 180 fatalities and an estimated $8 billion in damages, the floods were the deadliest natural disaster in Germany in roughly 60 years (Schmid, 2021). Within Germany, the flooding and subsequent damage was largely confined to the western-most part of the country, specifically in North-Rhine Westphalia and Rhineland Palatinate. Figure 2 in the main text presents the extent of flooding with shaded districts affected and the darker coloring within these districts showing specific areas that experienced flooding according to satellite data.

In the aftermath of the floods, but prior to the election, there was substantial coverage in the German media as well as official government reports of the connection between the intensity of the floods and anthropogenic climate change. For instance, the Germany Federal Agency for Civic Education explicitly linked the floods with climate change in its report published two weeks following the floods, describing it as a 100 year event.[29] Reports from the German Weather Service (Wetterdienst) likewise linked the heightened risk of flooding in Germany with climate change in the month following the flood.[30] This public report was then featured by prominent news outlets such as Südeutsche Zeitung, drawing public attention to climate change this specific flood event.[31]

[29] Jahrhunderthochwasser 2021 in Deutschland. 28 July 2021. *Bundeszentrale für Politische Bildung*. https://www.bpb.de/kurz-knapp/hintergrund-aktuell/337277/jahrhunderthochwasser-2021-in-deutschland/.

[30] Hydro-klimatologische Einordnung der Stark- und Dauerniederschläge in Teilen Deutschlands im Zusammenhang mit dem Tiefdruckgebiet Bernd" vom 12. bis 19. Juli 2021. 22 July 2021. Deutscher Wetterdienst. https://www.dwd.de/DE/leistungen/besondereereignisse/niederschlag/20210721_bericht_starkniedersc

[31] Studie: Klimawandel macht Hochwasser wahrscheinlicher. 24 August 2021.*Süddeutsche Zeitung*.https://www.sueddeutsche.de/wissen/wissenschaft-studie-klimawandel-macht-hochwasser-wahrscheinlicher-dpa.urn-newsml-dpa-com-20090101-210824-99-943304 Given the high baseline belief in Germany of anthropogenic climate change described in the following section, this coverage and linkage suggests that Germans were aware of the impact of climate change on the severity of the flooding event.

A.2 Climate Change as an Issue in Germany

According to public polling data throughout the summer of 2021, three issues were of great importance to the German public: climate change, immigration, and public health, specifically the response to the COVID-19 pandemic.[32] Indeed, the vast majority of Germans believe climate change is currently happening and will affect them personally to a moderate extent (Leiserowitz et al., 2021). Given this importance placed on environmental and climate issues, political parties have emphasized the issue. While traditionally the domain of the Green party, all major parties barring the far-right AfD dedicate substantial portions of their manifestos to climate and environmental issues. Indeed using data from the CAP, Grossman and Guinaudeau (2021, p.105, Fig 5.4) demonstrate not only the diversification of the Green platform over time, but the marginal differences in attention across parties for the environment beginning in the 2009 election. In Figure A1 I replicate this analysis to demonstrate the convergence in environmental issue attention up to 2013. This convergence underscores the systemic pressure parties face in addressing issues. However given that the center-left SPD and center-right CDU have jointly, and at times with the Greens, passed major environmental climate legislation over the past two decades as parts of the *Energiewende*, it is difficult to consider this overlap in manifestos as purely cheap talk. Due to the CAP only extending to 2013 in Germany, I provide a brief overview of the discussion of climate politics in the major parties manifestos for the 2021 election below to highlight this continuity in engagement.

As noted above, in its manifesto for the 2021 election, the SPD listed a climate-neutral Germany as its primary objective for the future.[33] Likewise, the CDU includes an entire chapter on industry, sustainable development, and climate-friendly prosperity in its manifesto.[34] In terms of replacing fossil fuels with renewables in energy production, the far-left, Die Linke, campaigned on a 2035 deadline, on equal footing with the Green party (Die Linke, 2021, p. 19). Meanwhile, the CDU advocated a 2045 deadline for departure from fossil fuels to stay in line with the European target of climate neutrality at 2050.[35] The SPD campaigned on 2045 climate neutrality deadline with fossil fuels being phased out by 2040.[36] Lastly, the liberal and

[32] (Forschungsgruppe Wahlen E.V., 2021)

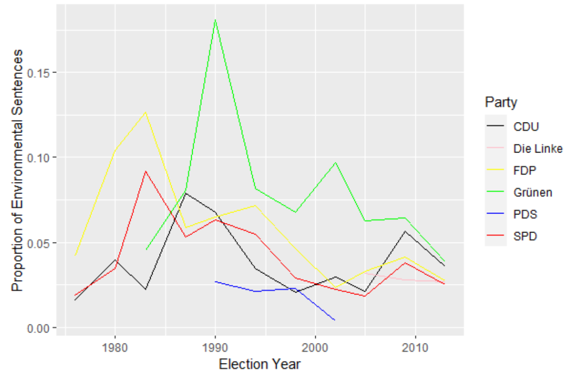
[33] Original in German: Zukunftmission I. Klimaneutrales Deutschland. (Sozialdemokratische Partei Deutschlands, 2021)

[34] (Christlich Demokratische Union Deutschlands, 2021) See chapter 3.

[35] (Christlich Demokratische Union Deutschlands, 2021, p. 42) In particular lines 1352-6.

[36] (Sozialdemokratische Partei Deutschlands, 2021, p. 9)

Figure A1: Proportion of Manifesto on Environmental Issues



traditional third party in German politics, the FDP pledged to achieve climate neutrality in line with the European deadline.[37] While it may be the case that the Greens traditionally dominated environmental issues, the party faces considerable issue competition, as well as programmatic competition, in the present. Furthermore, while the phase-out and neutrality pledges are but a small portion of climate policy, they are high-level objectives that shape finer grained details and highlight that the Greens are not substantially more ambitious than alternative parties. The centrality of climate issues across the platforms likewise challenges this earlier issue dominance.

[37](Freien Demokraten Partei, 2021, p. 58)

B Sample Descriptives

The final sample of accounts in Germany features 792 direct candidates for office. To be clear, this is not a random sample, nor does it cover all direct candidates in Germany, as a sizeable portion do not have Twitter accounts. Overall, there were 1,794 candidates competing for office, of these 1,201 had an account. To be able to assess whether rhetoric changed after the flood, a sufficient amount of tweets prior to the disaster is needed for comparison. Additionally, in order to be able to collect the tweets, an account must be set to public. In Belgium the final sample is 126 out of a possible 150 members of parliament.

Appendix Tables B1 and B2 present descriptive statistics of the analyzed samples compared to the population of direct candidates and MPs in Germany and Belgium respectively. Given the focus on direct candidates, I only compare the sample against the population that was directly running, and not against the population including candidates only with a list placement. In terms of gender and geographic distribution, the German sample is broadly representative (66% versus 69% male). The largest deviation from the population in terms of Lander is in the case of Bavaria, which is 15% of the sample versus only 13% of the population. Incumbents are much more likely to be in the sample (44% versus 30%) and the Green party and the SPD are more likely to feature in the sample (24% and 20% versus 16% respectively) whereas the AfD, CDU, and the Left parties are underrepresented (9%, 14%, and 14% respectively). With respect to Belgium, party affiliation as well as the distribution across party families is consistent between the sample and the population. Likewise, the distribution of districts across the final sample is similar to the population. There are Flemish politicians in the final sample compared with the lower house (57% versus 61%).

Table B1: Descriptive Statistics for the German STM Sample

Variable	Sample	Twitter Population	Candidate Population
Male	0.66	0.68	0.70
Female	0.34	0.32	0.30
New Candidate	0.56	0.61	0.69
Incumbent	0.44	0.39	0.31
AfD	0.10	0.13	0.16
CDU	0.14	0.17	0.17
DIE LINKE	0.14	0.15	0.17
FDP	0.17	0.17	0.17
GRÜNE	0.24	0.19	0.17
SPD	0.20	0.19	0.17
BB	0.04	0.04	0.03
BE	0.06	0.05	0.04
BW	0.14	0.13	0.13
BY	0.13	0.14	0.15
HB	0.01	0.01	0.01
HE	0.08	0.08	0.07
HH	0.03	0.02	0.02
MV	0.02	0.02	0.02
NI	0.08	0.09	0.10
NW	0.20	0.22	0.21
RP	0.05	0.04	0.05
SH	0.03	0.03	0.04
SL	0.01	0.01	0.01
SN	0.06	0.06	0.05
ST	0.03	0.03	0.03
TH	0.03	0.02	0.03
N	792	1201	1784

Table B2: Descriptive Statistics for the Belgian STM Sample

Variable	Sample	Population
CD&V	0.10	0.08
cdH	0.03	0.03
DeFi	0.02	0.01
Ecolo-Groen	0.13	0.14
Indep	0.02	0.01
MR	0.08	0.09
N-VA	0.16	0.16
Open VLD	0.09	0.08
PS	0.11	0.13
PVDA-PTB	0.08	0.08
VB	0.13	0.12
Vooruit	0.06	0.06
ChristianDem	0.13	0.11
Conservative	0.16	0.16
FarRight	0.13	0.12
Green	0.13	0.14
Liberal	0.26	0.27
SocialDem	0.17	0.19
1	0.18	0.16
2	0.13	0.11
3	0.12	0.11
4	0.06	0.08
5	0.13	0.12
6	0.10	0.12
7	0.09	0.10
8	0.01	0.03
9	0.04	0.04
10	0.03	0.03
11	0.11	0.10
Flemish (No)	0.37	0.41
Flemish (Yes)	0.61	0.58
Observations	126	150

C Topic Model Analysis

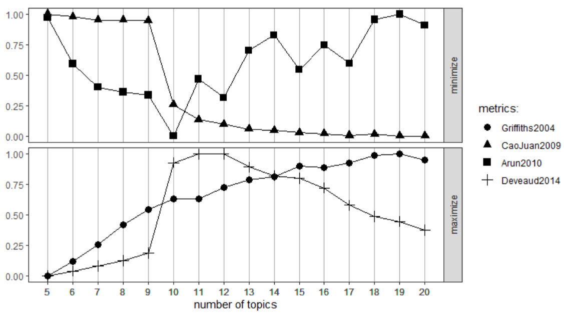
C.1 Text Data Cleaning and Model Selection

To prepare the tweets for the text analysis, I performed various cleaning procedures. First, I removed all URLs from the texts as these have no interpretable meaning on their own. Next, I removed hashtags and tagged accounts as the initial data collection process generated separate categories with this metadata rendering it redundant in the tweets. I then eliminated all emojis and numbers from the text. While these could provide some insight about sentiment or specifics related to policy, analyses that included them were similar to the results presented below. The numbers that emerged in the topic models were related to years; further close reading of these topics made it clear that these numbers were often in reference to certain memorial events. In terms of emojis, while they could be used as a gauge of sentiment or emotion, the various keyboards with which users can post Tweets makes many of them largely incompatible. Lastly, I removed all punctuation as is standard in text analyses which operate using the bag of words assumption described below. While there were some instances of tweets in other languages, the vast majority were written in German, therefore I did not translate the text prior to estimating the topic models. Google Translate was subsequently used to translate the text for the close reading described below.

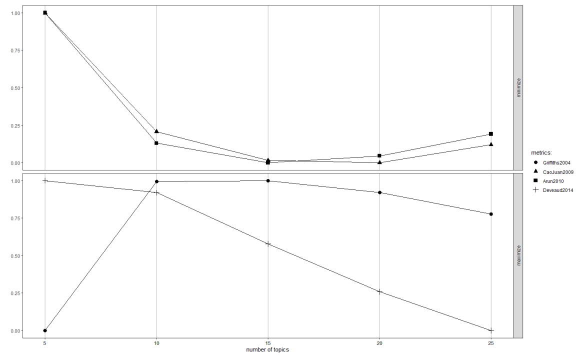
In order to assess how elites responded to the floods, I use an unsupervised approach to discover any latent topics in the Twitter commentary. Specifically, I employ the structural topic model (STM) (Roberts, Stewart and Tingley, 2019). The primary benefit of using the STM over other unsupervised procedures is the ease with which metadata can be incorporated into the analysis. Given the latent nature of the STM, there is no predetermined number of topics to be generated for a corpus of documents (Grimmer and Stewart, 2013), therefore I conduct a parameter search to assess which number of topics best fits the data.[38] The STM models topics using a latent Direchlet allocation (LDA) distribution which allows for a flexible modeling of different corpora of texts. Recent research has provided a variety of measures to assess the topic number fit to given a corpus (Arun et al., 2010; Cao et al., 2009; Deveaud, SanJuan and Bellot, 2014; Griffiths and Steyvers, 2004). To determine an appropriate number of topics, I conduct a parameter search from five to twenty topics. Figure C1a plots the results of this parameter search with the four different

[38]I implement this parameter search using the R package `ldatuning`. More information regarding this package can be found at: https://cran.r-project.org/web/packages/ldatuning/vignettes/topics.html.

Figure C1: Topic Parameter Search Measures



(a) Germany



(b) Belgium

Note: The figures present diagnostic tests for the "ideal" number of topics given the corpus using four different criteria from the topic model literature. A better topic parameter, k, maximizes values in the bottom panel and minimizes values in the top panel.

measures from the literature. While not completely indicative, I select 10 and 15 topics as the best-fitting parameters given the corpus at hand. As a robustness check, I use the built-in topic parameter search feature in the STM package with results being similar. Figure C1b plots the analogous topic search with the Belgian corpus.

Using both of these topic parameters, I conduct a model search using two different specifications for 10 and 15 topics using the built-in `selectModel` function in the `stm` package. The first includes no prior information about the possible formation of topics. That is, the model assumes topic allocation to documents is independent of document covariates. While such a relationship of independence is unlikely, I include this specification to demonstrate the robustness of the results to alternative priors or the lack thereof. The second includes the prior information described above related to time, flooding, and partisan affiliation. The `selectModel` function estimates 50 models and then selects the top 20 percent of models based on the log-likelihood. From these 10 models, I select the model which maximizes the product of the exclusivity and semantic coherence measures included in the output of this model search. Exclusivity is a measure of the overlap of words across topics. Semantic coherence is a measure of the co-frequency within documents of topic-associated words.

C.2 Description of Topic Model Analysis

For the initial model discovery I estimate two classes of STMs, in the first I assume that the distribution of topics is independent of document metadata, whereas in the second I include a prior specifying that the distribution of topics across documents is influenced by district flooded status, time period, and partisan affiliation. I include the spatial and temporal variables given the nature of the flood as a focusing event for issue attention while partisanship may influence the types of issues candidate speak about writ large as noted above. Within each class of models, I estimate two topic models of 10 and 15 topics. The base model is a 15 topic model with the prior prevalence function specified.

This initial analysis was conducted entirely using pre-built functions from the `stm` package. For the general analysis of issue attention across the period and beyond climate change, I use the in-house `EstimateEffect` function to run the series of regressions. All analyses in the main text are performed using `feols` from the `fixest` package. I extract the document topic proportions and then run all analyses with two way fixed effects. I opt for this procedure as the estimation of fixed effects is much faster than with the former package. In Table C3, I replicate the main result from Table 2 across the four classes of topic models described above (Column 4 below is the same as Column 4 in Table 2). There is a consistent evidence of a substantial surge in Green candidate issue attention across all models.

Table C3: Robustness of STM Results to Alternative Model Selection

	Model 1	Model 2	Model 3	Model 4
CDU × PostPeriod	-0.00	0.01	0.02	0.00
	(0.02)	(0.01)	(0.02)	(0.00)
Die Linke × PostPeriod	0.03^{**}	0.07^{***}	0.02	0.04^{***}
	(0.01)	(0.02)	(0.02)	(0.01)
FDP × PostPeriod	0.02	0.02^{**}	0.04^{**}	-0.00
	(0.01)	(0.01)	(0.02)	(0.00)
Green × PostPeriod	0.61^{***}	0.77^{***}	0.59^{***}	0.63^{***}
	(0.03)	(0.02)	(0.03)	(0.03)
SPD × PostPeriod	0.02	0.04^{***}	0.04^{**}	0.01
	(0.02)	(0.01)	(0.02)	(0.01)
Incumbent × PostPeriod	0.04^{**}	0.03^{**}	0.05^{***}	0.03^{**}
	(0.02)	(0.01)	(0.02)	(0.01)
Female × PostPeriod	-0.01	-0.01	0.01	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)
Only Direct × PostPeriod	-0.01			-0.03
	(0.02)			(0.02)
PostPeriod	-0.01	-0.02^{**}	-0.02	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
N	1584	1584	1584	1584
Candidates	795	795	795	795
R^2	0.84	0.90	0.79	0.87
Adj. R^2	0.68	0.79	0.56	0.73
Topics	10	10	15	15
Prior Specified?	×	✓	×	✓

CR2 errors clustered at the candidate and district. The models consider the same regression equation preformed on diffent classes of structural topic models captured by variation in the number of topics and whether a prior prevalence function was specified. The unit of analysis is the candidate-month. The outcome is the proportion of the topic devoted to a a given topic. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Top 20 Words from the 15 Topic Prior-Specified Model

Table C4 presents the top-20 words from the climate change topic in the primary STM model throughout the analysis. Note that words have been stemmed prior to running the model and hence may not correspond to a specific word in the German language. For example, in *klimavorsorg* the difference between singular (-e) and plural (-en) is omitted so that both are considered a similar occurrence of the more general climate protection. All translations from German to English were done with Google Translate.

Table C4: Top 20 words for Climate Change Topic in Base Model

klimaerhitzung, ozeanerwärmung, klimaanpassung, klimawirrwarr, risikovorsorg, bildungsoffens, klimaschutzsofortprogramm, waldbränd, handlungsmaßstab, klimakris, jahrhundertaufgab, extremwetterereignissen, vorsorg, landesfläch, wetterextremen, fachressort, gesetzesblockad, grundwarum, klimavorsorg, pariskompat
climate change, ocean warming, climate adaptation, climate confusion, risk provision, education offensive, immediate climate protection program, forest fire, standard of action, climate crisis, century task, extreme weather events, precaution, country, extreme weather, department, legal blockade, reason why, climate protection, Paris Agreement

C.3 Data Collection and Design for Belgian MPs

In this Appendix, I describe the data collection and topic model selection process for the Belgian members of parliament. While I replicate all the quantitative analyses in this second case, it is important to recognize the stronger linkage between MPs and the party compared with candidates and how this impacts the likelihood that the former group will address more topics in their online rhetoric, hence it is a better extension for the analyses related to responsiveness to issue salience shocks compared to issue concentration versus overlap. In what follows I describe the data collection process and measurement strategy for Germany, an analogous process was carried out in Belgium albeit with sitting MPs instead of candidates.

Twitter usernames were manually collected using information from the Belgian Parliament's website. Using these usernames, I scraped tweets using the `rtweet` package for the summer of 2021. With the raw text, I then performed the same pre-processing as in the German case: removing URLs, hashtags, emojis, and usernames. Given that MPs in Belgium may speak either French or Dutch, I then translated all texts into English to create a single-language corpus with *both* languages being translated rather than opting to use French or Dutch. With the tweets translated, I then aggregated them to the month level, that is each MP had two documents: one for the month prior to the floods and one for the afterwards. With this corpus of documents, I then tokenized the text, created the document-feature matrix and removed stem words from both languages as is common practice (Roberts, Stewart and Tingley, 2019).

With the data prepared for model estimation, I then conducted a parameter search to identify a suitable number of topics for the corpus with a function from the `ldatuning` package. The results of this topic parameter search are in Figure C1b. In a similar fashion to the German corpus, there diagnostic test also suggests that 10 or 15 topics are an appropriate number for the corpus. With these two topic parameters, I then conducted four model searches, specifying a prior function or omitting it for each topic number. The prior function included party family and time period. For each parameter setting (i.e., the four searches), I select the model which maximizes the product of the semantic coherence and exclusivity measures (for more details on these measures, see Roberts, Stewart and Tingley (2019)). The primary model, as in the German analysis, is the 15-topic prior specified model, whereas the 10-topic prior-omitted model serves as a robustness.

Flooding data for Belgian was again collected from the Copernicus Emergency Management System.[39] I use this data to code a dichotomous flooded indicator for

[39]The report for Belgium is EMSR Report 518. Flooding occurred in

MPs in the Liège and Luxembourg districts. I group parties by party family and include a variable for whether the MPs is from a Flemish party to make the results comparable. I take into account the ethnic cleavage present in Belgium, by including a binary indicator *Flemish* independently or interacted with a time variable in all models.

two districts: Liège and Luxembourg. An overview can be found at: https://emergency.copernicus.eu/mapping/list-of-components/EMSR518.

C.4 General Issue Attention – Pooled Analysis

To assess which strategy characterizes issue attention in the 2021 German election I first consider partisan predictors of all topics before focusing on the salient issue of climate change. If wave-riding characterizes party competition, partisan affiliation should be null or with several parties competing on a specific topic. Issue ownership would entail one party dominating a given topic, furthermore issue ownership would entail parties speaking about issues within their core competencies. Across all the regressions, the outcome variable is the document topic proportion which ranges from 0 to 1. I estimate a model which predicts the topic proportion for a given topic i in a given document d given certain characteristics of candidate c, that is:

$$\text{Topic Proportion}_{id} = \alpha + \beta_1 \text{Party ID}_c + \beta_2 \text{Gender}_c + \beta_3 \text{Incumbent}_c + \epsilon_{id} \quad (4)$$

Figure C2 presents the results from regression models assessing partisanship as a predictor of topic prevalence. A variety of issues characterized the 2021 federal election, among them the COVID-19 pandemic, climate change, and the cost of living. Across many of the issues, there is one party that is a stronger predictor of the topic compared to its competitors. Given that the far-right AfD serves as the baseline category, its candidates paid greater attention to issues of immigration and refugees. The Green party, as will be elaborated on below, clearly dominates the climate issue. Likewise, the SPD and CDU were both chiefly concerned with addressing the COVID-19 pandemic albeit with slightly different angles, whereas the SPD used it primarily as a means of highlighting shortcomings in the German public health system, CDU candidates were focused largely on reiterating the importance of vaccines. Generally, Figure C2 presents evidence that partisans concentrate their issue attention on a couple topics, often those for which their party is considered competent.

There are some issues which demonstrate overlap, for example most of the parties talked about gender and LGBT rights slightly more than the AfD. Likewise with digital technology, there is some overlap. Both mainstream parties were substantially more likely to speak about education and the need for reform in this policy area. Therefore, while issue concentration does not necessarily characterize all campaign rhetoric, it is worth noting that by only including a small number of topics, the estimation strategy lends itself towards finding greater levels of issue overlap.[40] Estimating a model with a much higher number of topics would allow for greater

[40] The Comparative Agendas Project measures 23 distinct issue areas, by using 15 topics the present estimation strategy lends itself to a greater level of overlap.

flexibility in the way that parties frame issues, thereby making concentration more likely. In Appendix Figure C3, I present similar results from the 10 topic model, again candidates from specific parties prioritize the same issues rather than overlap with each other. The clear association between candidates from specific parties and topics for most topics is descriptive evidence in support of the first hypothesis, especially considering these are the issues parties on the left and right generally prioritize (Seeberg, 2020*b*). In Appendix Figure F1, I plot the trend in environmental press releases in the lead-up to the 2021 elections (Ivanusch, Zehnter and Burst, 2023). While the CDU candidates did not speak about these issues in the Twitter data, they had the most environmental press releases of any party over the electoral campaign, highlighting again how centralized communication from the party differs starkly from candidate communication.

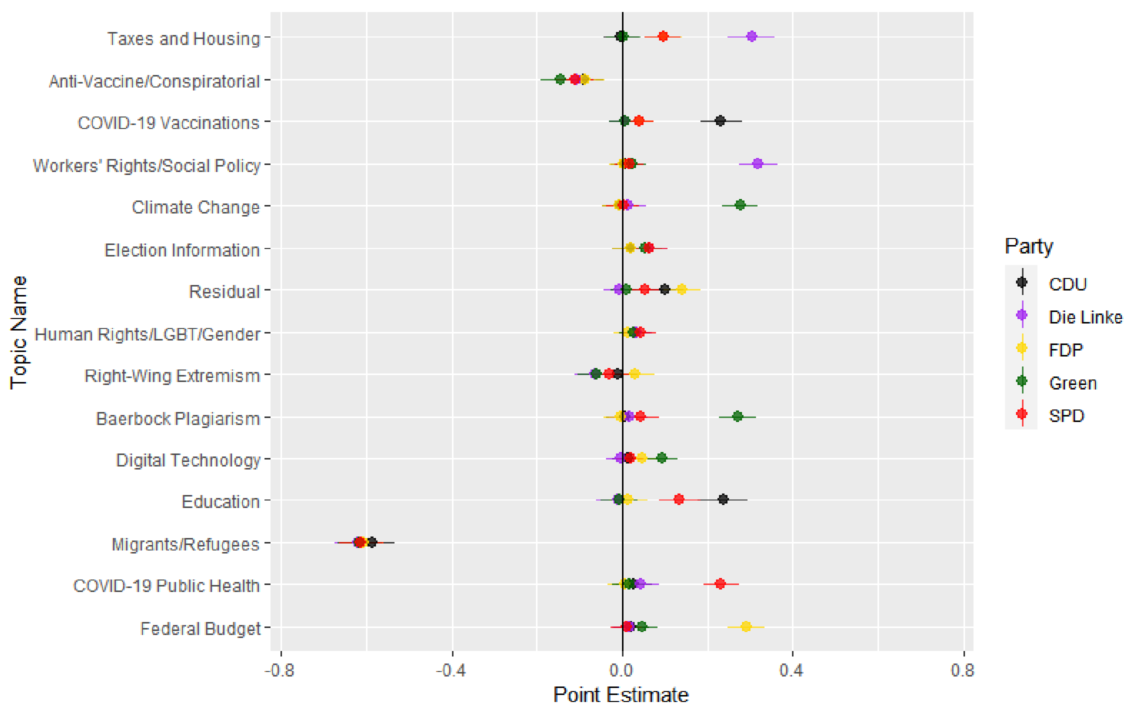
Appendix Figure C4 contains the analogous results amongst Belgian MPs, albeit grouping politicians by party family rather than party. While there are certainly topics for which each of the parties concentrate on, for example the Christian Democrats emphasized COVID response and consumer protection whereas the Social Democrats spoke more about foreign affairs, in particular human rights abuses, the coverage of topics was more evenly spread in Belgium compared to Germany. This is suggestive of ownership becoming less likely as politicians become socialized in party. It should be noted that the much smaller sample size (795 versus 238) makes it empirically demanding to precisely estimate differences between the party families, and eases the coordination challenge of conveying a similar message. The extent to which electoral cycles influence how political rhetoric corresponds with the broader vision of the party (e.g., the manifesto) should be considered in future work. Together, the results provide support for the first hypothesis, that candidates concentrate on issues rather than spread their attention evenly across myriad issues as has become common in party communication.

For the below figure as well as Figure C2, the regression analysis was conducted with the in-house `stm` function `EstimateEffect` with standards errors calculated using the default setting of global. The only difference between the figures is the topic model used. In both figures, the regression equation for each topic is the following:

$$TopicProportion_i = \alpha + \beta_1 PartyID + \beta_2 Gender + \beta_3 Incumbent + \epsilon$$

Therefore, for Figure C2 15 separate regression equations were run, while Figure C3 features ten separate regression analyses. I then include the analysis of issue

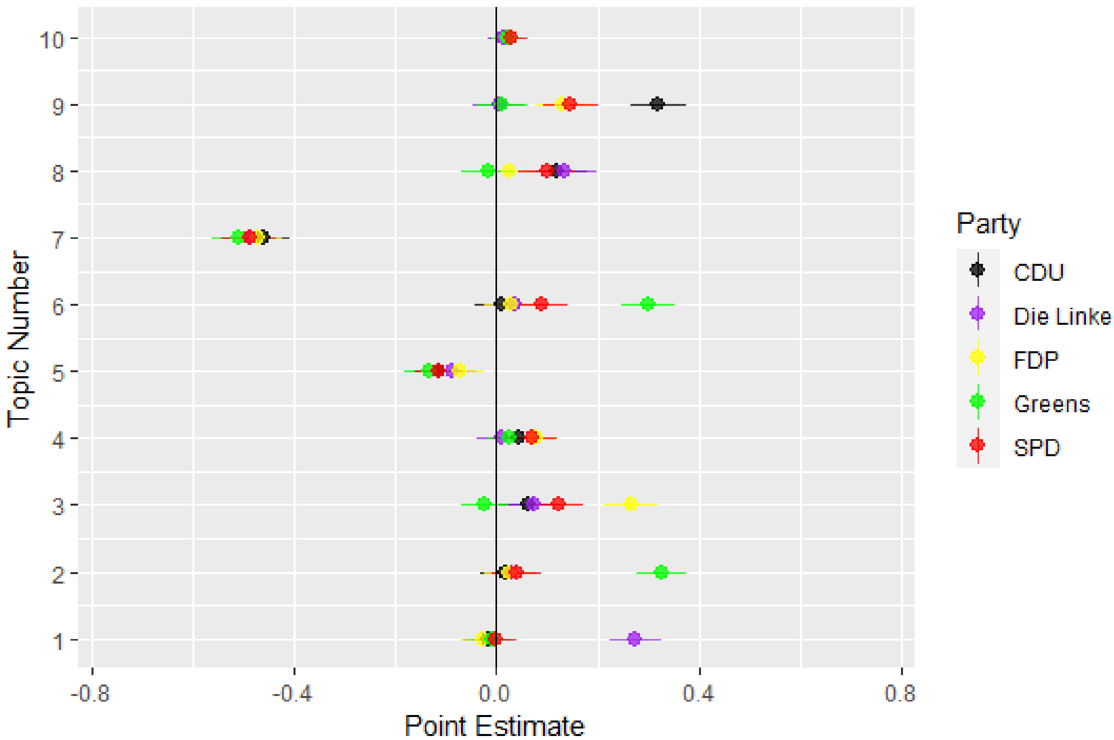
Figure C2: Issue Competition across 15 Issues in the 2021 German Federal Election



Note: Full results available in Appendix Table C5. The outcome variable is the topic proportion of a given document. The far-right AfD serves as the reference party.

attention in Belgium, featuring a 15-topic model with Party Family being the only explanatory variable. Following the figures, I include the full tables used to construct them in the respective order of appearance beginning with Figure C2.

Figure C3: Party Issue Competition 10 Topic No-Prior Model (Germany)



C.5 Additional Figures for General Issue Attention

Figure C4: Party Issue Competition 15 Topic Prior-Specified Model (Belgium)

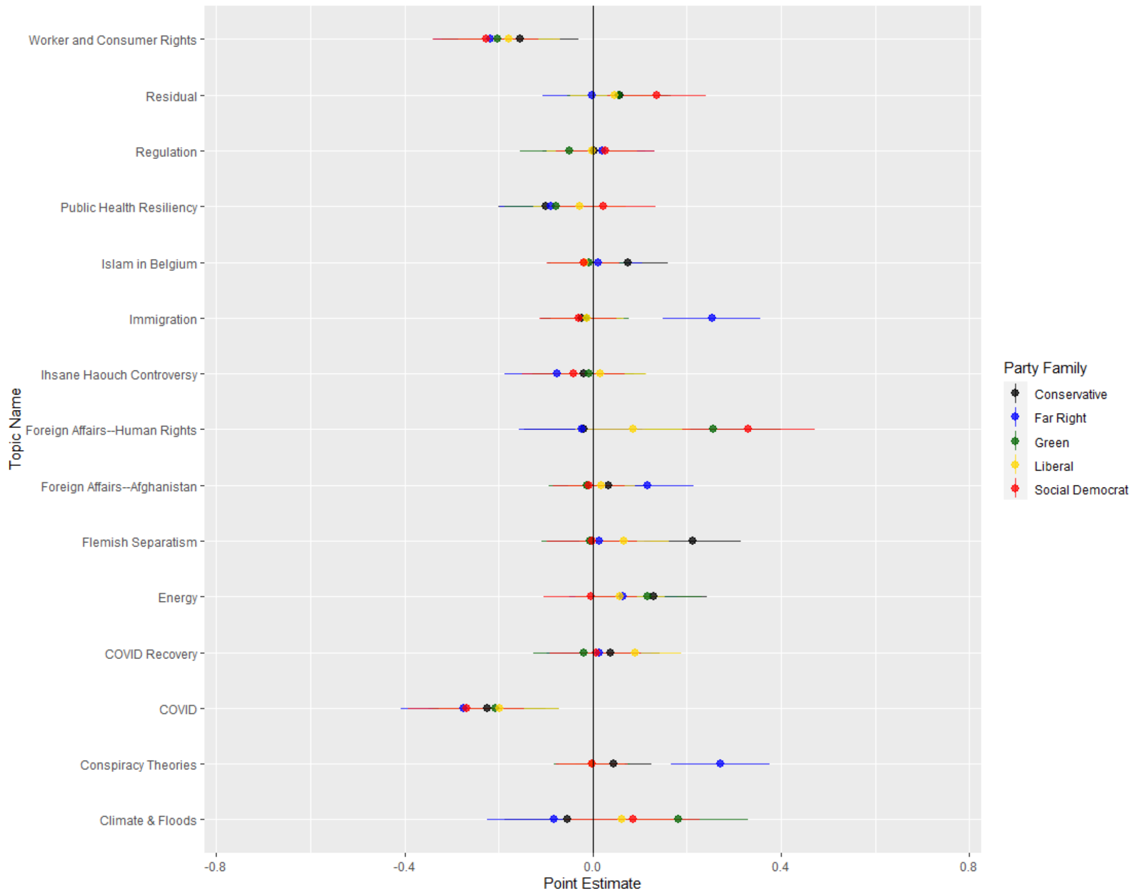


Table C5: Full Regression Results for Figure C2

Topic Number	Variable	Estimate	Std. Error	Pr(>|t|)	Topic Name
1	Constant	0.00	0.02	0.90	Taxes and Housing
1	CDU	-0.00	0.02	0.90	Taxes and Housing
1	Die Linke	0.31	0.03	0.00	Taxes and Housing
1	FDP	0.10	0.02	0.00	Taxes and Housing
1	Greens	0.00	0.02	0.96	Taxes and Housing

Topic Number	Variable	Estimate	Std. Error	Pr(>|t|)	Topic Name
1	SPD	0.09	0.02	0.00	Taxes and Housing
1	Incumbent	0.01	0.01	0.24	Taxes and Housing
1	Gender	-0.01	0.01	0.35	Taxes and Housing
2	Constant	0.18	0.02	0.00	Anti-Vaccine/Conspiratorial
2	CDU	-0.09	0.03	0.00	Anti-Vaccine/Conspiratorial
2	Die Linke	-0.11	0.03	0.00	Anti-Vaccine/Conspiratorial
2	FDP	-0.09	0.02	0.00	Anti-Vaccine/Conspiratorial
2	Greens	-0.14	0.03	0.00	Anti-Vaccine/Conspiratorial
2	SPD	-0.12	0.03	0.00	Anti-Vaccine/Conspiratorial
2	Incumbent	-0.05	0.01	0.00	Anti-Vaccine/Conspiratorial
2	Gender	-0.00	0.01	0.68	Anti-Vaccine/Conspiratorial
3	Constant	0.00	0.01	0.92	COVID-19 Vaccinations
3	CDU	0.22	0.02	0.00	COVID-19 Vaccinations
3	Die Linke	0.00	0.02	0.81	COVID-19 Vaccinations
3	FDP	0.04	0.02	0.03	COVID-19 Vaccinations
3	Greens	0.00	0.02	0.83	COVID-19 Vaccinations
3	SPD	0.03	0.02	0.05	COVID-19 Vaccinations
3	Incumbent	0.01	0.01	0.46	COVID-19 Vaccinations
3	Gender	-0.00	0.01	0.71	COVID-19 Vaccinations
4	Constant	0.00	0.01	0.90	Workers' Rights/Social Policy
4	CDU	0.01	0.02	0.71	Workers' Rights/Social Policy
4	Die Linke	0.32	0.03	0.00	Workers' Rights/Social Policy
4	FDP	0.00	0.02	0.86	Workers' Rights/Social Policy
4	Greens	0.02	0.02	0.16	Workers' Rights/Social Policy
4	SPD	0.02	0.02	0.28	Workers' Rights/Social Policy
4	Incumbent	0.00	0.01	0.68	Workers' Rights/Social Policy
4	Gender	-0.01	0.01	0.29	Workers' Rights/Social Policy
5	Constant	0.00	0.02	0.96	Climate Change
5	CDU	-0.01	0.02	0.79	Climate Change
5	Die Linke	0.02	0.02	0.48	Climate Change
5	FDP	-0.01	0.02	0.78	Climate Change
5	Greens	0.28	0.02	0.00	Climate Change
5	SPD	0.00	0.02	0.90	Climate Change
5	Incumbent	0.01	0.01	0.24	Climate Change
5	Gender	-0.00	0.01	0.71	Climate Change
6	Constant	0.07	0.02	0.00	Election Information

Topic Number	Variable	Estimate	Std. Error	Pr(>|t|)	Topic Name
6	CDU	0.02	0.02	0.42	Election Information
6	Die Linke	0.06	0.02	0.02	Election Information
6	FDP	0.02	0.02	0.44	Election Information
6	Greens	0.05	0.02	0.01	Election Information
6	SPD	0.06	0.02	0.00	Election Information
6	Incumbent	-0.05	0.01	0.00	Election Information
6	Gender	0.03	0.01	0.02	Election Information
7	Constant	0.02	0.02	0.23	Residual
7	CDU	0.10	0.02	0.00	Residual
7	Die Linke	-0.01	0.02	0.69	Residual
7	FDP	0.14	0.02	0.00	Residual
7	Greens	0.01	0.02	0.62	Residual
7	SPD	0.05	0.02	0.00	Residual
7	Incumbent	0.02	0.01	0.06	Residual
7	Gender	-0.00	0.01	0.77	Residual
8	Constant	0.01	0.01	0.57	Human Rights/LGBT/Gender
8	CDU	0.03	0.02	0.07	Human Rights/LGBT/Gender
8	Die Linke	0.03	0.02	0.06	Human Rights/LGBT/Gender
8	FDP	0.01	0.02	0.48	Human Rights/LGBT/Gender
8	Greens	0.03	0.02	0.09	Human Rights/LGBT/Gender
8	SPD	0.04	0.02	0.01	Human Rights/LGBT/Gender
8	Incumbent	0.01	0.01	0.09	Human Rights/LGBT/Gender
8	Gender	-0.02	0.01	0.05	Human Rights/LGBT/Gender
9	Constant	0.09	0.02	0.00	Right-Wing Extremism
9	CDU	-0.02	0.02	0.49	Right-Wing Extremism
9	Die Linke	-0.06	0.02	0.01	Right-Wing Extremism
9	FDP	0.03	0.02	0.19	Right-Wing Extremism
9	Greens	-0.06	0.02	0.01	Right-Wing Extremism
9	SPD	-0.03	0.02	0.17	Right-Wing Extremism
9	Incumbent	-0.02	0.01	0.03	Right-Wing Extremism
9	Gender	-0.00	0.01	0.77	Right-Wing Extremism
10	Constant	0.00	0.02	0.85	Climate Change/Green Party
10	CDU	0.01	0.02	0.69	Climate Change/Green Party
10	Die Linke	0.02	0.02	0.48	Climate Change/Green Party
10	FDP	-0.00	0.02	0.92	Climate Change/Green Party
10	Greens	0.27	0.02	0.00	Climate Change/Green Party

Topic Number	Variable	Estimate	Std. Error	Pr(>|t|)	Topic Name
10	SPD	0.05	0.02	0.02	Climate Change/Green Party
10	Incumbent	-0.00	0.01	0.99	Climate Change/Green Party
10	Gender	-0.00	0.01	0.92	Climate Change/Green Party
11	Constant	0.01	0.01	0.55	Digital Technology
11	CDU	0.01	0.02	0.46	Digital Technology
11	Die Linke	-0.00	0.02	0.81	Digital Technology
11	FDP	0.05	0.02	0.00	Digital Technology
11	Greens	0.10	0.02	0.00	Digital Technology
11	SPD	0.02	0.02	0.33	Digital Technology
11	Incumbent	-0.01	0.01	0.54	Digital Technology
11	Gender	-0.00	0.01	0.95	Digital Technology
12	Constant	0.02	0.02	0.34	Education
12	CDU	0.24	0.02	0.00	Education
12	Die Linke	-0.01	0.02	0.71	Education
12	FDP	0.01	0.02	0.60	Education
12	Greens	-0.01	0.02	0.75	Education
12	SPD	0.13	0.02	0.00	Education
12	Incumbent	-0.00	0.01	0.79	Education
12	Gender	0.03	0.01	0.03	Education
13	Constant	0.61	0.03	0.00	Migrants/Refugees
13	CDU	-0.58	0.03	0.00	Migrants/Refugees
13	Die Linke	-0.61	0.03	0.00	Migrants/Refugees
13	FDP	-0.60	0.03	0.00	Migrants/Refugees
13	Greens	-0.61	0.03	0.00	Migrants/Refugees
13	SPD	-0.61	0.03	0.00	Migrants/Refugees
13	Incumbent	0.01	0.01	0.32	Migrants/Refugees
13	Gender	0.00	0.01	0.79	Migrants/Refugees
14	Constant	0.00	0.02	0.97	COVID-19 Public Health
14	CDU	0.03	0.02	0.20	COVID-19 Public Health
14	Die Linke	0.04	0.02	0.08	COVID-19 Public Health
14	FDP	0.01	0.02	0.77	COVID-19 Public Health
14	Greens	0.01	0.02	0.53	COVID-19 Public Health
14	SPD	0.23	0.02	0.00	COVID-19 Public Health
14	Incumbent	0.02	0.01	0.18	COVID-19 Public Health
14	Gender	-0.00	0.01	0.90	COVID-19 Public Health
15	Constant	-0.02	0.02	0.35	Federal Budget

Topic Number	Variable	Estimate	Std. Error	Pr(>|t|)	Topic Name
15	CDU	0.02	0.02	0.28	Federal Budget
15	Die Linke	0.01	0.02	0.51	Federal Budget
15	FDP	0.29	0.02	0.00	Federal Budget
15	Greens	0.04	0.02	0.03	Federal Budget
15	SPD	0.01	0.02	0.65	Federal Budget
15	Incumbent	0.03	0.01	0.01	Federal Budget
15	Gender	0.00	0.01	0.90	Federal Budget

Notes: All models have 1584 observations. Topics defined based on a close reading of the top 25 texts in the topic.

Table C6: Full Regression Results from Appendix Figure C3

Topic Number	Variable	Estimate	Std. Error	Pr(>|t|)
1	Constant	0.06	0.02	0.00
1	CDU	-0.02	0.02	0.44
1	Die Linke	0.28	0.03	0.00
1	FDP	-0.03	0.02	0.20
1	Greens	-0.01	0.02	0.69
1	SPD	-0.00	0.02	0.94
1	Incumbent	-0.02	0.01	0.10
1	Gender	-0.00	0.01	0.75
2	Constant	0.01	0.02	0.64
2	CDU	0.02	0.02	0.49
2	Die Linke	0.03	0.02	0.26
2	FDP	0.02	0.02	0.32
2	Greens	0.33	0.02	0.00
2	SPD	0.04	0.02	0.10
2	Incumbent	0.02	0.01	0.15
2	Gender	0.00	0.02	0.78
3	Constant	0.08	0.02	0.00
3	CDU	0.06	0.03	0.03
3	Die Linke	0.07	0.03	0.01
3	FDP	0.27	0.03	0.00
3	Greens	-0.02	0.02	0.36
3	SPD	0.12	0.02	0.00
3	Incumbent	-0.00	0.01	0.84
3	Gender	-0.00	0.01	0.77
4	Constant	0.06	0.02	0.00
4	CDU	0.04	0.02	0.06
4	Die Linke	0.01	0.02	0.71
4	FDP	0.08	0.02	0.00
4	Greens	0.03	0.02	0.23
4	SPD	0.07	0.02	0.00
4	Incumbent	-0.04	0.01	0.00
4	Gender	0.02	0.01	0.11
5	Constant	0.18	0.02	0.00
5	CDU	-0.12	0.02	0.00
5	Die Linke	-0.09	0.03	0.00
5	FDP	-0.07	0.02	0.00
5	Greens	-0.13	0.02	0.00
5	SPD	-0.11	0.02	0.00
5	Incumbent	-0.04	0.01	0.00

Topic Number	Variable	Estimate	Std. Error	Pr(>|t|)
5	Gender	-0.00	0.01	0.86
6	Constant	0.02	0.02	0.31
6	CDU	0.01	0.03	0.66
6	Die Linke	0.04	0.03	0.23
6	FDP	0.03	0.03	0.28
6	Greens	0.30	0.03	0.00
6	SPD	0.09	0.03	0.00
6	Incumbent	0.01	0.01	0.60
6	Gender	-0.01	0.01	0.32
7	Constant	0.53	0.02	0.00
7	CDU	-0.46	0.03	0.00
7	Die Linke	-0.48	0.03	0.00
7	FDP	-0.47	0.03	0.00
7	Greens	-0.51	0.03	0.00
7	SPD	-0.49	0.03	0.00
7	Incumbent	-0.00	0.01	0.78
7	Gender	-0.00	0.01	1.00
8	Constant	0.05	0.02	0.03
8	CDU	0.12	0.03	0.00
8	Die Linke	0.13	0.03	0.00
8	FDP	0.02	0.03	0.40
8	Greens	-0.01	0.03	0.59
8	SPD	0.10	0.03	0.00
8	Incumbent	0.00	0.01	0.80
8	Gender	0.02	0.02	0.28
9	Constant	-0.00	0.02	0.94
9	CDU	0.32	0.03	0.00
9	Die Linke	0.00	0.03	0.86
9	FDP	0.13	0.03	0.00
9	Greens	0.01	0.02	0.66
9	SPD	0.15	0.03	0.00
9	Incumbent	0.06	0.01	0.00
9	Gender	-0.00	0.01	0.73
10	Constant	0.01	0.01	0.30
10	CDU	0.02	0.02	0.20
10	Die Linke	0.01	0.02	0.35
10	FDP	0.02	0.02	0.15
10	Greens	0.02	0.01	0.13
10	SPD	0.03	0.02	0.05
10	Incumbent	0.01	0.01	0.18

Topic Number	Variable	Estimate	Std. Error	Pr(>|t|)
10	Gender	-0.01	0.01	0.16

Notes: All models have 1584 observations. The unit of analysis is the candidate-month.

Table C7: Full Regression Results from Figure C4

Topic Number	Variable	Estimate	Std. Error	Pr(>|t|)	Topic Name
1	Constant	0.01	0.04	0.76	Flemish Separatism
1	Conservative	0.21	0.05	0.00	Flemish Separatism
1	Far Right	0.01	0.06	0.81	Flemish Separatism
1	Green	-0.01	0.05	0.88	Flemish Separatism
1	Liberal	0.07	0.05	0.17	Flemish Separatism
1	Social Democrat	-0.00	0.05	0.95	Flemish Separatism
2	Constant	0.05	0.04	0.21	Regulation
2	Conservative	0.00	0.05	0.98	Regulation
2	Far Right	0.02	0.06	0.72	Regulation
2	Green	-0.05	0.05	0.35	Regulation
2	Liberal	-0.00	0.05	0.95	Regulation
2	Social Democrat	0.03	0.05	0.61	Regulation
3	Constant	0.03	0.03	0.31	Immigration
3	Conservative	-0.02	0.04	0.58	Immigration
3	Far Right	0.25	0.05	0.00	Immigration
3	Green	-0.01	0.05	0.78	Immigration
3	Liberal	-0.01	0.04	0.75	Immigration
3	Social Democrat	-0.03	0.04	0.45	Immigration
4	Constant	0.08	0.04	0.06	Ihsane Haouch Controversy
4	Conservative	-0.02	0.06	0.72	Ihsane Haouch Controversy
4	Far Right	-0.08	0.06	0.18	Ihsane Haouch Controversy
4	Green	-0.01	0.06	0.89	Ihsane Haouch Controversy
4	Liberal	0.01	0.05	0.77	Ihsane Haouch Controversy
4	Social Democrat	-0.04	0.06	0.45	Ihsane Haouch Controversy
5	Constant	0.28	0.05	0.00	COVID
5	Conservative	-0.22	0.06	0.00	COVID
5	Far Right	-0.28	0.07	0.00	COVID
5	Green	-0.21	0.07	0.00	COVID
5	Liberal	-0.20	0.06	0.00	COVID
5	Social Democrat	-0.27	0.06	0.00	COVID
6	Constant	0.01	0.04	0.82	Residual
6	Conservative	0.06	0.05	0.27	Residual
6	Far Right	-0.00	0.05	0.98	Residual
6	Green	0.06	0.06	0.33	Residual
6	Liberal	0.05	0.05	0.34	Residual
6	Social Democrat	0.14	0.05	0.01	Residual
7	Constant	0.23	0.05	0.00	Worker and Consumer Rights
7	Conservative	-0.15	0.06	0.01	Worker and Consumer Rights
7	Far Right	-0.22	0.06	0.00	Worker and Consumer Rights

Topic Number	Variable	Estimate	Std. Error	Pr(>|t|)	Topic Name
7	Green	-0.20	0.06	0.00	Worker and Consumer Rights
7	Liberal	-0.18	0.06	0.00	Worker and Consumer Rights
7	Social Democrat	-0.23	0.06	0.00	Worker and Consumer Rights
8	Constant	0.03	0.03	0.27	Islam in Belgium
8	Conservative	0.07	0.04	0.08	Islam in Belgium
8	Far Right	0.01	0.05	0.81	Islam in Belgium
8	Green	-0.01	0.04	0.84	Islam in Belgium
8	Liberal	-0.02	0.04	0.65	Islam in Belgium
8	Social Democrat	-0.02	0.04	0.61	Islam in Belgium
9	Constant	0.01	0.03	0.67	Foreign Affairs–Afghanistan
9	Conservative	0.03	0.04	0.42	Foreign Affairs–Afghanistan
9	Far Right	0.12	0.05	0.02	Foreign Affairs–Afghanistan
9	Green	-0.01	0.04	0.78	Foreign Affairs–Afghanistan
9	Liberal	0.02	0.04	0.62	Foreign Affairs–Afghanistan
9	Social Democrat	-0.01	0.04	0.81	Foreign Affairs–Afghanistan
10	Constant	0.01	0.04	0.82	Energy
10	Conservative	0.13	0.06	0.03	Energy
10	Far Right	0.06	0.06	0.27	Energy
10	Green	0.12	0.06	0.05	Energy
10	Liberal	0.06	0.05	0.23	Energy
10	Social Democrat	-0.00	0.05	0.94	Energy
11	Constant	0.10	0.04	0.01	Public Health Resiliency
11	Conservative	-0.10	0.05	0.05	Public Health Resiliency
11	Far Right	-0.09	0.06	0.11	Public Health Resiliency
11	Green	-0.08	0.06	0.16	Public Health Resiliency
11	Liberal	-0.03	0.05	0.58	Public Health Resiliency
11	Social Democrat	0.02	0.06	0.70	Public Health Resiliency
12	Constant	0.02	0.05	0.63	Foreign Affairs–Human Rights
12	Conservative	-0.02	0.06	0.74	Foreign Affairs–Human Rights
12	Far Right	-0.02	0.07	0.74	Foreign Affairs–Human Rights
12	Green	0.26	0.07	0.00	Foreign Affairs–Human Rights
12	Liberal	0.08	0.06	0.17	Foreign Affairs–Human Rights
12	Social Democrat	0.33	0.07	0.00	Foreign Affairs–Human Rights
13	Constant	0.00	0.03	0.94	Conspiracy Theories
13	Conservative	0.04	0.04	0.29	Conspiracy Theories
13	Far Right	0.27	0.05	0.00	Conspiracy Theories
13	Green	-0.00	0.04	0.96	Conspiracy Theories
13	Liberal	-0.00	0.04	0.95	Conspiracy Theories
13	Social Democrat	-0.00	0.04	0.96	Conspiracy Theories
14	Constant	0.03	0.04	0.41	COVID Recovery

Topic Number	Variable	Estimate	Std. Error	Pr(>|t|)	Topic Name
14	Conservative	0.04	0.05	0.47	COVID Recovery
14	Far Right	0.01	0.06	0.81	COVID Recovery
14	Green	-0.02	0.05	0.71	COVID Recovery
14	Liberal	0.09	0.05	0.08	COVID Recovery
14	Social Democrat	0.01	0.05	0.89	COVID Recovery
15	Constant	0.09	0.05	0.10	Climate & Floods
15	Conservative	-0.05	0.07	0.44	Climate & Floods
15	Far Right	-0.08	0.07	0.26	Climate & Floods
15	Green	0.18	0.08	0.02	Climate & Floods
15	Liberal	0.06	0.06	0.33	Climate & Floods
15	Social Democrat	0.09	0.07	0.24	Climate & Floods

Notes: All models contain 238 observations. The unit of analysis is the candidate month. Topics classified by a close reading of the top 25 texts.

C.6 Additional Saturated Models for non-Climate Topics

Table C8: Non-Climate Topic Regression Analysis

	Topic Proportion		
	Economy	COVID-19	Immigration
Constant	0.022	0.007	0.637
	(0.025)	(0.02)	(0.034)
Flooded	-0.021	-0.007	0.029
	(0.07)	(0.058)	(0.085)
PostPeriod	-0.022	-0.007	-0.041
	(0.034)	(0.029)	(0.056)
CDU	-0.013	0.142	-0.584
	(0.031)	(0.032)***	(0.036)***
Die Linke	0.327	-0.001	-0.637
	(0.04)***	(0.026)	(0.037)***
FDP	0.156	0.033	-0.619
	(0.035)***	(0.027)	(0.038)***
Green	-0.02	-0.002	-0.634
	(0.029)	(0.024)	(0.036)***
SPD	0.148	0.043	-0.636
	(0.032)***	(0.025)*	(0.036)***
Flooded × PostPeriod	0.021	0.007	-0.083
	(0.097)	(0.082)	(0.142)
Flooded × CDU	0.014	-0.096	-0.077

	Economy	COVID-19	Immigration
	(0.089)	(0.086)	(0.095)
Flooded × Die Linke	-0.038	0.002	-0.030
	(0.124)	(0.082)	(0.099)
Flooded × FDP	0.021	-0.030	-0.046
	(0.095)	(0.071)	(0.090)
Flooded × Green	0.019	0.022	-0.019
	(0.085)	(0.073)	(0.094)
Flooded × SPD	-0.054	-0.020	0.002
	(0.092)	(0.073)	(0.089)
PostPeriod × CDU	0.014	0.191	0.020
	(0.044)	(0.054)***	(0.058)
PostPeriod × Die Linke	-0.058	0.009	0.041
	(0.054)	(0.037)	(0.059)
PostPeriod × FDP	-0.123	0.02	0.036
	(0.049)**	(0.039)	(0.060)
PostPeriod × Green	0.022	0.004	0.041
	(0.04)	(0.034)	(0.058)
PostPeriod × SPD	-0.114	-0.006	0.051
	(0.044)***	(0.036)	(0.058)
PostPeriod × Flooded × CDU	0.013	0.078	0.112
	(0.127)	(0.14)	(0.159)
PostPeriod × Flooded × Die Linke	0.048	-0.009	0.083
	(0.172)	(0.116)	(0.159)
PostPeriod × Flooded × FDP	-0.052	0.004	0.087
	(0.127)	(0.102)	(0.15)
PostPeriod × Flooded × Green	-0.020	-0.011	0.071
	(0.119)	(0.105)	(0.15)
PostPeriod × Flooded × SPD	0.02	-0.003	0.057
	(0.125)	(0.103)	(0.146)
Observations	1584	1584	1584
Topics	15	15	15
Prior	Y	Y	Y

The table reports the expected topic proportion of a document given the covariates estimated by STM, with uncertainty calculated via method of composition by STM. The unit of analysis is the candidate month. *p<0.1; **p<0.05; ***p<0.01.

D Issue Attention after the Floods

In this Appendix, I include additional details regarding how candidates responded to the floods as well as robustness analyses of the monthly regressions in the main text. First I include the definition of indicators used to guide the close readings, before including the analyses of both random and flooded samples. I then include the tables using the dictionary-approach at the month level, before including the Belgian analyses.

D.1 Climate Change Indicators

Table D1: Coding definitions for close reading

Flood–Climate Change	Coded as 1 when a document links flood with climate change or highlight flood was exacerbated by climate change.
Climate Mitigation	Coded as 1 when a document mentions climate change mitigation or prevention, emission reductions, or climate protection policies.
Climate Adaptation	Coded as 1 when a document mentions adaptation policy explicitly or generally refers to the need for resilience to climate change.
Currently Happening	Coded as 1 when a document stresses that climate change is happening now not in the future.
Mitigation–Prosperity	Coded as 1 when a document frames climate policy as a means of future prosperity.
Climate Science	Coded as 1 when a document uses a scientific angle such as degree target or referencing the IPCC.
Climate Justice	Coded as 1 when a document utilizes equity issues and distributional consequences of changing energy provisions and weather patterns.

D.2 Close Reading of Random Sample

I complement and validate the quantitative analysis with two close readings. The first being a random sample of tweets from 30 candidates from each of the CDU, SPD and Green parties to explore in greater detail how candidates' engaged with the climate issue after the shock to issue salience. In addition, I examine all the tweets in affected districts to see whether these candidates differed in their climate rhetoric compared to the random sample. These findings are in line with the results discussed below. In both cases, the documents were translated from German to English and then coded for several indicators related to climate mitigation, adaptation, flood blame attribution, and various frames by which the candidates could talk about climate change and policy. Appendix Table D1 presents a list of these variables along with definitions used to guide the coding exercise.

Table D2 presents the party level averages for the random sample in the month before and after the flood. Overall, CDU candidates increased engagement on four climate indicators, SPD candidates increased on seven indicators, and the Greens increased on five issues. For issues on which candidates increased attention, the average increase was 5%, 8% and 18% respectively. While it is certainly true that candidates from the traditional parties did not completely ignore the climate issue, the baseline averages across the indicators for the CDU and SPD are 10% and 3% respectively. For parties that labeled climate change as one of the *key* issues facing the country and climate change being the number one issue for voters for most of the summer (see above), this is shockingly low as a baseline. Put differently, prior to the shock to issue salience, candidates in the traditional parties barely engaged with climate politics. Taken together, these results support the findings in the regression analysis. Below I illustrate more clearly the discrepancy in issue engagement between manifestos and campaign rhetoric across the different indicators for climate issue engagement.

While the trends are not unidirectional for each of the indicators, the averages highlight the issue dominance of climate rhetoric by the Greens compared to its mainstream competitors. The increase in climate rhetoric by the Greens following the flood in the topic models is reflected in both the indicators for mitigation and adaptation policy.[41] Furthermore, the sampled candidates also increasingly used

[41] Compared with the topic model analysis that estimates the proportion of a document related to climate politics, the close reading is much rougher. A single tweet regarding climate mitigation policy, for example, is coded as a mention. Even with this looser classification criteria, the findings are in line with the topic model regression analysis above.

the term climate crisis rather than climate change. This difference in framing from change to crisis is well captured by the following tweet from a candidate in North-Rhine Westphalia, "Hopefully the IPCC climate report is a wake-up call: In 2021 it should be difficult for all of us to pretend that the climate crisis is still far away in terms of time and space....Now is the right time at the latest for consistent climate protection at all levels."[42] While the use of climate crisis was generally widespread across the party, this tweet more clearly demonstrates the rhetorical frame than the typical tweet. Related to climate science, there was what appears to be a coordinated effort by Green candidates to post about the leak of the IPCC report as not only a means of highlighting the scientific consensus and demand for action pertaining to climate change, but also to push this framing of the climate crisis.

The focus on the current threat posed by climate change is also evident in the differing interpretations of the flood event. While nearly all candidates noted the clear suffering, material damages and praised the efforts of firefighters and military service members in aiding affected areas, sampled Greens were more likely to link the flood with climate change. Whereas roughly one in four candidates made an explicit link between the disaster and climate change, only one and two from the SPD and CDU did the same respectively. Lastly, with respect to the clean energy transition, roughly a third of Green candidates explicitly mentioned expanding renewables, compared with 10 and 3 percent for the CDU and SPD respectively. Given that these parties have been alternating or sharing power over the past two decades, each has enacted policies driving the dramatic growth of renewable electricity production. The absence of any effort by candidates to champion further expansion of clean energy or highlight the success of their party's climate policies contrasts strongly with the call to push the energy transition forward in their platforms.

When did mainstream candidates talk about climate issues? Across both parties, candidates often shared similar messages about the central tenants of their platforms. Among SPD candidates this took the form of the following tweet, "Affordable rents. Innovative climate protection. Stable pensions. A strong candidate for chancellor. A strong SPD."[43] Meanwhile the CDU candidates mentioned climate policy as one of the triad of pillars for their party, alongside social and economic policy. Yet beyond these talking points about climate protection or policy in abstract, there was little

[42]Zoe Mayer, 9 August 2021. Original in German: "Der IPCC Klimabericht ist hoffentlich ein Weckruf: In 2021 sollte es für uns alle langsam schwierig werden so zu tun als wäre die Klimakrise zeitlich und räumlich noch in weiter Ferne....Für konsequenten Klimaschutz auf allen Ebenen ist spätestens jetzt die richtige Zeit."

[43]Saskia Christina Esken, 4 August 2021. Original tweet barring emojis in German: Innovativen Klimaschutz stabile Renten starken Kanzlerkandidaten eine starke SPD.

Table D2: Party Averages on Climate Indicators before and after Flooding

	CDU		SPD		Greens	
	Pre	Post	Pre	Post	Pre	Post
Flood–Climate Change	0.00	0.07	0.00	0.03	0.00	0.27
Climate Mitigation	0.47	0.47	0.10	0.30	0.60	0.73
Climate Adaptation	0.00	0.07	0.00	0.07	0.17	0.43
Currently Happening	0.03	0.07	0.03	0.10	0.53	0.60
Mitigation–Prosperity	0.10	0.07	0.03	0.10	0.57	0.23
Climate Science	0.03	0.10	0.00	0.07	0.47	0.63
Climate Justice	0.10	0.07	0.07	0.10	0.50	0.30
Observations	30	30	30	30	30	30

Note: Values in the table present the party averages before and after the floods for various indicators.

by way of specifics or engagement with the issue beyond slogans. For the CDU, this contrasts sharply with the extensive plans for a carbon neutral economy and clean technology innovation championed in its manifesto as noted above. While the SPD manifesto was more concise in general, the platform consistently linked climate issues and general social equality when discussing its climate policy goals, yet candidates did not mention climate justice or mitigation policy at high levels.

The clearest deviation from the platform is the absence of strong linkages between robust climate policy and future economic prosperity from candidates of the traditional parties. Recall, the SPD's primary future task was a climate-neutral Germany with clean energy serving as a *Jobmotor* and the basis of export industries in mid-century (Sozialdemokratische Partei Deutschlands, 2021, p. 8-9). Likewise, the CDU claimed that climate neutrality will be a comparative advantage for the German economy of the future. In describing its plan for Germany's energy supply, the party "will decisively advance the expansion of renewable energies and therefore expand them much faster to meet the rapidly growing energy demand" (Christlich Demokratische Union Deutschlands, 2021, p. 42).[44] Taken together, while there has been system-level convergence in manifestos, issue ownership is still quite clear in more quotidian forms of political communication. Whereas Green candidates appear to have used the flood as an opportunity to speak in greater detail about their core issue, this was not the case for their mainstream competitors. Candidates at times

[44]Original in German: Wir werden den Ausbau der Erneuerbaren Energien entscheidend voranbringen und daher deutlich schneller ausbauen, damit der stark steigende Energiebedarf gedeckt wird.

employed general slogans of the party, as noted above, but beyond these talking points engagement was infrequent. The general increase in climate mitigation and adaptation references following the flood falls in line with the findings of the topic models.

D.3 Close Reading of Flooded Accounts

Focusing on affected districts and considering the top six parties, Appendix Table D3 presents similar findings to the findings from a random sample in the main text. Across most of the indicators the Green candidates' shift is larger aside from a few cases. Furthermore, in Appendix Table D4, the baseline amongst the Green is again much higher than its competition. Although the party has diversified its manifesto to a significant extent compared to the final two decades of the 20$^{\text{th}}$ century (see Figure A1), candidates still focus ample attention on climate and environmental issues on Twitter. Among the others parties not considered in the random sample in the main text, it is unsurprising to see that AfD candidates did not mention climate issues as the party does not accept that climate change is largely attributable to human activity. Barring the notable increase in climate mitigation references following the flood, FDP candidates rarely spoke on the issue. Similarly candidates from the Left party infrequently mentioned climate issues (at most 1 or 2 candidates). Overall, the findings here corroborate the results of the close reading of a random sample of tweets from candidates in the CDU, Greens, and SPD: Greens dominated the climate issue across the entire campaign and candidates ramped up their climate rhetoric following the floods. In contrast to the other parties, which have likewise emphasized the importance and centrality of climate policy in their manifestos, daily rhetoric on Twitter is characterized by issue ownership rather than overlap.

Table D3: Party Differences in Rhetoric in Affected Districts

	CDU	SPD	Greens	Die Linke	FDP	AfD
Flood–Climate Change	0.14	0.11	0.44	0	0	0
Climate Mitigation	0.07	0.11	0.17	0.11	0.35	0
Climate Adaptation	0.07	0.06	0.33	0	0	0
Currently Happening	0.14	0.16	0.27	0.11	0.05	0
Mitigation-Prosperity	0	0.11	-0.17	0.22	0.1	0
Climate Science	0.14	0	0.15	0.22	0	0
Climate Justice	-0.14	0	-0.11	0	0	0
Observations	14	18	18	9	20	9

Note: Values in the table denote the difference the party level averages for the months surrounding the flood for each of the indicators.

Table D4: Party Averages on Climate Indicators in Affected Districts

	CDU		SPD		Greens		Die Linke		FDP		AfD	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Flood–Climate Change	0.00	0.14	0.00	0.11	0.00	0.44	0.00	0.00	0.00	0.00	0.00	0.00
Climate Mitigation	0.36	0.43	0.17	0.28	0.61	0.78	0.22	0.33	0.05	0.40	0.00	0.00
Climate Adaptation	0.00	0.07	0.00	0.06	0.28	0.61	0.00	0.00	0.00	0.00	0.00	0.00
Currently Happening	0.00	0.14	0.06	0.22	0.56	0.83	0.00	0.11	0.00	0.05	0.00	0.00
Mitigation–Prosperity	0.14	0.14	0.00	0.11	0.56	0.39	0.00	0.22	0.00	0.10	0.00	0.00
Climate Science	0.07	0.21	0.06	0.06	0.44	0.61	0.00	0.22	0.00	0.00	0.00	0.00
Climate Justice	0.14	0.00	0.11	0.11	0.44	0.33	0.11	0.11	0.00	0.00	0.00	0.00
Observations	14	14	18	18	18	18	9	9	20	20	9	9

D.4 STM Analysis Issue Attention over Time: Germany

This Appendix presents the results analogous to the analysis in Section 6.2, albeit with the robustness topic model and a placebo topic outcome: immigration. Table D5 presents the results from the analysis using the 10-topic, no prior specified STM. Column 3 is the same as Column 4 in Table 2 in the main text. The results below support the conclusions in the main text, suggesting that the results are not driven by model selection. Table D6 presents the results using the immigration topic as an outcome rather than climate change. The baseline AfD again serves as the baseline omitted category in the second and third columns. There is not evidence that the salience shock extended to another important issue in Germany.

Table D5: Regression Results: Flooding and Climate Change Candidate Rhetoric

	Climate Topic Proportion		
	Model 1	Model 2	Model 3
Green Binary × PostPeriod	0.59***		
	(0.03)		
CDU × PostPeriod		0.00	−0.00
		(0.01)	(0.02)
Die Linke × PostPeriod		0.02	0.03**
		(0.01)	(0.01)
FDP × PostPeriod		0.01	0.02
		(0.01)	(0.01)
Green × PostPeriod		0.60***	0.61***
		(0.03)	(0.03)
SPD × PostPeriod		0.02	0.02
		(0.01)	(0.02)
Incumbent × PostPeriod			0.04**
			(0.02)
Female × PostPeriod			−0.01
			(0.02)
Only Direct × PostPeriod			−0.01
			(0.02)
ID & Month FE	Yes	Yes	Yes
Num. obs.	1584	1584	1584
R^2	0.84	0.84	0.84
Adj. R^2	0.49	0.48	0.68

CR2 Errors clustered at individual and district. The unit of analysis is the candidate-month. STM is the 10 Topic No-Prior used as a robustness in Table 2.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D6: Regression Results: Flooding and Immigration Candidate Rhetoric

	Immigration Topic Proportion		
	Model 1	Model 2	Model 3
Green Binary × PostPeriod	0.00		
	(0.01)		
CDU × PostPeriod		0.02	0.02
		(0.04)	(0.04)
Die Linke × PostPeriod		0.04	0.03
		(0.04)	(0.04)
FDP × PostPeriod		0.04	0.04
		(0.04)	(0.04)
Green × PostPeriod		0.03	0.03
		(0.04)	(0.04)
SPD × PostPeriod		0.04	0.04
		(0.04)	(0.04)
Incumbent × PostPeriod			0.00
			(0.01)
Female × PostPeriod			0.01
			(0.01)
Only Direct × PostPeriod			0.00
			(0.02)
ID & Month FE	Yes	Yes	Yes
Num. obs.	1584	1584	1584
R^2	0.92	0.92	0.92
Adj. R^2	0.74	0.74	0.84

CR2 Errors clustered at individual and district. The unit of analysis is the candidate-month. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

D.5 STM Analysis Issue Attention over Time: Belgium

This appendix presents the results from the issue attention analysis using the document topic proportions from Belgium in a two-way fixed effects regression with specifications analogous to those presented in Table 2, albeit with the comparison between party families rather than individual parties. This motivates the inclusion of the Flemish indicator in theses analyses. As evident in the first model as well as the remaining columns, there is a consistent increase in Green climate issue attention following the floods, however other parties also increase their climate rhetoric in the month afterwards. As noted in the main text, in contrast to the more well delineated topics amongst German candidates, the Belgian corpus in general had more overlap. Likewise, in the process of labeling the topics the bundling of the climate topic alongside the floods was evident. This is somewhat unsurprising: in Germany many candidates also spoke about the floods and noted the valiant efforts of emergency crews alongside the need to rebuild. Similar statements were prevalent among MPs in Belgium. Given that most parties address climate change, it is somewhat unsurprising that there is a greater level of overlap in the Belgian case for two reasons. First, MPs have been integrated into the party and hence are likely more familiar with the general contours of the manifesto. Second, the size of parties in Belgium (the largest is 24 individuals) makes coordination easier. Together this suggests that wave-riding should be more likely in Belgium than in Germany, especially in terms of broad issue categorization compared to a more conservative measure, such as the one employed in the dictionary approach.

In terms of the placebo analysis, the far right parties increased their immigration rhetoric in the month after the floods, hence the negative significant effect for all the remaining parties. This is likely driven by the dismissal of Gender Equality Minister Ihsane Haouach regarding comments over the separation of the church and the state and potential connections to the Muslim Brotherhood.[45] This episode was referenced by far-right politicians as an example of the threat of immigration to fundamental values.

[45] "Ihsane Haouach démissionne de son poste de commissaire à l'égalité femmes-hommes, de possibles liens avec les Frères musulmans." 7 July 2021. *La Libre*. https://www.lalibre.be/belgique/politique-belge/2021/07/09/en-pleine-polemique-ihsane-haouach-demissionne-de-son-poste-de-commissaire-a-legalite-hommes-femmes-532I47EDEBGSFPOJ3HIPI53WBQ/. Accessed 9 April 2024.

Table D7: Regression Results: Flooding and MP Climate Change Rhetoric

	Climate Topic Proportion		
	Model 1	Model 2	Model 3
Green Binary × PostPeriod	0.34^{**}		
	(0.11)		
Christian Democrat × PostPeriod		0.21^{**}	0.19^{**}
		(0.08)	(0.07)
Conservative × PostPeriod		0.06	0.06
		(0.04)	(0.05)
Green × PostPeriod		0.54^{***}	0.49^{**}
		(0.10)	(0.17)
Liberal × PostPeriod		0.30^{***}	0.28^{**}
		(0.08)	(0.09)
Social Democrat × PostPeriod		0.32^{***}	0.29^{**}
		(0.09)	(0.11)
# of Tweets			0.00
			(0.00)
Flemish Party × PostPeriod			-0.05
			(0.10)
ID & Month FE	Yes	Yes	Yes
Num. obs.	238	238	238
R^2	0.63	0.67	0.67
Adj. R^2	0.15	0.21	0.27

CR2 Errors clustered at individual and district. The unit of analysis is the MP-month. * p < 0.1, ** p < 0.05, *** p < 0.01

Table D8: Regression Results: Flooding and MP Immigration Rhetoric

	Immigration Topic Proportion		
	Model 1	Model 2	Model 3
Green Binary × PostPeriod	−0.05		
	(0.04)		
Christian Democrat × PostPeriod		−0.70***	−0.71***
		(0.12)	(0.13)
Conservative × PostPeriod		−0.63***	−0.63***
		(0.09)	(0.09)
Green × PostPeriod		−0.60***	−0.66***
		(0.10)	(0.10)
Liberal × PostPeriod		−0.61***	−0.63***
		(0.09)	(0.09)
Social Democrat × PostPeriod		−0.64***	−0.67***
		(0.09)	(0.09)
# of Tweets			−0.00
			(0.00)
Flemish Party × PostPeriod			−0.06
			(0.04)
ID & Month FE	Yes	Yes	Yes
Num. obs.	238	238	238
R^2	0.51	0.76	0.76
Adj. R^2	−0.13	0.42	0.47

CR2 Errors clustered at individual and district. The unit of analysis is the MP-month. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

D.6 Dictionary Approach: Month Analysis Germany

As a second robustness check, I leverage a dictionary approach coding a tweet as mentioning the climate change issue when they mention climate change or the energy transition as described above. This tweet-level indicator is then summed for the months before and after the flood. As in the analysis above, I include candidate and month fixed effects to consider heterogeneity between parties in response to the exogenous timing of a natural disaster, but consider the shift within individuals over time. The three models in Table D9 mirror the results in Table 2, Green candidates clearly increase their issue attention following the floods, whereas candidates from other parties have no discernible difference in references to climate change afterwards. Substantively, the increase by the Green party is roughly a quarter of a standard deviation increase. By relying solely on a dictionary analysis, I am able to increase

Table D9: Regression Results: Flooding and Climate Change Campaign Rhetoric

	Climate Count		
	Model 1	Model 2	Model 3
Num. of Tweets	0.07^{***}	0.07^{***}	0.07^{***}
	(0.01)	(0.01)	(0.01)
Green Binary × PostPeriod	2.66^{***}		
	(0.70)		
CDU × PostPeriod		−0.48	−0.60
		(0.38)	(0.38)
FDP × PostPeriod		−0.32	−0.23
		(0.45)	(0.44)
Die Linke × PostPeriod		0.01	0.21
		(0.50)	(0.52)
Greens × PostPeriod		2.55^{***}	2.77^{***}
		(0.77)	(0.79)
SPD × PostPeriod		0.20	0.27
		(0.36)	(0.38)
Incumbent × PostPeriod			0.88^{**}
			(0.41)
Female × PostPeriod			0.01
			(0.43)
ID and Month FE	Yes	Yes	Yes
Num. obs.	1838	1838	1838
R^2	0.88	0.88	0.88
Adj. R^2	0.76	0.76	0.76

CR2 Errors clustered at individual and district. The unit of analysis is the candidate-month. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

the number of candidates that are considered in the analysis as no preprocessing of the text was necessary. Likewise, even accounts with very few tweets could be considered, whereas the insufficient document length led them to be dropped from the topic model analysis above.

D.7 Dictionary Approach: Month Analysis Belgium

Table D10: Regression Results: Flooding and Climate Change MP Rhetoric

	Climate Count	
	Model 1	Model 2
Num. of Tweets	0.02^{**}	0.02^{**}
	(0.01)	(0.01)
PostPeriod	0.48^{**}	0.46
	(0.15)	(0.40)
Christian Democrat × PostPeriod		-0.13
		(0.40)
Conservative × PostPeriod		0.26
		(0.62)
Green × PostPeriod		1.05^{*}
		(0.53)
Liberal × PostPeriod		-0.49
		(0.42)
Social Democrat × PostPeriod		-0.02
		(0.42)
ID and Month FE	Yes	Yes
Num. obs.	252	248
R^2	0.82	0.85
Adj. R^2	0.64	0.67

CR2 Errors clustered at individual and district. The unit of analysis is the candidate-month. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

D.8 Retweet Robustness

In this subsection, I probe the robustness of the results to the exclusion of retweets as well as an alternative dictionary measure developed from reading mainstream parties' treatment of the climate issue in their manifestos (Schwörer, 2024).[46] A concern about the inclusion of retweeted content is that candidates simply mimic external opinion and the issue attention is therefore less genuine. A sizable portion

[46]The dictionary in German includes: klima, erhitzung, erwärmung, treibhaus, glashaus, aufheizung, temperatur. In English: clima*, warming, greenhouse, heat, calefaction, temperatur*, where the asterisk denotes acceptance of any suffix from the root.

of tweets are retweets ($\approx 40\%$). To assess whether retweets are driving the results presented in the main text, I perform two sets of analyses. In the first, I omit all retweets to better gauge individual issue attention. In the second, I leverage the source of the retweet to only exclude those retweets that are directly sourced from a party account. I choose to subset only to party accounts for several reasons. First, given the focus on candidate issue attention, the interpretation of the results would be fundamentally different if the trends in issue attention between and within parties is driven by selective uptake of party messaging, begging questions of the independence of candidates or whether the results are merely a coordinated strategy by the Green party. Such a finding would challenge claims of weak sanctioning methods enjoyed by central party elites over the local rank and file. Second, by allowing retweets from non-party sources, it is more flexible in allowing candidates to demonstrate issue expertise through the provision of specific sources on a given issue. Awareness of issue domain specific sources that serve as the basis of retweets could be viewed as a way of demonstrating competence: the candidate is able to identify and follows expert sources. It should be noted that it is impractical to identify the expertise level of every retweet source, hence I opt for both strategies to probe the robustness of the results presented in the primary text. In general, the results of the primary analysis are robustness to both strategies, while the effect sizes slightly attenuate the increase by the Greens is evident in both analyses with incumbents likewise increasing issue attention.

Table D11 replicates the monthly issue attention analysis omitting any retweets. In Models 1 through 3, I include the narrow dictionary described in the main text to assess issue attention, whereas Models 4-6 use a dictionary developed from an assessment of climate issue attention by mainstream parties in the European context (Schwörer, 2024). Across both outcome measures, the positive shift in climate issue attention is replicated by Green candidates, providing further robustness to the main results. Omitting retweets does attenuate the coefficient sizes across each of the models. Coefficients in Table D9 are typically 1 tweet larger, suggesting that candidates leveraged both original and reused content when discussing the climate issue following the floods. Incumbents increase their climate issue attention, where as there is no observable difference in issue attention shift by gender, mirroring the results in the main text.

Table D12 presents the results omitting retweets sourced from official party accounts. While this again somewhat attenuates the results from Table D9, it is clear that Green candidates were not simply retweeting posts from the central party in isolation. Across both dictionary measures the results are broadly similar albeit with slightly smaller point estimates using the broader climate change dictionary. This

Table D11: Replication of Table D9 omitting retweets

	Climate Count			Schwörer Dictionary		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Tweet Count	0.05^{***}	0.05^{***}	0.05^{***}	0.05^{***}	0.05^{***}	0.05^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Green Binary × PostPeriod	1.18^{***}			1.09^{**}		
	(0.46)			(0.45)		
CDU × PostPeriod		-0.02	-0.09		-0.15	-0.22
		(0.26)	(0.26)		(0.26)	(0.27)
Die Linke × PostPeriod		0.32	0.43		0.21	0.30
		(0.31)	(0.32)		(0.32)	(0.33)
FDP × PostPeriod		-0.04	0.01		-0.14	-0.09
		(0.29)	(0.28)		(0.30)	(0.30)
Greens × PostPeriod		1.28^{***}	1.41^{***}		1.08^{**}	1.20^{**}
		(0.48)	(0.49)		(0.48)	(0.49)
SPD × PostPeriod		0.21	0.25		0.07	0.10
		(0.25)	(0.27)		(0.25)	(0.26)
Incumbent × PostPeriod			0.56^{*}			0.50^{*}
			(0.30)			(0.30)
Female × PostPeriod			0.04			0.06
			(0.29)			(0.28)
N	1710	1710	1710	1710	1710	1710
Candidates	855	855	855	855	855	855
R^2	0.80	0.80	0.80	0.80	0.80	0.80
Adj. R^2	0.60	0.60	0.60	0.59	0.59	0.59

The outcome is the number of tweets referencing the climate issue. Models 1-3 use the dictionary measure described in the main text. Models 4-6 use an alternative more expansive climate change dictionary from Schwörer (2024). CR2 standard errors clustered at the individual and district. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

likely results from the inclusion of the "energy transition" phrase in the proposed narrow dictionary compared with the less policy-relevant, but more weather-based dictionary created by Schwörer. Given that this dictionary was derived from mainstream party rhetoric on the climate issue in manifestos, but not the Green party, it presents clear evidence of the lack of transmission of climate ideas from the central party to the rank and file among the center-left and -right in the present setting. Indeed, if we consider the negative coefficients on the CDU, it suggests that center-right candidate climate issue attention consisted of retweeting party account messages *prior* to the floods. We can arrive at this conclusion by comparing shifts in trends across the different samples: the coefficient in the non-party sample (Table D12) is twice the magnitude of the full sample (Table D9); both of these negative shifts sharply contrast with the insignificant positive coefficient in the no-retweet sample (Table D11). This is consistent with evidence from the close-reading in which CDU candidates often re-tweeted the party's campaign slogan that mentioned a focus on climate protection and the energy transition. A similar interpretation is consistent with the negative coefficient among FDP candidates as well.

Taken together, the results in this appendix section demonstrate the resilience of the results in the main text. Conditional wave-riding by the issue owning Green candidates is not driven by retweets, in general or from partisan sources. Second, using an alternative dictionary developed from climate issue attention by mainstream parties throughout Europe does not change the results: across all specifications the differences between the narrow dictionary proposed herein and this broader dictionary are small.

Table D12: Replication of Table D9 omitting party retweets

	Climate Count			Schwörer Dictionary		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Tweet Count	0.04^{***}	0.04^{***}	0.04^{***}	0.04^{***}	0.04^{***}	0.04^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Green Binary × PostPeriod	2.40^{***}			2.31^{***}		
	(0.66)			(0.65)		
CDU × PostPeriod		-1.14^{***}	-1.21^{***}		-1.32^{***}	-1.38^{***}
		(0.43)	(0.43)		(0.43)	(0.43)
Die Linke × PostPeriod		-0.02	0.06		-0.17	-0.11
		(0.50)	(0.52)		(0.50)	(0.53)
FDP × PostPeriod		-0.74^{*}	-0.71^{*}		-0.90^{**}	-0.87^{**}
		(0.42)	(0.41)		(0.42)	(0.42)
Greens × PostPeriod		1.92^{***}	2.01^{***}		1.67^{**}	1.74^{**}
		(0.73)	(0.74)		(0.73)	(0.74)
SPD × PostPeriod		-0.35	-0.33		-0.53	-0.53
		(0.58)	(0.61)		(0.58)	(0.61)
Incumbent × PostPeriod			0.43			0.37
			(0.40)			(0.40)
Female × PostPeriod			0.04			0.08
			(0.40)			(0.40)
N	1838	1838	1838	1838	1838	1838
Candidates	919	919	919	919	919	919
R^2	0.84	0.84	0.84	0.83	0.84	0.84
Adj. R^2	0.67	0.67	0.67	0.67	0.67	0.67

The outcome is the number of tweets referencing the climate issue. Models 1-3 use the dictionary measure described in the main text. Models 4-6 use an alternative more expansive climate change dictionary from Schwörer (2024). CR2 standard errors clustered at the individual and district. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

D.9 Campaign Communication Dynamics

In this Appendix, I consider trends in candidate campaign communication given that the physical damage from flooding may have increased the utility of online communication strategies at the expense of in person campaigning. To assess these dynamics, I consider trends in the number of tweets posted, irrespective of content in Table D13. Recall that the baseline in the monthly analysis is the far-right AfD, hence the interpretation should be that barring the mainstream parties which decreased their Twitter communication, there were not significant differences in communication medium. Furthermore, this monthly analysis neglects spatial variation in flood exposure; as I demonstrate in Table E9, these differences with the AfD largely disappear once we consider intra-party variation. In general, the floods did not have an impact on the usage of Twitter as a form of campaign communication, if anything candidates reduced their reliance on it over the course of the electoral campaign.

Table D13: Campaign Communication Dynamics

	Tweet Count
	Model 1
CDU × PostPeriod	-9.52^{*}
	(4.90)
Die Linke × PostPeriod	-9.21
	(7.20)
FDP × PostPeriod	-5.10
	(6.07)
Greens × PostPeriod	-8.60
	(5.65)
SPD × PostPeriod	-9.35^{*}
	(5.46)
N	1838
Candidates	919
R^2	0.87
Adj. R^2	0.74

The unit of analysis is the candidate-month. The outcome variable is the number of tweets per month. Robust standard errors clustered at the individual and district in parentheses. The omitted category is the shift by the far-right AfD. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

E Event Study Analyses

In this Appendix I include the full results from the analysis testing H3 and H4 related to intra-party heterogeneity. I first include the referenced table (4) from the main text for Germany as well as the full table used to make Figure 4. I then include the analysis that subsets to the two affected states within Germany (E3). Lastly, I include the full results from Belgium referenced in the extension section. Table E6 provides the results referenced in the main text and Table E7 provides the data used to generate Figure 5.

E.1 Germany

Table E1: Regression Results: Flooding and Climate Change Campaign Rhetoric by Week

	Climate Count	
	Model 1	Model 2
Num. of Tweets	0.06^{***}	0.06^{***}
	(0.01)	(0.01)
Week -3 × Flood	-0.02	
	(0.16)	
Week -2 × Flood	-0.21	
	(0.19)	
Week -1 × Flood	-0.03	
	(0.17)	
Week 1 × Flood	0.64^{*}	
	(0.35)	
Week 2 × Flood	0.44^{**}	
	(0.18)	
Week 3 × Flood	0.47^{***}	
	(0.17)	
Week 4 × Flood	0.34	
	(0.29)	
Week -3 × Flood × Green		-0.65
		(0.67)
Week -2 × Flood × Green		-0.50
		(0.82)
Week -1 × Flood × Green		0.18
		(0.88)
Week 1 × Flood × Green		3.04^{**}

	Model 1	Model 2
		(1.52)
Week 2 × Flood × Green		1.30*
		(0.78)
Week 3 × Flood × Green		0.78
		(0.48)
Week 4 × Flood × Green		2.52**
		(1.26)
N	7352	7352
R^2	0.70	0.71
Adj. R^2	0.66	0.66

CR2 Errors clustered at individual and district. The unit of analysis is the candidate-week. All models include candidate and week fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E2: Results to produce Figure 4

	Model 1
Tweet Count	0.06***
	(0.01)
Week -3 × Flood × AfD	0.54
	(0.34)
Week -2 × Flood × AfD	0.45
	(0.59)
Week -1 × Flood × AfD	−0.21
	(0.16)
Week 1 × Flood × AfD	0.78
	(0.80)
Week 2 × Flood × AfD	0.83
	(0.69)
Week 3 × Flood × AfD	0.44
	(0.36)
Week 4 × Flood × AfD	−0.48
	(0.42)
Week -3 × Flood × CDU	−0.00
	(0.19)
Week -2 × Flood × CDU	−0.45***
	(0.14)
Week -1 × Flood × CDU	0.06
	(0.26)
Week 1 × Flood × CDU	−0.38**
	(0.19)
Week 2 × Flood × CDU	0.21
	(0.29)
Week 3 × Flood × CDU	−0.23
	(0.26)
Week 4 × Flood × CDU	−0.04
	(0.53)
Week -3 × Flood × Die Linke	0.05
	(0.22)
Week -2 × Flood × Die Linke	0.21
	(0.34)
Week -1 × Flood × Die Linke	−0.18
	(0.24)
Week 1 × Flood × Die Linke	0.17
	(0.25)
Week 2 × Flood × Die Linke	0.29*
	(0.17)

	Model 1
Week 3 × Flood × Die Linke	1.16**
	(0.54)
Week 4 × Flood × Die Linke	0.35
	(0.52)
Week -3 × Flood × FDP	0.08
	(0.20)
Week -2 × Flood × FDP	−0.24
	(0.23)
Week -1 × Flood × FDP	−0.09
	(0.20)
Week 1 × Flood × FDP	0.38
	(0.50)
Week 2 × Flood × FDP	0.05
	(0.35)
Week 3 × Flood × FDP	0.80**
	(0.34)
Week 4 × Flood × FDP	−0.51*
	(0.26)
Week -3 × Flood × Green	−0.63
	(0.67)
Week -2 × Flood × Green	−0.51
	(0.82)
Week -1 × Flood × Green	0.17
	(0.89)
Week 1 × Flood × Green	3.05**
	(1.52)
Week 2 × Flood × Green	1.33*
	(0.78)
Week 3 × Flood × Green	0.81*
	(0.48)
Week 4 × Flood × Green	2.50**
	(1.26)
Week -3 × Flood × SPD	0.06
	(0.20)
Week -2 × Flood × SPD	−0.30*
	(0.16)
Week -1 × Flood × SPD	−0.07
	(0.13)
Week 1 × Flood × SPD	−0.15
	(0.18)
Week 2 × Flood × SPD	0.14

	Model 1
	(0.25)
Week 3 × Flood × SPD	0.06
	(0.20)
Week 4 × Flood × SPD	0.06
	(0.32)
N	7352
Candidates	919
R^2	0.71
Adj. R^2	0.66

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

E.1.1 Affected State Analysis

Table E3: Regression Results: Flooding and Climate Change Campaign Rhetoric by Week

	Climate Count
	Model 1
Num. of Tweets	0.09***
	(0.02)
Week -3 × Flood × Green	−0.32
	(0.67)
Week -2 × Flood × Green	−0.13
	(0.79)
Week -1 × Flood × Green	0.20
	(0.82)
Week 1 × Flood × Green	2.75*
	(1.40)
Week 2 × Flood × Green	1.26
	(0.77)
Week 3 × Flood × Green	0.72
	(0.49)
Week 4 × Flood × Green	2.36*
	(1.22)
ID and Week FE	Yes
N	1880
Candidates	235
R^2	0.72
Adj. R^2	0.68

CR2 Errors clustered at individual and district. The unit of analysis is the candidate-week.The analysis here is restricted to the two states that experienced flooding: North-Rhine Westphalia and Rhineland Palatinate. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

E.1.2 Retweet Robustness

In this appendix I probe the robustness of the event study analysis to the omission of retweets as well as an alternative dictionary measure in a similar fashion to Appendix D.8. Table E4 replicates the three event study designs omitting all retweets, whereas Table E5 omits those retweets sourced from the party account. In general, across both outcome measures there is consistent evidence for an increase in climate issue attention by affected Green candidates, mirroring the primary results in the paper. There is, in a similar fashion to month analysis, a slight attenuation in the coefficients, suggesting once again that candidates are blending the original content with retweets from both partisan and non-partisan sources when speaking climate change on Twitter.

Table E4: Event Study Replication omitting retweets

	Climate Count			Schwörer Dictionary		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Week -3 × Flood × Green Bin	−0.06			−0.07		
	(0.40)			(0.40)		
Week -2 × Flood × Green Bin	0.11			0.12		
	(0.24)			(0.24)		
Week -1 × Flood × Green Bin	0.41			0.41		
	(0.32)			(0.32)		
Week 1 × Flood × Green Bin	2.12*			2.12*		
	(1.14)			(1.14)		
Week 2 × Flood × Green Bin	0.41			0.41		
	(0.40)			(0.40)		
Week 3 × Flood × Green Bin	0.71*			0.72*		
	(0.43)			(0.43)		
Week 4 × Flood × Green Bin	1.45**			1.40**		
	(0.70)			(0.67)		
Week -3 × Flood × AfD		0.24	0.16		0.23	0.15
		(0.18)	(0.21)		(0.18)	(0.21)
Week -2 × Flood × AfD		0.00	−0.08		0.00	−0.08
		(0.04)	(0.08)		(0.04)	(0.08)
Week -1 × Flood × AfD		0.04	−0.02		0.03	−0.02
		(0.04)	(0.06)		(0.04)	(0.06)
Week 1 × Flood × AfD		0.01	−0.20		−0.00	−0.20
		(0.10)	(0.23)		(0.10)	(0.23)
Week 2 × Flood × AfD		0.13	−0.05		0.13	−0.02
		(0.10)	(0.11)		(0.10)	(0.11)
Week 3 × Flood × AfD		0.25**	0.05		0.24*	0.08

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
		(0.12)	(0.15)		(0.12)	(0.14)
Week 4 × Flood × AfD		−0.38***	−0.69***		−0.38***	−0.66***
		(0.06)	(0.18)		(0.06)	(0.17)
Week -3 × Flood × CDU		0.00	−0.15		−0.01	−0.15
		(0.12)	(0.22)		(0.12)	(0.22)
Week -2 × Flood × CDU		−0.05	−0.22		−0.05	−0.22
		(0.12)	(0.18)		(0.12)	(0.18)
Week -1 × Flood × CDU		0.25	0.13		0.24	0.15
		(0.22)	(0.24)		(0.22)	(0.24)
Week 1 × Flood × CDU		−0.03	−0.35		−0.04	−0.35
		(0.20)	(0.38)		(0.20)	(0.38)
Week 2 × Flood × CDU		0.30	−0.02		0.30	0.02
		(0.26)	(0.26)		(0.26)	(0.26)
Week 3 × Flood × CDU		−0.09	−0.40*		−0.10	−0.35
		(0.12)	(0.21)		(0.12)	(0.21)
Week 4 × Flood × CDU		0.15	−0.31		0.15	−0.27
		(0.53)	(0.50)		(0.53)	(0.49)
Week -3 × Flood × Die Linke		−0.03	−0.11		−0.05	−0.12
		(0.10)	(0.14)		(0.10)	(0.14)
Week -2 × Flood × Die Linke		0.00	−0.10		0.00	−0.09
		(0.14)	(0.14)		(0.14)	(0.14)
Week -1 × Flood × Die Linke		−0.06	−0.11		−0.07	−0.11
		(0.10)	(0.12)		(0.10)	(0.11)
Week 1 × Flood × Die Linke		0.19	0.09		0.18	0.08
		(0.19)	(0.27)		(0.19)	(0.26)
Week 2 × Flood × Die Linke		−0.05	−0.20		−0.05	−0.20
		(0.10)	(0.13)		(0.10)	(0.13)
Week 3 × Flood × Die Linke		0.34*	0.24		0.33*	0.25
		(0.19)	(0.18)		(0.19)	(0.18)
Week 4 × Flood × Die Linke		0.08	−0.05		0.08	−0.04
		(0.31)	(0.35)		(0.31)	(0.34)
Week -3 × Flood × FDP		−0.04	−0.20		−0.05	−0.20
		(0.08)	(0.19)		(0.08)	(0.19)
Week -2 × Flood × FDP		0.05	−0.14		0.05	−0.13
		(0.11)	(0.15)		(0.11)	(0.15)
Week -1 × Flood × FDP		0.13	0.01		0.07	−0.01
		(0.12)	(0.13)		(0.11)	(0.13)
Week 1 × Flood × FDP		0.39	0.10		0.38	0.10
		(0.43)	(0.70)		(0.43)	(0.70)
Week 2 × Flood × FDP		0.28	−0.05		0.37	0.08
		(0.17)	(0.21)		(0.25)	(0.29)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Week 3 × Flood × FDP		0.40	0.13		0.39	0.16
		(0.26)	(0.21)		(0.26)	(0.22)
Week 4 × Flood × FDP		−0.09	−0.49**		−0.09	−0.46*
		(0.26)	(0.25)		(0.26)	(0.24)
Week -3 × Flood × Green		−0.05	−0.14		−0.07	−0.15
		(0.40)	(0.32)		(0.40)	(0.32)
Week -2 × Flood × Green		0.11	−0.00		0.11	0.00
		(0.24)	(0.21)		(0.24)	(0.21)
Week -1 × Flood × Green		0.42	0.36		0.41	0.37
		(0.32)	(0.28)		(0.32)	(0.28)
Week 1 × Flood × Green		2.14*	2.10*		2.13*	2.09*
		(1.15)	(1.10)		(1.15)	(1.11)
Week 2 × Flood × Green		0.43	0.30		0.43	0.27
		(0.40)	(0.32)		(0.40)	(0.33)
Week 3 × Flood × Green		0.73*	0.70*		0.73*	0.69
		(0.43)	(0.41)		(0.43)	(0.42)
Week 4 × Flood × Green		1.46**	1.46**		1.40**	1.40**
		(0.70)	(0.63)		(0.67)	(0.61)
Week -3 × Flood × SPD		0.06	−0.06		−0.01	−0.12
		(0.04)	(0.14)		(0.07)	(0.15)
Week -2 × Flood × SPD		−0.05	−0.19		−0.05	−0.19
		(0.12)	(0.15)		(0.12)	(0.15)
Week -1 × Flood × SPD		0.09	−0.00		0.03	−0.04
		(0.06)	(0.10)		(0.04)	(0.08)
Week 1 × Flood × SPD		0.13	−0.04		0.06	−0.10
		(0.13)	(0.26)		(0.09)	(0.25)
Week 2 × Flood × SPD		0.30*	0.08		0.20**	−0.02
		(0.17)	(0.19)		(0.09)	(0.14)
Week 3 × Flood × SPD		0.12*	−0.04		−0.10	−0.24
		(0.07)	(0.14)		(0.16)	(0.19)
Week 4 × Flood × SPD		0.31	0.09		0.15	−0.05
		(0.39)	(0.38)		(0.29)	(0.30)
Week -3 × Flood × Incumbent			0.22			0.20
			(0.21)			(0.21)
Week -2 × Flood × Incumbent			0.23			0.23
			(0.15)			(0.15)
Week -1 × Flood × Incumbent			0.16			0.12
			(0.11)			(0.10)
Week 1 × Flood × Incumbent			0.56			0.54
			(0.59)			(0.59)
Week 2 × Flood × Incumbent			0.50**			0.40*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
			(0.20)			(0.21)
Week 3 × Flood × Incumbent			0.54**			0.44*
			(0.23)			(0.24)
Week 4 × Flood × Incumbent			0.85**			0.78**
			(0.37)			(0.35)
Week -3 × Flood × Female			0.07			0.09
			(0.19)			(0.18)
Week -2 × Flood × Female			0.13			0.13
			(0.15)			(0.15)
Week -1 × Flood × Female			0.05			0.04
			(0.17)			(0.16)
Week 1 × Flood × Female			−0.18			−0.17
			(0.53)			(0.52)
Week 2 × Flood × Female			0.03			0.13
			(0.25)			(0.28)
Week 3 × Flood × Female			−0.19			−0.11
			(0.26)			(0.25)
Week 4 × Flood × Female			−0.38			−0.35
			(0.35)			(0.32)
N	7352	7352	7352	7352	7352	7352
Candidates	919	919	919	919	919	919
R^2	0.50	0.50	0.50	0.49	0.49	0.49
Adj. R^2	0.42	0.42	0.42	0.41	0.41	0.41

The unit of analysis is the number of tweets per week mentioning the climate topic. Models 1-3 use the dictionary measure described in the main text. Models 4-6 use an alternative more expansive climate change dictionary from Schwörer (2024). CR2 standard errors clustered at the individual and district. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table E4 presents the results of the event study replication omitting all retweets. The first three models demonstrate the robustness of the results in the main text through original content from candidates. In the remaining models, I use the alternative dictionary measure described in Appendix D. Across all six models, the evidence is consistent with conditional wave-riding in which affected candidates from the issue-owning Greens increased their climate rhetoric to a larger extent than their non-affected peers. In a similar fashion to the results in the main texts, we observe a slight uptick in issue attention from the far-left Die Linke party's candidates that we also affected, although this effect is not robust to the inclusion of demographic controls (i.e., gender and incumbency). In both models, there is evidence of affected incumbents increasing their climate issue attention following the floods. In Table 2, I demonstrated that these effects were entirely driven by the Green party, given the inclusion of an additional dimension of difference, thereby reducing statistical power, it is unreliable to further probe trends by partisanship, incumbency and affected status.

Table E5 omits retweets coming from the central party account. The evidence in favor of a conditional wave-riding hypothesis remains unchanged. While coefficients, in a similar fashion to the monthly analysis attentuate slightly, the conditional response by affected status within the Green party remains. This is true for both the original dictionary (Models 1-3) as well as an alternative (Models 4-6). In line with the monthly results in Appendix D, there is evidence of CDU candidates in affected districts *descreasing* their climate issue attention – this is evident in both measures of climate issue attention.

Table E5: Event Study Replication omitting party retweets

	Climate Count			Schwörer Dictionary		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Week -3 × Flood × Green Bin	−0.72			0.98		
	(0.74)			(0.90)		
Week -2 × Flood × Green Bin	−0.50			1.35		
	(0.88)			(1.02)		
Week -1 × Flood × Green Bin	0.21			1.96*		
	(0.90)			(1.01)		
Week 1 × Flood × Green Bin	3.69**			4.19**		
	(1.72)			(1.85)		
Week 2 × Flood × Green Bin	1.21			1.38		
	(0.96)			(0.99)		
Week 3 × Flood × Green Bin	0.83			1.12*		
	(0.62)			(0.67)		
Week 4 × Flood × Green Bin	2.89**			2.74**		
	(1.39)			(1.38)		
Week -3 × Flood × AfD		0.48**	0.38		0.55**	0.37
		(0.20)	(0.24)		(0.26)	(0.33)
Week -2 × Flood × AfD		−0.06	−0.27		−0.13	−0.52*
		(0.07)	(0.21)		(0.11)	(0.30)
Week -1 × Flood × AfD		0.02	−0.07		−0.12	−0.32
		(0.11)	(0.16)		(0.11)	(0.23)
Week 1 × Flood × AfD		1.07	0.71		1.53	1.17
		(1.04)	(0.93)		(1.40)	(1.27)
Week 2 × Flood × AfD		0.38	0.12		0.66*	0.46
		(0.24)	(0.23)		(0.36)	(0.37)
Week 3 × Flood × AfD		0.36**	0.20		0.58***	0.50**
		(0.15)	(0.17)		(0.20)	(0.23)
Week 4 × Flood × AfD		−0.58**	−1.07***		−0.66*	−1.20***

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
		(0.28)	(0.35)		(0.37)	(0.45)
Week -3 × Flood × CDU		0.01	−0.20		−0.12	−0.54
		(0.19)	(0.36)		(0.24)	(0.36)
Week -2 × Flood × CDU		−0.17	−0.59		−0.32	−1.06**
		(0.21)	(0.45)		(0.29)	(0.48)
Week -1 × Flood × CDU		0.14	−0.04		0.19	−0.23
		(0.26)	(0.40)		(0.43)	(0.50)
Week 1 × Flood × CDU		−0.29	−1.02*		−0.46*	−1.15
		(0.18)	(0.57)		(0.27)	(0.86)
Week 2 × Flood × CDU		0.54	0.04		0.92*	0.43
		(0.34)	(0.43)		(0.53)	(0.67)
Week 3 × Flood × CDU		−0.23	−0.50*		−0.52	−0.65
		(0.19)	(0.28)		(0.36)	(0.48)
Week 4 × Flood × CDU		−0.06	−0.80		0.11	−0.72
		(0.63)	(0.73)		(0.86)	(0.96)
Week -3 × Flood × Die Linke		−0.07	−0.19		−0.33	−0.72*
		(0.18)	(0.25)		(0.30)	(0.41)
Week -2 × Flood × Die Linke		0.12	−0.11		0.09	−0.56
		(0.29)	(0.34)		(0.44)	(0.53)
Week -1 × Flood × Die Linke		−0.07	−0.17		−0.17	−0.47
		(0.14)	(0.22)		(0.20)	(0.33)
Week 1 × Flood × Die Linke		0.16	−0.25		0.24	−0.26
		(0.25)	(0.44)		(0.32)	(0.73)
Week 2 × Flood × Die Linke		0.11	−0.16		0.19	−0.22
		(0.11)	(0.27)		(0.15)	(0.46)
Week 3 × Flood × Die Linke		0.99**	0.89*		1.58**	1.52**
		(0.48)	(0.51)		(0.68)	(0.75)
Week 4 × Flood × Die Linke		0.33	0.12		0.79	0.58
		(0.60)	(0.75)		(0.84)	(1.15)
Week -3 × Flood × FDP		−0.07	−0.30		−0.26*	−0.82**
		(0.14)	(0.32)		(0.16)	(0.41)
Week -2 × Flood × FDP		−0.02	−0.46		−0.14	−1.06*
		(0.20)	(0.44)		(0.24)	(0.59)
Week -1 × Flood × FDP		−0.02	−0.22		−0.14	−0.68
		(0.18)	(0.33)		(0.21)	(0.47)
Week 1 × Flood × FDP		0.28	−0.50		0.32	−0.46
		(0.47)	(0.91)		(0.57)	(1.23)
Week 2 × Flood × FDP		0.25	−0.27		0.40	−0.20
		(0.22)	(0.44)		(0.35)	(0.62)
Week 3 × Flood × FDP		0.61	0.36		0.77	0.52
		(0.38)	(0.34)		(0.50)	(0.46)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Week 4 × Flood × FDP		−0.42	−1.07*		−0.55	−1.25
		(0.32)	(0.62)		(0.37)	(0.84)
Week -3 × Flood × Green		−0.72	−0.86		0.97	0.61
		(0.74)	(0.59)		(0.90)	(0.73)
Week -2 × Flood × Green		−0.51	−0.78		1.33	0.79
		(0.88)	(0.65)		(1.02)	(0.78)
Week -1 × Flood × Green		0.21	0.09		1.95*	1.64
		(0.91)	(0.91)		(1.02)	(1.05)
Week 1 × Flood × Green		3.71**	3.23**		4.21**	3.72**
		(1.72)	(1.50)		(1.86)	(1.69)
Week 2 × Flood × Green		1.24	0.95		1.42	0.97
		(0.96)	(0.77)		(0.99)	(0.79)
Week 3 × Flood × Green		0.86	0.80		1.15*	1.09*
		(0.62)	(0.49)		(0.68)	(0.60)
Week 4 × Flood × Green		2.87**	2.86**		2.72*	2.74**
		(1.39)	(1.25)		(1.39)	(1.24)
Week -3 × Flood × SPD		0.12	−0.06		−0.10	−0.54
		(0.10)	(0.27)		(0.16)	(0.35)
Week -2 × Flood × SPD		−0.12	−0.46		−0.31	−1.02**
		(0.14)	(0.37)		(0.21)	(0.49)
Week -1 × Flood × SPD		−0.07	−0.22		−0.23**	−0.61**
		(0.10)	(0.26)		(0.11)	(0.31)
Week 1 × Flood × SPD		−0.08	−0.69		−0.20	−0.83
		(0.14)	(0.48)		(0.15)	(0.72)
Week 2 × Flood × SPD		0.23	−0.17		0.23	−0.23
		(0.19)	(0.35)		(0.18)	(0.42)
Week 3 × Flood × SPD		0.14	−0.02		−0.26	−0.38
		(0.11)	(0.23)		(0.30)	(0.39)
Week 4 × Flood × SPD		−0.06	−0.42		−0.29	−0.72
		(0.42)	(0.60)		(0.40)	(0.71)
Week -3 × Flood × Incumbent			0.29			0.56
			(0.38)			(0.45)
Week -2 × Flood × Incumbent			0.57			1.02
			(0.50)			(0.62)
Week -1 × Flood × Incumbent			0.25			0.60
			(0.35)			(0.48)
Week 1 × Flood × Incumbent			0.98			0.92
			(0.89)			(1.18)
Week 2 × Flood × Incumbent			0.71*			0.58
			(0.43)			(0.56)
Week 3 × Flood × Incumbent			0.44			0.36

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
			(0.27)			(0.37)
Week 4 × Flood × Incumbent			1.36*			1.34
			(0.72)			(0.90)
Week -3 × Flood × Female			0.16			0.51
			(0.37)			(0.49)
Week -2 × Flood × Female			0.28			0.66
			(0.45)			(0.59)
Week -1 × Flood × Female			0.13			0.32
			(0.44)			(0.57)
Week 1 × Flood × Female			0.52			0.48
			(0.81)			(1.10)
Week 2 × Flood × Female			0.26			0.58
			(0.50)			(0.67)
Week 3 × Flood × Female			−0.06			−0.07
			(0.37)			(0.51)
Week 4 × Flood × Female			−0.57			−0.68
			(0.68)			(0.86)
N	7352	7352	7352	5583	5583	5583
Candidates	919	919	919	919	919	919
R^2	0.59	0.60	0.60	0.65	0.65	0.65
Adj. R^2	0.54	0.53	0.54	0.58	0.58	0.58

The unit of analysis is the number of tweets per week mentioning the climate topic. Models 1-3 use the dictionary measure described in the main text. Models 4-6 use an alternative more expansive climate change dictionary from Schwörer (2024). CR2 standard errors clustered at the individual and district. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

E.2 Belgium

Table E6: Regression Results: Flooding and Climate Change Campaign Rhetoric by Week

	Climate Count	
	Model 1	Model 2
Num. of Tweets	0.01***	0.01***
	(0.00)	(0.00)
Week -3 × Flood	0.17*	
	(0.08)	
Week -2 × Flood	0.05	
	(0.10)	
Week -1 × Flood	0.10	
	(0.10)	
Week 1 × Flood	0.10	
	(0.14)	
Week 2 × Flood	0.17	
	(0.10)	
Week 3 × Flood	0.20*	
	(0.09)	
Week 4 × Flood	0.08	
	(0.10)	
Week -3 × Flood × Green		0.35***
		(0.07)
Week -2 × Flood × Green		0.02
		(0.09)
Week -1 × Flood × Green		0.10
		(0.09)
Week 1 × Flood × Green		1.72***
		(0.12)
Week 2 × Flood × Green		0.63***
		(0.10)
Week 3 × Flood × Green		1.07***
		(0.09)
Week 4 × Flood × Green		0.54***
		(0.09)
ID and Week FE	Yes	Yes
N	1008	1008
R^2	0.39	0.40
Adj. R^2	0.29	0.30

CR2 Errors clustered at individual and district. The unit of analysis is the MP-week. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E7: Data used to produce Figure 5

	Climate Count
	Model 1
Tweet Count (per week)	0.01^{***}
	(0.00)
Week -3 × Christian Democrat	-0.06
	(0.09)
Week -3 × Green	0.35^{**}
	(0.08)
Week -3 × Liberal	0.34^{*}
	(0.15)
Week -3 × Social Democrat	-0.11
	(0.08)
Week -2 × Christian Democrat	0.04
	(0.10)
Week -2 × Green	0.01
	(0.10)
Week -2 × Liberal	0.04
	(0.10)
Week -2 × Social Democrat	0.07
	(0.11)
Week -1 × Christian Democrat	0.06
	(0.10)
Week -1 × Green	0.10
	(0.10)
Week -1 × Liberal	0.11
	(0.10)
Week -1 × Social Democrat	0.09
	(0.10)
Week 1 × Christian Democrat	-0.25
	(0.15)
Week 1 × Green	1.69^{***}
	(0.14)
Week 1 × Liberal	-0.25
	(0.15)
Week 1 × Social Democrat	-0.20
	(0.15)
Week 2 × Christian Democrat	0.07
	(0.10)
Week 2 × Green	0.63^{***}
	(0.11)
Week 2 × Liberal	0.06

Table E7: Data used to produce Figure 5

	Climate Count
	Model 1
	(0.10)
Week 2 × Social Democrat	0.09
	(0.11)
Week 3 × Christian Democrat	0.00
	(0.09)
Week 3 × Green	1.06^{***}
	(0.10)
Week 3 × Liberal	0.02
	(0.09)
Week 3 × Social Democrat	−0.00
	(0.09)
Week 4 × Christian Democrat	−0.04
	(0.10)
Week 4 × Green	0.53^{***}
	(0.11)
Week 4 × Liberal	−0.04
	(0.10)
Week 4 × Social Democrat	0.01
	(0.10)
ID and Week FE	Yes
Yes	
N	992
Candidates	124
R^2	0.40
Adj. R^2	0.29

The unit of analysis is the number of tweets per week mentioning the climate topic. CR2 standard errors clustered at the individual and district. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

E.3 Geographic Spillovers

In this appendix, I consider the extent of geographic spillovers in issue attention. To do this, I generate a novel measure of flooded status with an intermediate category for those districts that are adjacent to flooded districts. This disaggregation of unaffected status lets me assess whether indirect exposure to a salience shock may likewise drive increases in issue attention. Descriptively, Figure E1 presents the daily trends in the average number of climate tweets by party at varying levels of flooded status. In Table E8, I present analogous regression equations to Table E2. In general, there is some descriptive evidence of spillovers, that is adjacent districts do increase their climate issue attention. However, Green candidates in fully flooded districts differ in their issue attention following the floods even with adjacent districts as the baseline; once again, this heterogeneity in issue attention is only evident among the Green party.

Figure E1: Daily Trends in Climate Issue Attention by Flood Exposure

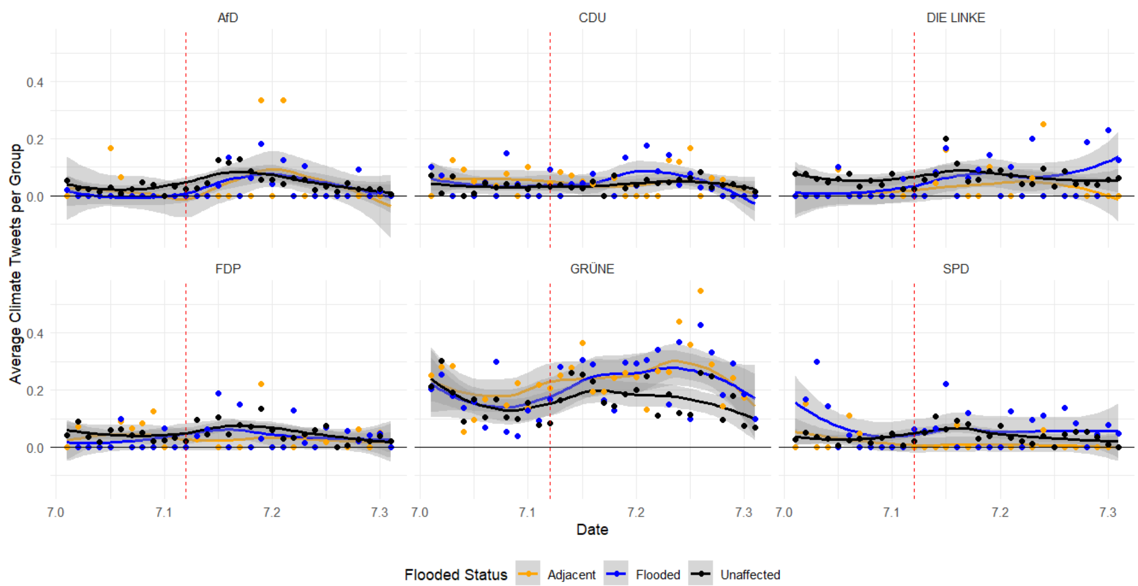


Figure E1 breaks down the trends in the average number of climate-referencing tweets by party. Two trends are of interest. First, outside of the Green party, there is little to no daily engagement with the climate issue as measured by the dictionary. Second, within the Green party, there is a clear increase in attention by directly and indirectly exposed districts following the flood. This divergence persists for the remainder of July. Given that only 25 districts share a border with a district that was flooded, these spillovers are not strong enough to bias the core results towards zero. This is clear in Figure E2, which replicates Figure E1, albeit with the primary measure of flooded status used in the main text. In cases where individuals and communities in adjacent communities regularly interact, for example for work or leisure, with the affected districts, it is unsurprising that candidates in these neighboring districts might increase their attention to climate change as their constituents are likewise affected. More broadly, while the impacts of flooding were restricted to those districts with rivers running through them, the torrential downpours were more widespread.

Figure E2: Daily Trends in Climate Issue Attention by Flood Exposure

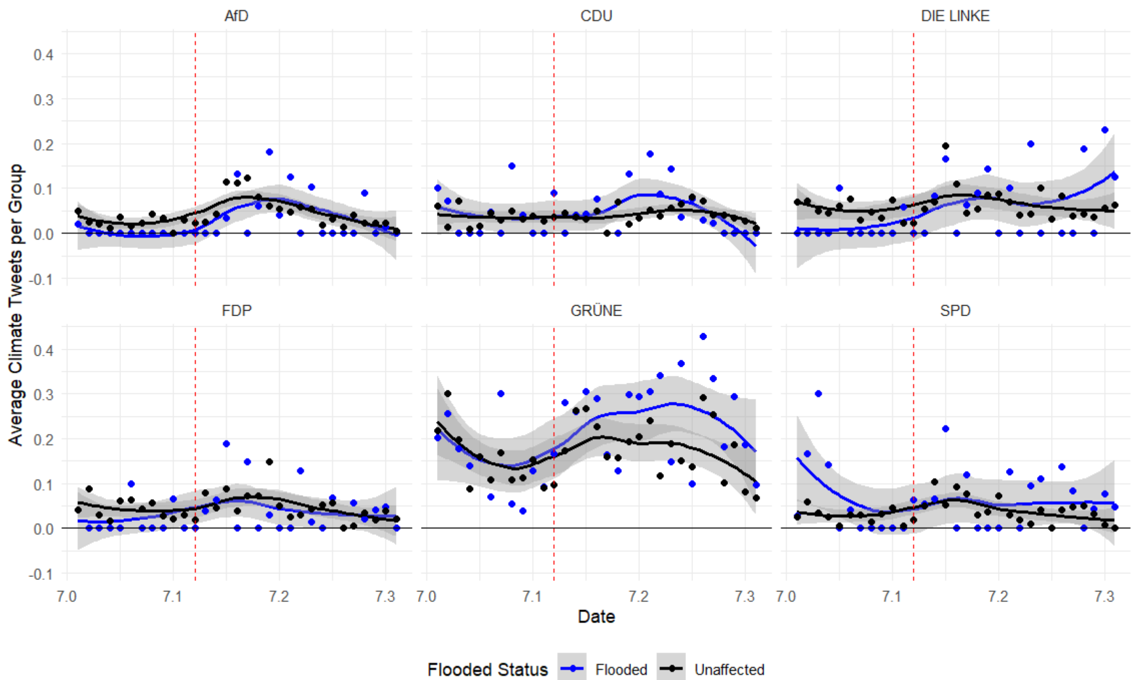


Table E8 presents the results of two regression analyses to more rigorously assess the presence of spillovers. In Model 1, I consider whether variation in issue attention exists between candidates in districts adjacent to flooding compared to the unaffected districts. Model 2 uses these adjacent districts as a baseline for the flooded districts. There is little evidence of spillovers in issue attention – candidates representing adjacent districts increase their climate issue attention; It is not statistically distinguish from unaffected candidates however. Compared against their neighbors, Green candidates representing flooded districts increased their climate issue attention mirroring the results in Figure 4.

Table E8: Impact of Flooding Dosage on Climate Issue Attention

	Model 1	Model 2
Week -3 × Flood × AfD	-0.03	0.59
	(0.13)	(0.44)
Week -2 × Flood × AfD	-0.30^{***}	0.70

	Model 1	Model 2
	(0.11)	(0.75)
Week -1 × Flood × AfD	-0.49^{***}	-0.12
	(0.16)	(0.24)
Week 1 × Flood × AfD	-0.31^{**}	0.83
	(0.13)	(0.79)
Week 2 × Flood × AfD	0.07	0.85
	(0.11)	(0.83)
Week 3 × Flood × AfD	-0.16	0.58
	(0.13)	(0.46)
Week 4 × Flood × AfD	-0.61^{***}	-0.59
	(0.21)	(0.50)
Week -3 × Flood × CDU	0.58	0.06
	(0.55)	(0.28)
Week -2 × Flood × CDU	0.57	-0.39^{*}
	(0.57)	(0.20)
Week -1 × Flood × CDU	-0.18	0.18
	(0.40)	(0.29)
Week 1 × Flood × CDU	-0.70^{**}	-0.27
	(0.29)	(0.25)
Week 2 × Flood × CDU	0.05	0.05
	(0.30)	(0.33)
Week 3 × Flood × CDU	-0.19	-0.12
	(0.37)	(0.35)
Week 4 × Flood × CDU	-0.10	-0.17
	(0.36)	(0.56)
Week -3 × Flood × Die Linke	0.06	0.15
	(0.27)	(0.33)
Week -2 × Flood × Die Linke	0.07	0.31
	(0.32)	(0.40)
Week -1 × Flood × Die Linke	-0.38^{**}	-0.07
	(0.15)	(0.30)
Week 1 × Flood × Die Linke	0.07	0.30
	(0.45)	(0.31)
Week 2 × Flood × Die Linke	0.26	0.25
	(0.42)	(0.26)
Week 3 × Flood × Die Linke	0.26	1.30^{**}
	(0.30)	(0.58)
Week 4 × Flood × Die Linke	0.07	0.22
	(0.49)	(0.55)
Week -3 × Flood × FDP	-0.26	0.18
	(0.47)	(0.32)

	Model 1	Model 2
Week -2 × Flood × FDP	-0.59^{***}	-0.18
	(0.21)	(0.30)
Week -1 × Flood × FDP	-0.25	0.03
	(0.31)	(0.24)
Week 1 × Flood × FDP	-0.31^{*}	0.53
	(0.19)	(0.56)
Week 2 × Flood × FDP	-0.79^{**}	-0.10
	(0.31)	(0.44)
Week 3 × Flood × FDP	-0.26	0.97^{**}
	(0.21)	(0.40)
Week 4 × Flood × FDP	-1.36^{**}	-0.66^{*}
	(0.69)	(0.35)
Week -3 × Flood × Green	-0.40	-0.39
	(0.53)	(0.68)
Week -2 × Flood × Green	-0.34	-0.23
	(0.56)	(0.81)
Week -1 × Flood × Green	0.09	0.32
	(0.36)	(0.86)
Week 1 × Flood × Green	0.52	3.10^{**}
	(0.63)	(1.46)
Week 2 × Flood × Green	0.70	1.36^{*}
	(0.46)	(0.80)
Week 3 × Flood × Green	-0.27	1.01^{*}
	(0.60)	(0.53)
Week 4 × Flood × Green	2.07^{***}	2.41^{*}
	(0.76)	(1.27)
Week -3 × Flood × SPD	-0.03	0.11
	(0.16)	(0.31)
Week -2 × Flood × SPD	0.09	-0.22
	(0.25)	(0.22)
Week -1 × Flood × SPD	0.00	0.06
	(0.19)	(0.18)
Week 1 × Flood × SPD	-0.45^{***}	-0.04
	(0.16)	(0.26)
Week 2 × Flood × SPD	-0.09	0.03
	(0.17)	(0.32)
Week 3 × Flood × SPD	-0.11	0.16
	(0.16)	(0.29)
Week 4 × Flood × SPD	-0.23	-0.05
	(0.24)	(0.37)
Num. obs.	6560	1432

	Model 1	Model 2
Group?	Adjacent + Control	Treatment + Adjacent
R^2	0.70	0.75
Adj. R^2	0.66	0.70

The outcome is the number of tweets per candidate per week that discuss the climate issue. Model 1 drops flooded districts and compares shifts in rhetoric between districts adjacent to flooding and those unaffected, or with two degrees of separation. Model 2 drops unaffected districts and compares flooded districts to the districts adjacent to them. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

E.4 Campaign Communication Dynamics

In this appendix, I consider whether the flooding impacted general candidate camapign rhetoric, given that physical destruction might have reduced the ability for candidates to campaign in person. Table E9 presents the results of analagous event study to that in Figure 4, albeit where the outcome is the number of tweets, irrespective of content. In general, there are no clear trends in terms of communication medium based on flood exposure within the various parties. Absent clear increases in the amount that candidates posted, this suggests an interpretation of the main results in line with affected Green candidates dedicating increased attention to climate at the expense of other issues.

Table E9: Campaign Communication Dynamics

	Tweet Count
	Model 1
Week -3 × Flood × AfD	0.67
	(3.50)
Week -2 × Flood × AfD	−9.02
	(9.02)
Week -1 × Flood × AfD	3.35
	(2.71)
Week 1 × Flood × AfD	4.44
	(4.67)
Week 2 × Flood × AfD	−6.77
	(7.25)
Week 3 × Flood × AfD	−0.96
	(3.90)
Week 4 × Flood × AfD	−2.26
	(3.16)
Week -3 × Flood × CDU	0.36
	(1.50)
Week -2 × Flood × CDU	3.30*
	(1.85)
Week -1 × Flood × CDU	1.05
	(1.83)
Week 1 × Flood × CDU	1.25
	(1.88)
Week 2 × Flood × CDU	5.27***
	(1.58)

	Tweet Count
	Model 1
Week 3 × Flood × CDU	1.10
	(3.66)
Week 4 × Flood × CDU	−0.31
	(2.92)
Week -3 × Flood × Die Linke	−1.70
	(2.17)
Week -2 × Flood × Die Linke	0.34
	(2.63)
Week -1 × Flood × Die Linke	1.54
	(2.58)
Week 1 × Flood × Die Linke	−0.20
	(2.17)
Week 2 × Flood × Die Linke	−2.68
	(2.38)
Week 3 × Flood × Die Linke	−0.87
	(2.04)
Week 4 × Flood × Die Linke	−0.99
	(1.89)
Week -3 × Flood × FDP	−2.25
	(3.02)
Week -2 × Flood × FDP	2.54
	(2.85)
Week -1 × Flood × FDP	0.88
	(2.34)
Week 1 × Flood × FDP	−1.62
	(3.17)
Week 2 × Flood × FDP	4.10
	(4.96)
Week 3 × Flood × FDP	−2.66
	(2.93)
Week 4 × Flood × FDP	0.61
	(2.57)
Week -3 × Flood × Green	-11.45^{*}
	(6.13)
Week -2 × Flood × Green	-11.25^{*}
	(6.60)
Week -1 × Flood × Green	−0.51
	(5.33)
Week 1 × Flood × Green	4.95
	(5.35)

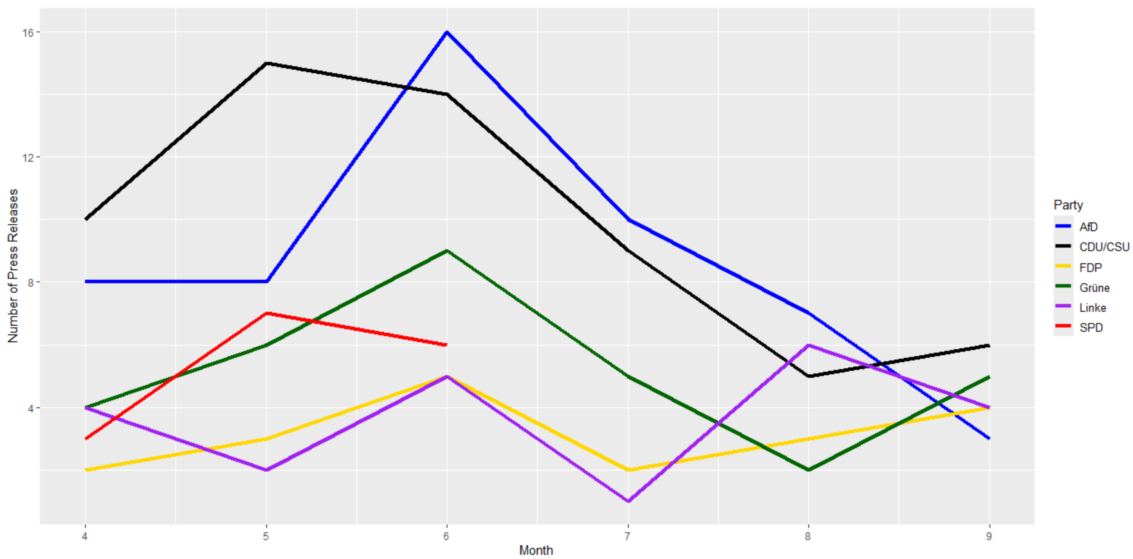
	Tweet Count
	Model 1
Week 2 × Flood × Green	−7.21
	(6.46)
Week 3 × Flood × Green	−4.88
	(7.96)
Week 4 × Flood × Green	−2.79
	(7.00)
Week -3 × Flood × SPD	1.04
	(2.48)
Week -2 × Flood × SPD	1.83
	(1.22)
Week -1 × Flood × SPD	0.63
	(1.30)
Week 1 × Flood × SPD	0.99
	(1.82)
Week 2 × Flood × SPD	1.54
	(1.70)
Week 3 × Flood × SPD	1.52
	(2.23)
Week 4 × Flood × SPD	−1.78
	(2.85)
N	7352
Candidates	919
R^2	0.71
Adj. R^2	0.66

The outcome is the number of tweets per candidate per week. Robust standard errors clustered at the candidate and district level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

F Environmental Issue Attention in Press Releases

The figure below highlights the variation in issue attention in press releases related to the environment from Ivanusch, Zehnter and Burst (2023). The authors train a BERT model using hand-coded manifesto texts to then classify the press releases from each party. While the directional position of the documents is not measured with this strategy, the two parties speaking most about the issue are the CDU and the AfD, the latter of which is staunchly against climate policy. In terms of the CDU, we again see high engagement at the level of the party that does not extend to rank and file candidates, highlighting the importance of studying a variety of communication media to understand issue competition.

Figure F1: Monthly Environmental Press Releases from the major parties



G Electoral Outcomes

A large literature in political science studies the electoral impacts of natural disasters, such as wildfires or floods. Notable in this broader literature are studies focusing on the German case. Early work by Bechtel and Hainmueller (2011) assess the long term implications of disaster relief for the incumbent SPD, finding durable electoral gains by the party in the aftermath of the 2002 Elbe floods. Analyzing the electoral impacts of the 2021 floods in Western Germany, Hilbig and Riaz (2024) focus on North-Rhineland Westphalia and Rhineland Palatinate, the two most affected states. Their findings show no impact of direct exposure to flooding between municipalities in these states. Garside and Zhai (2022) find a modest impact of flooding, largely driven by those areas moderately affected by the floods rather than in municipalities in districts such as Ahrweiler, which saw substantial destruction. In their analysis of the drivers of this shift, they conclude that persuasion, rather than mobilization is likely to be driving the modest shift to the Green party, primarily from its mainstream (CDU & SPD) competitors.

In the tables that follow, I first present a full country analysis, before subsetting to the two most affected states, in effect replicating the results of Hilbig and Riaz (2024), albeit with a focus on the first vote rather than the second. The similarity in results in Tables G1 and G2 (in particular Models 5 & 6 in each Table) suggest that treatment spillovers occurred. The null estimates in the subset analysis focusing on the two most affected states, alongside the smaller coefficient size when considering all districts in the affected states as treated suggests that both direct and indirect exposure to flooding may have impacted green vote share. Finally I present the pre-period trends of the analysis that focuses on those districts for which I have candidate rhetoric data and describe in greater detail the doubly robust estimation strategy (Callaway and Sant'Anna, 2021).

Table G1 presents results using a TWFE estimator for all districts in Germany. Odd columns present results using data from the 2021 and 2017 elections, whereas even columns use data from 2017 and 2013, acting as placebo tests for potential violations of the parallel trends assumption. As is evident in columns 4 & 6, flooded districts diverged from their non-affected comparison districts for both the SPD and the Greens. These pretrends along with the fact that propensity to be flooded is not strictly exogenous motivates by decision to implement the doubly robust estimator below alongside the traditional TWFE estimator.

Table G2 presents the results using an alternative treatment coding (odd columns) and the subset analysis (even columns). Similar to above, there is no evidence of the floods having any impact on CDU vote share. However, when considering all districts

Table G1: Regression Results: Flooding and Electoral Outcomes

	CDU Vote Share Shift		SPD Vote Share Shift		Green Vote Share Shift	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
DiD	0.00	−0.00	-0.01^{**}	0.01^{**}	0.01^{***}	-0.01^{**}
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
% Foreign Pop	0.01^{**}	-0.30^{**}	−0.00	0.13	-0.01^{**}	−0.07
	(0.00)	(0.11)	(0.00)	(0.09)	(0.00)	(0.08)
Pop Density	0.00	−0.00	0.00	−0.00	−0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Birth Balance	0.00	0.01^{**}	-0.01^{***}	-0.01^{***}	0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Migration Balance	-0.00^{*}	−0.00	0.00	0.00	-0.00^{**}	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Social Insurance Payment	0.00	0.00	-0.00^{**}	0.00	0.00^{*}	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Percent Manufacturing	−0.00	0.00	0.00	−0.00	−0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Unemployment Rate	−0.00	0.01^{**}	-0.01^{**}	−0.00	0.00	−0.00
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Post-Period	0.00	0.30^{**}	−0.00	−0.13	0.00	0.07
× Foreign Pop	(0.00)	(0.11)	(0.00)	(0.09)	(0.00)	(0.08)
Post-Period	0.00^{*}	0.00	−0.00	0.00	0.00	-0.00^{*}
× Pop Density	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Post-Period	−0.00	−0.00	−0.00	0.00^{**}	0.00^{**}	0.00
× Birth Balance	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Post-Period	−0.00	0.00	0.00^{**}	−0.00	−0.00	−0.00
× Migration Balance	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Post-Period	−0.00	−0.00	−0.00	−0.00	0.00	0.00
× Social Insurance Payment	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Post-Period	−0.00	−0.00	0.00	0.00	-0.00^{***}	−0.00
× Percent Manufacturing	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Post-Period	−0.00	0.00^{*}	0.00	-0.00^{*}	0.00	−0.00
× Unemployment Rate	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
District and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	592	592	592	592	592	592
Num. groups: district_number	299	299	299	299	299	299
R^2	0.97	0.97	0.97	0.99	0.96	0.97
Adj. R^2	0.95	0.93	0.94	0.97	0.91	0.94

CR2 errors clustered at state. The unit of analysis is the district-year. The analysis includes all districts with complete sets of covariates. Odd columns present the DiD estimator for the shift in vote share between 2021 and 2017. Odd columns present the analogous estimation but with the difference between 2017 and 2013. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

in North Rhineland Westphalia and Rhineland Palatinate as treated in columns 3 & 5 the results parallel the findings in Table G1. Furthermore, when subsetting to just these districts, there is no evidence of a direct effect of flooding exposure in line with other work (Hilbig and Riaz, 2024). I take this as suggestive evidence that flooding generated spillovers–districts adjacent to flooding may have been impacted (e.g., road or bridge closures)–hence understanding the total impact at the local level is challenging. Given that treatment is not exogenous and that certain districts may have been more likely to receive it than others I discuss in further detail the inverse propensity weighting (IPW) component of the doubly robust estimator.

The general intuition behind doubly robust estimators is that they provide the researcher with two chances to get identification correct–either via the correct specification of the propensity score measure or via the correct specification of the regression equation (Aronow and Miller, 2019; Callaway and Sant'Anna, 2021). In either case, the goal is conditional independence to identify the causal effect of some observational treatment variable. In selecting variables to include in the IPW specification, ideal variables are those which are believed to predict treatment assignment. At the same time, overfitting is a concern as certain variables may generate large weights in the resulting propensity score (Morgan and Winship, 2015, p. 238-39). In the present context, using an indicator of district's state would be a case of overfitting–in most cases it perfectly predicts the absence of treatment, thereby assigning these units with no weight. As noted above, studies of the electoral impacts of flooding in Germany cover collectively almost the entirety of the national territory. The specific occurrence of flooding in the 2021 floods should, therefore, not be used to model, the likelihood that a given district *could* be exposed to flooding in general.

At the district level, I used socio-demographic data to capture the extent of development based off a logic that more developed or urban areas likely have more infrastructure to mitigate the impact of flooding (e.g., embankments). I regress all district socio-demographic variables included above to assess predictors of treatment with unemployment and social insurance contributions per 1000 as statistically significant predictors of treatment. These variables serve as my regressors in the inverse propensity score measure used to weight observations in the ultimate regression equation. Table G3 replicates the TWFE estimates from Table 5 Columns 1 & 3. The even columns present the analogous regressions albeit with the time indicator taking a value of 1 for all elections after 2013. The significant coefficients for the DiD and DiD $\times$ Climate Shift provide evidence of violations of the parallel trends assumption, hence motivating my usage of the DR estimator. In Table G4, I present the coefficients for the pre-period tests of parallel trends violations along with the coefficients from Table 5. The results suggest no evidence of violations of the parallel trends

Table G2: Regression Results: Flooding and Electoral Outcomes

	CDU Vote Share Shift		SPD Vote Share Shift		Green Vote Share Shift	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
DiD	0.00	0.00	-0.02^{***}	0.00	0.02^{*}	0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
% Foreign Pop	0.01^{**}	0.00	-0.00	0.01	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
Pop Density	0.00	-0.00	0.00	-0.00^{*}	-0.00	0.00^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Birth Balance	0.00	-0.01	-0.01^{***}	0.01	0.00	-0.01
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Migration Balance	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00^{**}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Social Insurance Payment	0.00	-0.00	-0.00^{*}	0.00	0.00	0.00^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Percent Manufacturing	-0.00	0.00	0.00	-0.00	0.00	-0.01^{*}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Unemployment Rate	-0.00	-0.01^{*}	-0.01^{**}	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
Post-Period	0.00	-0.00	-0.00	0.00	-0.00	-0.00^{**}
× Foreign Pop	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Post-Period	0.00^{*}	-0.00	-0.00	0.00^{*}	0.00	0.00
× Pop Density	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Post-Period	-0.00	-0.00	-0.00	-0.00	0.00^{**}	0.01^{*}
× Birth Balance	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Post-Period	-0.00	0.00	0.00^{**}	-0.00^{*}	-0.00	0.00
× Migration Balance	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Post-Period	-0.00	0.00	-0.00^{**}	-0.00^{**}	0.00	0.00^{*}
× Social Insurance Payment	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Post-Period	-0.00	0.00	0.00^{*}	-0.00	-0.00^{***}	-0.00
× Percent Manufacturing	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Post-Period	-0.00	0.01^{***}	0.01^{***}	-0.01^{***}	-0.00	0.00
× Unemployment Rate	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
District and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	592	158	592	158	592	158
Num. groups: district number	299	79	299	79	299	79
R^2	0.97	0.99	0.98	0.94	0.96	0.96
Adj. R^2	0.95	0.97	0.95	0.85	0.92	0.90

CR2 errors clustered at state. The unit of analysis is the district-year. Odd columns code all districts in North-Rhine Westphalia and Rhineland-Palatinate as receiving treatment. Even columns subset to only these states. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

with the pre-period interaction coefficients an order of magnitude smaller.

Table G3: Regression Results: Flooding and Electoral Outcomes

	Implicit Measure		Explicit Measure	
	Model 1	Model 2	Model 3	Model 4
DiD	0.02^{***}	-0.01^{**}	0.10^{**}	-0.11^{***}
	(0.00)	(0.00)	(0.04)	(0.02)
DiD × Climate Shift			0.01^{**}	-0.00^{***}
			(0.00)	(0.00)
% Foreign Pop	-0.00	0.00^{***}	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Pop Density	-0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Birth Balance	-0.00	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Migration Balance	-0.00^{**}	-0.00^{**}	-0.00^{***}	-0.00^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
Social Insurance Payment	0.00	0.00	0.00^{**}	0.00^{**}
	(0.00)	(0.00)	(0.00)	(0.00)
Percent Manufacturing	0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Unemployment Rate	0.01^{***}	0.00	0.01^{***}	0.01^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
Post-Period × Foreign Pop	0.00	-0.00^{***}		
	(0.00)	(0.00)		
Post-Period × Pop Density	-0.00	-0.00^{**}		
	(0.00)	(0.00)		
Post-Period × Birth Balance	0.00	-0.00		
	(0.00)	(0.00)		
Post-Period × Migration Balance	-0.00	0.00		
	(0.00)	(0.00)		
Post-Period × Social Insurance Payment	0.00^{*}	-0.00^{*}		
	(0.00)	(0.00)		
Post-Period × Percent Manufacturing	-0.00^{***}	0.00^{***}		
	(0.00)	(0.00)		
Post-Period × Unemployment Rate	-0.00	0.00		
	(0.00)	(0.00)		
DiD × Foreign Pop			-0.00^{***}	-0.00
			(0.00)	(0.00)
DiD × Pop Density			0.00	0.00
			(0.00)	(0.00)
DiD × Birth Balance			-0.00	-0.00
			(0.00)	(0.00)
DiD × Migration Balance			-0.00	0.00^{**}
			(0.00)	(0.00)
DiD × Social Insurance Payment			0.00^{***}	0.00^{***}
			(0.00)	(0.00)
DiD × Percent Manufacturing			-0.00^{**}	0.00^{***}
			(0.00)	(0.00)
DiD × Unemployment Rate			0.00^{**}	-0.00
			(0.00)	(0.00)
District and Year FE	Yes	Yes	Yes	Yes
N	577	577	574	574
Districts:	194	194	193	193
R^2	0.95	0.93	0.93	0.92
Adj. R^2	0.92	0.89	0.88	0.88

CR2 errors clustered at state. The unit of analysis is the district-year. The first two columns present results using the implicit measure of rhetoric by subsetting. In columns 3 and 4, I interact the DiD measure with a binary indicator for above average climate rhetoric shift. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table G4: Regression Results: Flooding and Electoral Outcomes

	Model 1	Model 2
2017 × Flooded	−0.002	
	(0.004)	
2021 × Flooded	0.029**	
	(0.012)	
2017 × Flooded		0.002
× Bin-Shift		(0.005)
2021 × Flooded		0.04***
× Bin-Shift		(0.01)
District and Year FE	Yes	Yes
N	577	577
Districts:	194	194

CR2 errors clustered at state. The unit of analysis is the district-year. The first column present results using the implicit measure of rhetoric by subsetting. In column 2, I interact the DiD measure with a binary indicator for above average climate rhetoric shift. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

G.1 Geographic Spillovers

In this section, I assess the possibility of geographic spillovers to adjacent districts to those that actually experienced flooding. If individuals move and work in adjacent districts we may expect positive spillovers for the Greens, especially since these candidates likewise increased their climate rhetoric albeit to a slightly lesser extent than those candidates in fully flooded districts. To assess these geographic spillovers, I replicate the coding procedure in Appendix F, assess differential vote trends over time between unaffected, adjacent, and flooded districts within the two most affected provinces in Table G5.

As noted in the primary text, this dosage model also provides a means of reconciling the differences in the electoral impacts of flooding on the Green vote shares in the main text with those found by Hilbig and Riaz (2024). To reiterate, in their study, Hilbig and Riaz (2024) find little evidence of a direct impact of flooding on the Green vote share. In contrast, in Table G5, even subsetting to the two provinces that suffered almost all of the damages from flooding, I find that there is still a slight shift towards the Greens in districts that experienced flooding. There is also a slight increase among the adjacent counties, although this falls below conventional levels of statistical significance.

Several potential explanations exist for the difference in these results, I elaborate here the two most probable given the findings on candidate rhetoric and variation in the research designs. First given the evidence that Green candidates in both adjacent and flooded districts increased their rhetoric more than those in unaffected districts, it plausible that provides an account of why the green party did better, even in places that were not directly affected by flooding. These geographic spillovers would bias against an electoral finding, even in the present design, but even more so in a design focused on municipalities. Given that the average district in North Rhineland Westphalia and Rhineland Palatinate features on average roughly 20 municipalities, voters in these municipalities are exposed to the same candidates, candidates who I find significantly increased their climate rhetoric following the floods. The spatial decay in voting we observe in Table G5, would bias against a result at municipal level, even we are skeptical of candidate rhetoric having an effect as it demonstrates that places indirectly exposed increased their Green voting. Put differently, while direct exposure to flood may not have increased Green voting, proximate exposure appears to have done so.

Table G5: Dosage Model in North Rhineland Westphalia & Rhineland Palatinate

	Model 1
2013 × Adjacent	-0.00
	(0.00)
2021 × Adjacent	0.01
	(0.01)
2013 × Flooded	0.00
	(0.00)
2021 × Flooded	0.02^{*}
	(0.01)
N	237
R^2	0.87
Adj. R^2	0.80

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

G.2 Intra-District Rhetoric Shifts

In this section, I probe the robustness of the electoral analysis to an alternative baseline: climate rhetoric shifts within the district. The results are in line with the findings in Table 5, although the coefficient on the interaction between Flooded and a binary indicator for a climate attention shift above the district average falls below conventional levels of significance. When I assess the marginal effects of Flooding in each sub-group, I find a larger vote gain for those candidates that engaged with the climate issue at higher rates than their district peers.

Table G6: Intra-District Rhetoric Shifts and Green Voting

	Model 1
Bin Shift	-0.02^{***}
	(0.01)
Flooded	0.03^{**}
	(0.01)
Bin Shift × Flooded	0.02
	(0.02)
Marginal Effect	
Bin Shift = 0	0.03^{**}
	0.01
Bin Shift = 1	0.04^{**}
	0.01
N	579
R^2	0.91
Adj. R^2	0.86

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

H Ethical Considerations and Conflict of Interest

The research presented in this project does not use any evidence that required direct engagement with human subjects. As noted in the text, all Twitter data was collected from accounts that are public. The author declares no conflict of interest.

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Appendix References

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