Online Appendix for "If not now, when? Climate disaster and the Green vote following the 2021 Germany floods"

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Disaster Management

As defined in the Federal Civil Protection and Disaster Assistance Act of 25 March 1997, responsibility for disaster management in Germany is at the level of federal states. According to the disaster management laws of each federal state, administrative and operational tasks may be further delegated to the regional and local levels. The federal government can support the local and regional authorities, and the federal states with their own operational forces (e.g., the Federal Agency for Technical Relief, the Federal Police, and the Armed Forces) as well as with services provided by the Federal Office of Civil Protection and Disaster Assistance (BKK).

In the aftermath of the 2021 floods, the federal government announced emergency aid programmes with funds of up to €400 million (Federal Ministry of the Interior and Finance Ministry, 2021) and concluded administrative agreements with the affected states. In addition, a €30 billion reconstruction fund was set up, with €28 billion of this destined for states' reconstruction programmes. Half of the €28 billion was funded by the 16 federal states, and the other half by the federal government. The remaining €2 billion were provided by the federal government to repair damages to national infrastructure, such as motorways and railway networks (*Deutsche Welle*, 2021).

Description of Variables

Flood Exposure

As explained in the main text, we use two complementary measures of flood exposure. Figure 3 relates to the secondary, satellite-based measure. It shows the activation extent of the area mapped by the Copernicus Emergency Management Service (EMS, 2021), which was requested by the German Joint Information and Situation Centre (GMLZ). The GMLZ, which falls under the Federal Office for Protection and Disaster Assistance (BKK) is the only body in Germany authorised to activate the Copernicus EMS. Since the Copernicus EMS mapping covers emergencies and humanitarian crises related to natural disasters, the geographical areas requested to be mapped by the GMLZ are assumed to be those most vulnerable to serious damages from the floods. In this sense, by comparison to our primary measure which captures flood exposure at the county level, our secondary measure is more granular in capturing direct exposure to flooding disaster.

To get as close as possible to capturing true flood exposure, we measure the proportion of land in each municipally covered by the satellite flood mapping and code as affected only those in the top 95%. We thus exclude the bottom 5% of municipalities with the least overlay with the satellite flood mapping, since these constitute instances where the satellite mapping shows too insignificant an amount of flooding to warrant the municipality being coded as affected by flooding.

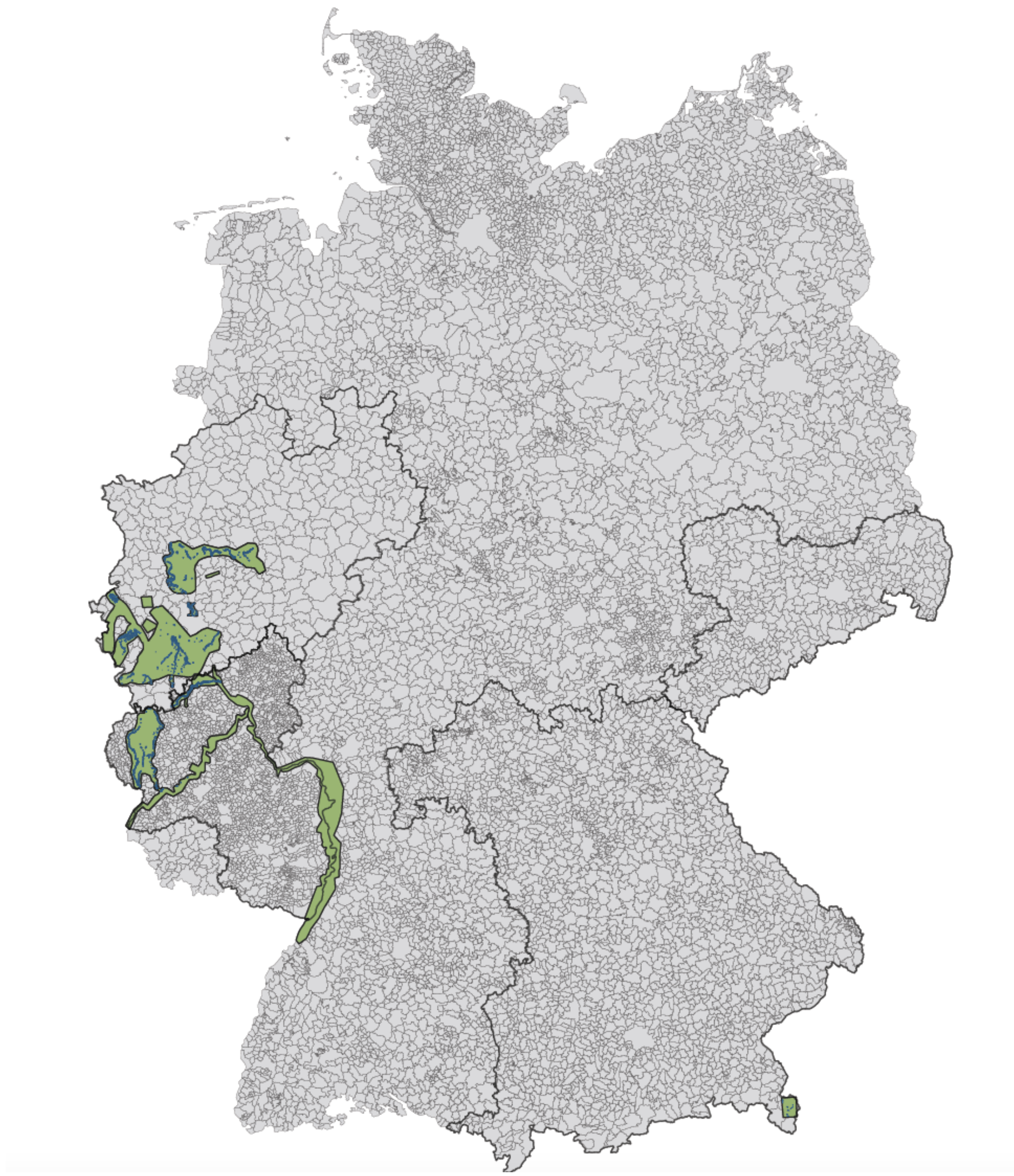

Figure 3: Satellite-based flood mapping of the 2021 Germany floods from the Copernicus Emergency Management Service (EMS) is shown in blue. Activation extent of the satellite mapping requested by the German Joint Information and Situation Centre (GMLZ) is shown in green. Boundaries of affected states are marked in black.

From a total of 5,172 municipalities in the four affected states, the number of affected municipalities is 1,698 (32.8%) under our primary measure and 167 (3.22%) under our secondary measure.

Flooding Severity

Our measure of flooding severity is coded with reference to municipalities within counties which declared flooding catastrophe (Federal Ministry of the Interior and Finance Ministry, 2021). The declaration of a catastrophe allows for the application of local disaster control laws which provide for the cooperation of relevant authorities, organisations and institutions involved in hazard prevention to work together under the uniform leadership of the locally competent disaster control authorities.

When measuring flooding severity, we follow the structure of the aforementioned two-stage measurement strategy for flood exposure. Under our primary measure, all municipalities within counties which declared a flooding catastrophe will be considered severely affected. Under our secondary measure, we code as severely affected the intersection between municipalities in counties which declared a flooding catastrophe and municipalities mapped as flooded using the Copernicus Emergency Management Service (EMS) satellite data.

From a total of 5,172 municipalities in the four affected states, the number of severely affected municipalities is 545 (10.5%) under our primary measure and 133 (2.57%) under our secondary measure.

Spatial Proximity

To ascertain the indirect effects of the floods we use the following spatial DID model developed by Delgado and Florax (2015):

$$\begin{aligned} Vote_{it} \quad &= UnitFE_i + TimeFE_t + ATT^D \cdot Flood_{it} \\ &+ATT^{\neg D} \cdot Flood_{it} \cdot Neighbours_i + X_{it}'\beta + \epsilon_{it} \end{aligned}$$

where $Neighbours_i$ is the treated neighbours scale counting the (normalised) numbers of neighbours of municipality i that are themselves treated. ATT^D and $ATT^{\neg D}$ are the direct (oneself being treated) and indirect (neighbours being treated) treatment effects of interest. The spatial DID model will allow us to depart from standard assumptions about the DID setup, in particular, those of unit independence and common trends, and estimate both direct and indirect effects of flood exposure (Delgado and Florax, 2015). Here we rely on our secondary, satellite-based measure of flood exposure.

We construct a spatial interaction term which measures proximity to, and degrees of exposure from treated neighbours. We construct a spatial weights matrix that quantifies the level of “connectedness” each municipality is relative to the others. This is an $N \times N$ symmetrical matrix with entries being the quantified distances between each unit and all the rest of the units. By convention, this matrix has an all-zero diagonal, non-zero entries for those municipalities counted as “connected/neighbouring” under a chosen weight metric (discussed below), and zeros for all remaining cells. The matrix is further row-standardised such that each row sums up to unity, indicating that all a given unit’s neighbours together make up 100% of the total weight.

Pre-multiplying the column vector ($N \times 1$) for the treatment indicator by this classical spatial weights matrix then leads to our second-order treatment indicator, which is essentially the sum of every other unit’s treatment status weighted by their distance to a given unit.

There are two predominant ways of defining spatial weights, a *distance*-based one and a *contiguity*-based one. The former counts as neighbours those that fall within a particular radius from a given unit, whether in absolute (i.e., against a pre-set standard) or relative (against each other) terms. The latter by contrast counts as neighbours those units that share some part of their boundaries, i.e., an edge (rook), a vertex (bishop), or both (queen). Both metrics have their own strengths and drawbacks, and it is not uncommon to use both as alternative checks on each other, depending on the research design and question.

We use both a distance and a contiguity based method, with the k-nearest neighbour (KNN) criterion for the former and the queen criterion for the latter. As mentioned above, the KNN criterion includes the K units with the K shortest distances from a given unit (usually defined on centroids and/or borders) as neighbours; whilst the queen criterion includes both common edges and vertices as evidence for being neighbours. We use a common K choice, $K = 5$, and inter-centroid distance for our KNN neighbour measure. The matrices estimated using these standards are then piped into the procedure described above, and eventually used in our main and alternative analyses for the spatial DID model.

For a better sense of the spatial distribution of neighbouring units in our study, below gives two maps showing what such relationship looks like in a cartographic way, with black circles representing the centroid of each municipality in Germany and coloured lines connecting neighbours under each criterion:

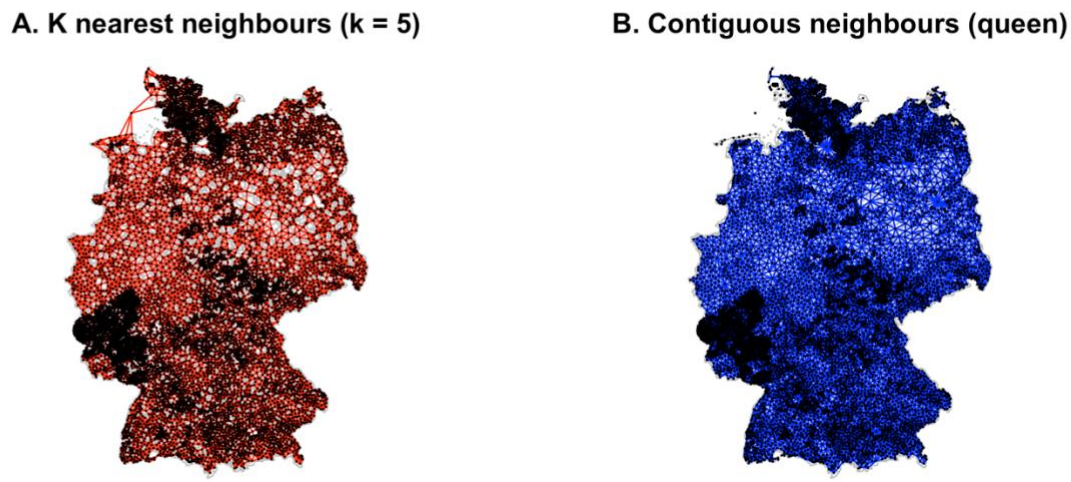

Figure 4: Spatial distribution of neighbouring municipalities. Data from the Database of Global Administrative Areas (GADM, 2021).

Notice the broad agreement in terms of neighbour distribution as a result of the densely populated nature of our grid (≈ 11,000 units). The one on the left with red lines (KNN) will be used in our main analysis, and the other on the right with blue lines (Queen) will be used in the corresponding robustness check.

Covariates

Below is the list of covariates we use in our main models (at municipality level). Unless otherwise stated, all variable data are available from the *Statistische Ämter des Bundes und der Länder*. For each election year, we use covariate data from the preceding year (or failing that, the closest available prior year).

- *Population Density*: Inhabitants per square kilometre.
- *Population Outflow*: Net out-migration (inflows minus out outflows) per 1000.
- *Share of Elderly*: Share of population aged 60 years and over in total population.
- *Income*: Mean salary for the working population.
- *Unemployment Rate*: Annual average unemployment rate.
- *Land Use - Settled Land*: Percentage of settled land.
- *Land Use - Agricultural Land*: Percentage of land used as agricultural land.
- *Green in Land*: Coded 1 if the Green Party is in the governing coalition in the Land parliament (Landtag) at the time of the election and 0 otherwise. *Information available from official sources.*
- *Distance to Flooded Area*: Shortest as-the-crow-flies distance (in kilometres) from district centroid to next affected municipality. *Original computation.*

Survey Data

In testing for perception-induced effect heterogeneity, and for mobilisation and persuasion mechanisms we use a combination of voting data and survey data from the German Longitudinal Election Surveys in 2021 and 2017 (GLES 2019, 2022). We use questions from the 2021 GLES pre-election survey detailing self-reported voting records in the previous election and voting in intentions for the current federal elections. We also draw on GLES survey data from 2021 and 2017 pre-election surveys which measures citizens' positions on climate change and their judgements on the salience of the issue**.** The 2021 pre-election survey was carried out between 26 August and 25 September 2021 and the 2017 data collection period was 31 July to 23 September 2017.

Our measures of climate change position and climate change salience are drawn from questions in the 2021 GLES cross-section pre-election survey and compared with similar questions from the 2017 pre-election survey. For 2021 the survey has a sample size of 5,220 and uses a multi-stage register sample, with respondents randomly selected from a sample of 162 municipalities. The two pairs of most-similar questions are as follows:

Climate Position:

2021: "What position do you take on the fight against climate change?" on an 11-point scale, ranging from "1- Politics should do much more to combat climate change" to "11- Politics to combat climate change have already gone way too far".

2017: "What position do you take on the fight against climate change and economic growth?", with answers on an 11-point scale, ranging from "1- Fight against climate change should take precedence, even if it impairs economic growth" to "11- Economic growth should take precedence, even if it impairs the fight against climate change".

Climate Salience:

2021: "How important is the issue of combating climate change to you?", with answers on a 5-point scale from (very important, somewhat important, in between, not very important, not important at all).

2017: "How important is the topic of climate change and economic growth to you?", with answers on a 5-point scale from (very important, somewhat important, in between, not very important, not important at all).

Randomisation Checks

We conduct two types of tests: (1) a balance test to check covariate balance in the pre-treatment period across treated and untreated units, and (2) a parallel trends test to check non-divergent pre-trends in outcome movement in the three previous elections between the two groups. Both can serve as randomisation tests as they both check the (non-)correlation between treatment assignment and attribute differentials between treated and untreated units, albeit one with a covariate and another an outcome-based emphasis. Note that the first is not necessary for the difference-in-differences design to be valid (Wing et al., 2018).

For the balance test (1), we follow Wing et al. (2018) in assessing the stability of differences in covariate distributions over time, by examining coefficient estimates on lagged treatment dummies in each of the pre-treatment period, from the following covariate balance regression:

$$X_{it} = UnitFE_i + TimeFE_t + \sigma \cdot Flood_{it} + \epsilon_{it}$$

where X_{it} refers to any of our nine covariates of interest introduced in the previous section, and $Flood_{it}$ the main treatment dummy lagged to each pre-treatment period for which data are available. σ is the average difference in treated and untreated groups across periods. In our sample we can lag the treatment dummy to 2009, 2017, and 2021 (before the election), leaving 2009 as the baseline to escape the "dummy variables trap". We standardise all continuous covariates to facilitate interpretation and comparison across covariates. Note that our last covariate, *Distance to Flooded Area*, is by construction time-invariant — geographical distance does not change over time — so only last-period testing is conducted. In a natural flood setting, we should expect reasonable though inevitably imperfect balance across treated and untreated groups over time.

We display results graphically in Figure 5 where the standardised coefficient estimate ($\hat{\sigma}$ in the model above) for each covariate is plotted for each sample (the four affected states and the entire country, respectively) and under each measure of flood exposure (the primary and the secondary measure, respectively). Point estimates are bounded with 95% confidence intervals computed with robust standard errors. Intuitively, the closer these dot-whiskers are to the zero no-difference line, the less difference there was for the corresponding covariates in the periods assessed, and the greater the balance in their distributions therefore. We see that the covariates are, with some exceptions, quite balanced in their pre-treatment distribution: most of the standardised coefficient estimates are quite close to the zero benchmark. With the sole exception of *"Distance to Flooded Area"* on top, none of the estimates exceed half a standard deviation in the covariate distribution under testing, and are mostly above the conventional level of statistical significance ($p > 0.05$). The outlying case of *"Distance to Flooded Area"* is unsurprising because by definition those areas that are flooded are systematically closer to the flooded area (i.e., themselves) then those that are not. We nonetheless display this information for completeness with respect to our covariate control scheme.

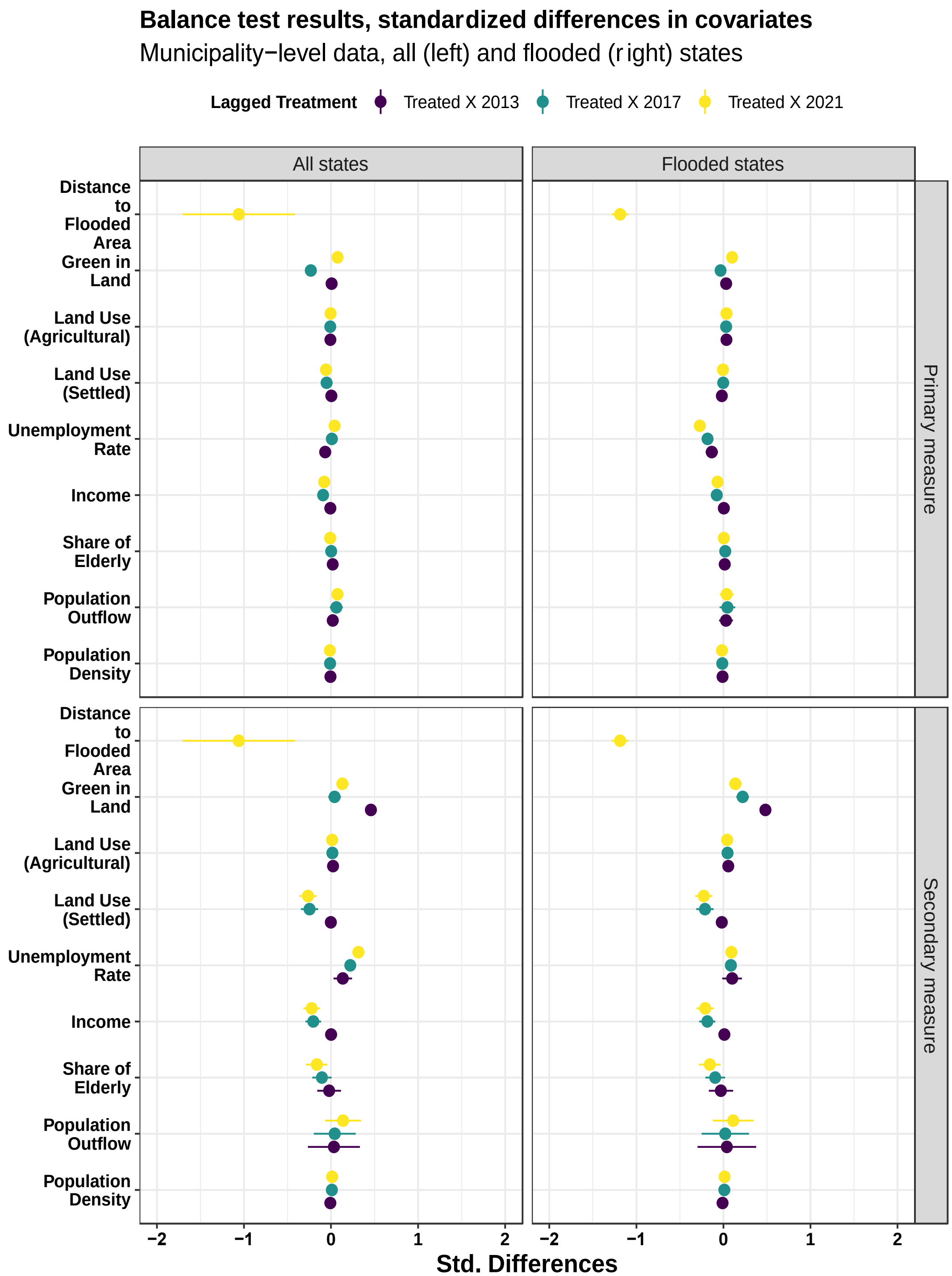

Figure 5: Balance test results. Standardised differences in covariate distribution over time.

For the parallel trends test (2), we use both (a) a visual and (b) a statistical method to check if pre-trends in Green Party votes evolved differently among treated and untreated municipalities. We combine our treatment status data with data on election outcomes from the three most recent — 2009, 2013, and 2017 — national elections, to build a panel of pre-2021 voting records for the municipalities (Federal and State Statistical Offices, 2021).

For (2a), we plot the group trends in voting for the Green Party, summarised by their means and 95% confidence intervals, to see if they have been parallel to each other across the periods. Results are shown graphically in Figures 6 and 7.

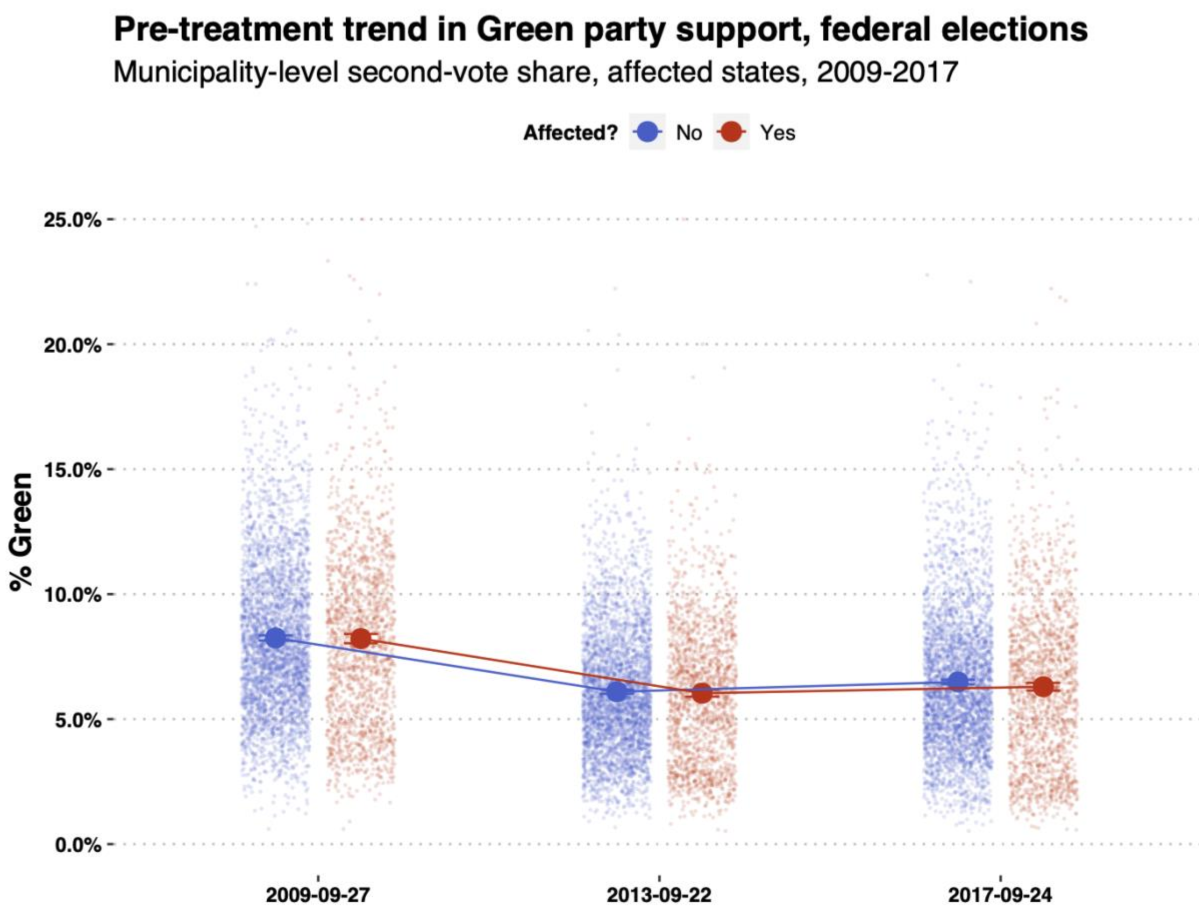

Figure 6: Pre-trends in Green voting for the municipality- level second vote in past federal elections for the core sample of four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony).

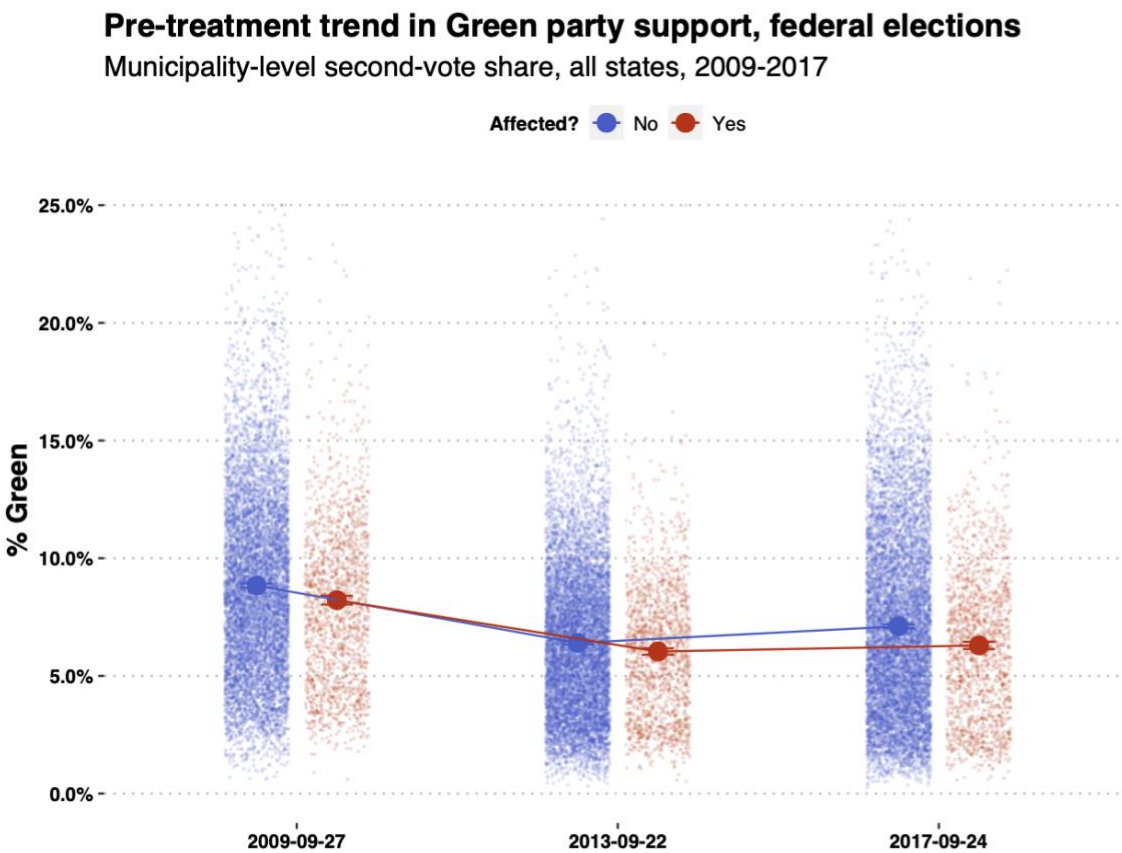

Figure 7: Pre-trends in Green voting for the municipality-level second vote in past federal elections for the full sample of all German states.

As both figures show, in neither the core nor the full sample do we spot major divergence in pre-treatment voting records. The red (flooded in 2021) and the blue (not flooded in 2021) trends seem fairly parallel in their movement over time, lending strong preliminary evidence for the non-violation of the parallel trends assumption.

For (2b), we run a placebo regression of historical voting patterns on the interaction between present treatment status and election dummies for each party, to see if the former show no difference between themselves due to the latter, i.e., pre-treatment trends do not differ by future (present) treatment status, at the 5% level. We estimate the following model:

$$Vote_{it} = UnitFE_i + TimeFE_t + \phi \cdot Flood_{it} + X_{it}'\beta + \epsilon_{it}$$

which is the same as our main model except with lagged treatments as key regressors and previous voting records as the outcome. We use two-way clustered standard errors by unit (municipality) and time (election) to account for potential heteroscedasticity and serial correlation on the multi-period sample. We want the estimate for ϕ to be as small and statistically insignificant as possible for the parallel trends assumption to hold on our sample.

Results are shown in Tables 2 and 3, where Table 2 shows the core four-state sample and Table 3 the full nationwide sample. As before, both the primary and the secondary measure are used for defining the treatment dummy. In each case, we estimate first a basic (no control) and then a fully controlled model and display results side by side. Controls are the same covariates just examined in the balance test. Notice that we interact our "*Distance to Flooded Area*" variable with the time dummy since it is time invariant.

The results are reassuring. We see little evidence for substantial divergence in pre-treatment trends in Green vote share. This holds for all model results — on both samples (core/full) with both measures (primary/secondary) and under both specifications (uncontrolled/controlled). In all but two cases we find neither statistical nor substantive differences in estimated pre-trends between the affected and unaffected municipalities. For the two cases where we do find a statistically significant estimate in pre-trend differences, both only just reach statistical significance at the 5% level and are substantively trivial (0.3-0.5%). Neither affects the latest pre-treatment period under fully controlled conditions.

In summary, we have detected few signs of pre-trend divergence among affected and unaffected municipalities from our tests, which serves as evidence for the general upholding of parallel trends between treatment and control groups in our sample throughout the pre-treatment period.

Parallel Trends: Core Sample	**Primary Measure**		**Secondary Measure**	
	Base	**Full**	**Base**	**Full**
Treated x 2013	0.0002 (0.0005)	0.003* (0.0006)	-0.0005 (0.001)	0.001 (0.002)
Treated x 2017	-0.001 (0.0006)	0.002 (0.0007)	-0.004 (0.002)	-0.0008 (0.002)
FE: Municipality	✔	✔	✔	✔
FE: Election	✔	✔	✔	✔
S.E.: Clustered	by: GMD & Elec.	by: GMD & Elec.	by: GMD & Elec.	by: GMD & Elec.
N Obs.	15,370	15,100	15,370	15,100
R^2	0.851	0.870	0.851	0.870
Within R2	0.0005	0.010	0.0006	0.008

Note: GMD = Gemeinden (municipality); covariate results omitted to save space and available from the authors; *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 2: Parallel trends test results, core sample of the four flood-affected states. DV = Municipality-level Green Party second vote share. OLS estimates with robust standard errors clustered by municipality. Base = baseline model without controls. Full = fully controlled model with all covariates. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect.

Parallel Trends: Full Sample	**Primary Measure**		**Secondary Measure**	
	Base	**Full**	**Base**	**Full**
Treated x 2013	-0.0000 (0.0006)	-0.0010 (0.0007)	-0.0007 (0.001)	0.0004 (0.001)
Treated x 2017	-0.005* (0.0006)	-0.002 (0.0008)	-0.007 (0.002)	-0.003 (0.002)
FE: Municipality	✔	✔	✔	✔
FE: Election	✔	✔	✔	✔
S.E.: Clustered	by: GMD & Elec.	by: GMD & Elec.	by: GMD & Elec.	by: GMD & Elec.
N Obs.	31,136	30,860	31,136	30,860
R^2	0.893	0.904	0.893	0.904
Within R2	0.004	0.041	0.0009	0.041

Note: GMD = Gemeinden (municipality); covariate results omitted to save space and available from the authors; *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 3: Parallel trends test results, full sample of all German states. DV = Municipality-level Green Party second vote share. OLS estimates with robust standard errors clustered by municipality. Base = baseline model without controls. Full = fully controlled model with all covariates. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect.

Municipality Redistricting

We note that due to municipality redistricting by name, boundaries or administrative codes, a small proportion of the municipalities recorded in the 2017 election results (158 out of 10,790) cannot be directly matched with municipalities in the 2021 election. For these units, we have imputed with mean remaining votes as their results in the main analyses. We also do an extensive, parallel set of tests where we drop these few units and replicate our main tests. All results are substantively similar. Results are available from the authors.

Further Results

This section reports additional tables and figures for the results reported in the main body of the article, inclusive of the design and results for all remaining analyses specified in the updated Pre-Analysis Plan and registered report submitted to EGAP/OSF and *Research & Politics*.

Direct Effects

Figure 8 corresponds to Table 1 in the main text, presenting the results of the difference-in-difference (DID) analysis for our main hypothesis on our core sample of the four flood-affected states.

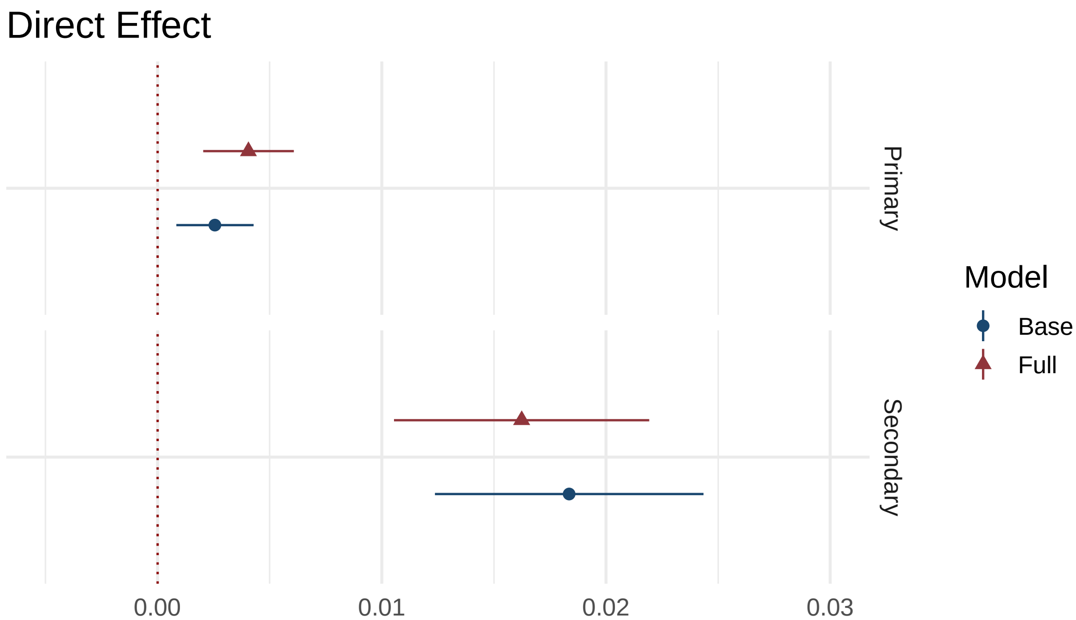

Figure 8: Estimated effects of flood exposure on municipality-level Green Party second vote share in the 2021 federal election for the core sample of four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). Each dot represents a point estimate, and each bar represents the corresponding 95% confidence interval. The x-axis measures change in percentage vote share. Blue circle = baseline model estimate without controls. Red triangle = full model estimate with controls.

Differential Effects by Severity

Table 4 corresponds to Figure 2 in the main text, which reports differential effects of the floods according to severity. We estimate the differential effect of flooding on Green vote share by estimating the following DID model:

$$\begin{aligned} Vote_{it} &= UnitFE_i + TimeFE_t + ATT \cdot Flood_{it} \\ &+ATT^{+} \cdot High_{it} + X_{it}'\beta + \epsilon_{it} \end{aligned}$$

where $High_{it}$ is the treatment intensity indicator indicating additional affectedness. ATT^{+} is the additional effect from extra intense treatment relative to the main effect, ATT, which we expect to be positive and statistically significant at the 5% level as before.

Differential Effect	**Primary Measure**		**Secondary Measure**	
	Base	**Full**	**Base**	**Full**
Post Period	0.029*** (0.0004)	0.033*** (0.001)	0.030*** (0.0004)	0.034*** (0.001)
Post x Low	0.003** (0.001)	0.005*** (0.001)	0.040*** (0.006)	0.037*** (0.005)
Post x High	0.002 (0.002)	0.001 (0.002)	0.012*** (0.003)	0.010*** (0.003)
FE	✔	✔	✔	✔
N Obs.	10,145	10,032	10,145	10,032
Adj. R^2	0.760	0.780	0.765	0.782

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 4: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election for the core sample of the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. "High" indicates the subset of severely affected municipalities which lie within counties which declared a flooding catastrophe (Federal Ministry of the Interior and Finance Ministry, 2021). "Low" indicates the other affected municipalities which do not lie within these counties. Base = baseline model without controls. Full = fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

Differential Effects by Flooded Area[1]

We construct a continuous scale of the percentage of area affected for each municipality within the two most affected states: Rhineland-Palatinate and North Rhine-Westphalia. We log-transform this measure given its right-skewed sample distribution and substitute it for the dummy measure in the main model. Results are shown in Table 5. The main estimate of interest is negative and significant at the 10% level, thus largely confirming our speculation that the pro-Green effect of flooding is decreasing with the degree of flood exposure.

Flooded Area	**Secondary Measure**
Post Period	0.062*** (0.007)
Post x Flooded Area	-0.343† (0.176)
FE	✓
N Obs.	326
Adj. R^2	0.676

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 5: This table shows the differential effects of the percentage of flooded area in affected municipalities in North Rhine-Westphalia and Rhineland-Palatinate. Flooded area is calculated as the percentage of flooded area mapped as by satellite-based flood mapping from the Copernicus Emergency Management Service (EMS).

We also divide the single scale of flooded area into four quartiles, using the second, third and fourth quartiles as dummies and the first as the reference category. We use this quartile measure as an alternative treatment indicator and replicate the analysis shown in Table 5. The results in Table 6 show that the decreasing effect appears to be concentrated among the most heavily affected areas, as the negative coefficient estimate is largest in absolute magnitude and greatest in precision for the dummy for most highly affected areas falling into the last quartile. This strengthens our conjecture that particularly severe

[1] Note that this analysis is additional: it was not pre-registered in our registered report or Pre-Analysis Plan.

affectedness actually reduces the tendency of citizens in the most devastated areas to support the Greens as a result of their direct exposure to the flooding disaster.

Flooded Area by Quartile	**Secondary Measure**
Post Period	0.060*** (0.008)
Post x Flooded Area Q2	-0.004 (0.008)
Post x Flooded Area Q3	-0.002 (0.007)
Post x Flooded Area Q4	-0.020* (0.008)
FE	✓
N Obs.	326
Adj. R^2	0.673

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 6: This table shows the differential effects of the percentage of flooded area in affected municipalities in North Rhine-Westphalia and Rhineland-Palatinate. Flooded area is calculated as the percentage of flooded area mapped as by satellite-based flood mapping from the Copernicus Emergency Management Service (EMS).

Indirect Effects

Table 7 and Figure 9 show the results for our analysis of spatial spillover effects among neighbouring municipalities. See appendix section "Spatial Proximity" for further details on our measures.

Indirect Effect	Secondary Measure	
	Base	**Full**
Post Period	0.029*** (0.0004)	0.034*** (0.001)
Post x Direct	0.018*** (0.003)	0.016*** (0.003)
Post x Indirect	0.012 (0.007)	0.007 (0.007)
FE	✓	✓
N Obs.	10,145	10,032
Adj. R^2	0.764	0.781

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 7: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election for the core sample of the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). Direct indicates first-order exposure to the flood. Indirect indicates second-order exposure to the flood via neighbouring municipalities. Neighbourliness is measured with the K-nearest neighbour metric (K=5). The secondary measure of flood exposure combines the primary measure, (which is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) and maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte") with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Base = baseline model without controls. Full = fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

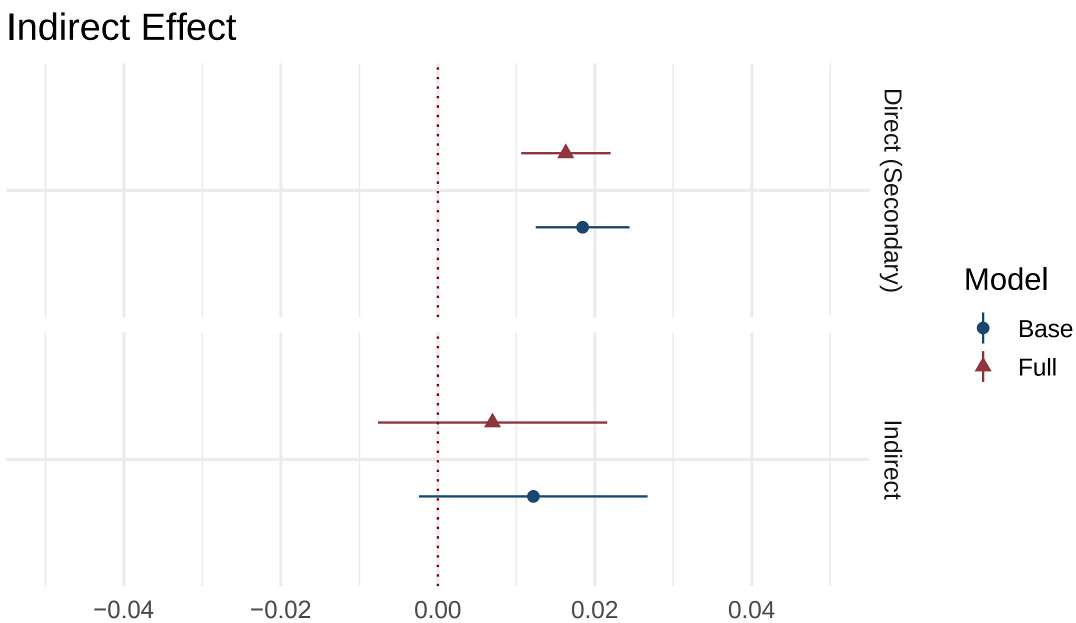

Figure 9: Estimated effects of flood exposure on municipality-level Green Party second vote share in the 2021 federal election, by degree of affectedness (direct and indirect) using the core sample of four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). Each dot represents a point estimate, and each bar represents the corresponding 95% confidence interval. Indirect exposure is measured at municipality level using the K-nearest neighbour metric (K=5). The x-axis measures change in percentage vote share. Blue circle = baseline model estimate without controls. Red triangle = full model estimate with controls. Note that only the secondary, satellite-based measure of flood exposure is used for the current estimation.

Perception-Induced Effect Heterogeneity

We also investigate effect heterogeneity by pre-existing public opinion about climate change to determine whether prior climate concerns have a positive moderating effect on the main relationship between flood exposure and Green Party support. We interact the pre-treatment climate position and salience variable from the GLES survey with the treatment dummy in the main model. The variables are drawn from questions in the 2017 GLES pre-election survey which ask the following:

- **Climate Position:** "What position do you take on the fight against climate change and economic growth?", with answers on an 11-point scale, ranging from "1- Fight against climate change should take precedence, even if it impairs economic growth" to “11- Economic growth should take precedence, even if it impairs the fight against climate change”.

- **Climate Salience:** “How important is the topic of climate change and economic growth to you?”, with answers on a 5-point scale from (very important, somewhat important, in between, not very important, not important at all).

We use pre-treatment climate concern to avoid inducing post-treatment bias. The coefficient estimate on this three-way interaction term tells us the extent to which the effect of flood exposure differs by previous public opinion about climate change. The results are shown in Tables 8 and 9.

Perception Effect: Position	**Primary Measure**		**Secondary Measure**	
	Base	**Full**	**Base**	**Full**
Post Period	0.049 (0.034)	0.105** (0.031)	0.013 (0.032)	0.092** (0.031)
Post x Flooded	-0.084 (0.076)	-0.072* (0.031)	0.110† (0.061)	-0.021 (0.039)
Post x Pre-Position	0.002 (0.004)	-0.008* (0.003)	0.005 (0.004)	-0.005† (0.003)
Post x Flooded x Pre-Position	0.012 (0.009)	0.010* (0.004)	-0.007 (0.007)	0.006 (0.004)
FE	✔	✔	✔	✔
N Obs.	100	100	100	100
Adj. R^2	0.839	0.956	0.893	0.962

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 8: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election for the core sample of the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). Pre-position indicates pre-treatment positions on climate change based on German Longitudinal Election Study (GLES) survey data. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Base = baseline model without controls. Full = fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

Perception Effect: Salience	Primary Measure		Secondary Measure	
	Base	**Full**	**Base**	**Full**
Post Period	0.032 (0.065)	0.120* (0.049)	0.011 (0.064)	0.097* (0.045)
Post x Flooded	-0.108 (0.165)	-0.101† (0.057)	0.089 (0.153)	-0.005 (0.081)
Post x Pre-Salience	0.008 (0.016)	-0.019† (0.011)	0.010 (0.016)	-0.011 (0.008)
Post x Flooded x Pre-Salience	0.027 (0.040)	0.026† (0.014)	-0.008 (0.036)	0.008 (0.019)
FE	✔	✔	✔	✔
N Obs.	100	100	100	100
Adj. R^2	0.834	0.953	0.890	0.960

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 9: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election for the core sample of the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). Pre-salience indicates pre-treatment salience of climate change based on German Longitudinal Election Study (GLES) survey data. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Base = baseline model without controls. Full = fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

Results by State

We stratify our four-state core sample by state and look at within-state patterns for the direct and differential effects of flooding on Green vote share**.** This allows us to examine effect heterogeneity between the affected states in a more explicit way.

Statistically speaking, the causal effect we observe for either our core sample of four affected states or full sample of all German states is a weighted average of the individual state-level effects, with the weights being roughly the share of units within each state (assuming random assignment holds). The state-level effect is thus a conditional effect depending on the particular state under analysis and all its observable and latent local particularities.

We first illustrate the vote share changes by state (Figures 10 and 11) and then replicate our main model on the four state-specific subsamples (Table 10 and Figure 12). As shown in Table 10 and Figure 12, we see considerable effect heterogeneity between states and between measures. Under our secondary measure, we see positive effects for Rhineland-Palatinate ($p<0.1$) and North Rhine-Westphalia ($p<0.001$), but a negative effect for Bavaria ($p<0.001$). Under our primary measure, we observe weakly positive effects for Rhineland-Palatinate and Bavaria, but these are no longer statistically significant at the 5% level. For North Rhine-Westphalia we see no effect, and for Saxony the effect is significantly negative. These results relate to parallel work by Hilbig and Riaz (2022) which we discuss in the appendix section "Parallel Work by Hilbig and Riaz".

Table 11 and Figure 13 show the by-state results for the differential effects model. We again observe the earlier pattern of differential effects whereby the increase in Green Party support is mostly driven by the less severely affected municipalities. However, this result is subject to greater inconsistency both between measures and across states. From a statistical perspective, we tentatively attribute this inconsistency to two major factors: the uneven distribution of "severely" affected municipalities between the four states, and the limited coverage of the EMS satellite mapping.

Vote Share Changes by State

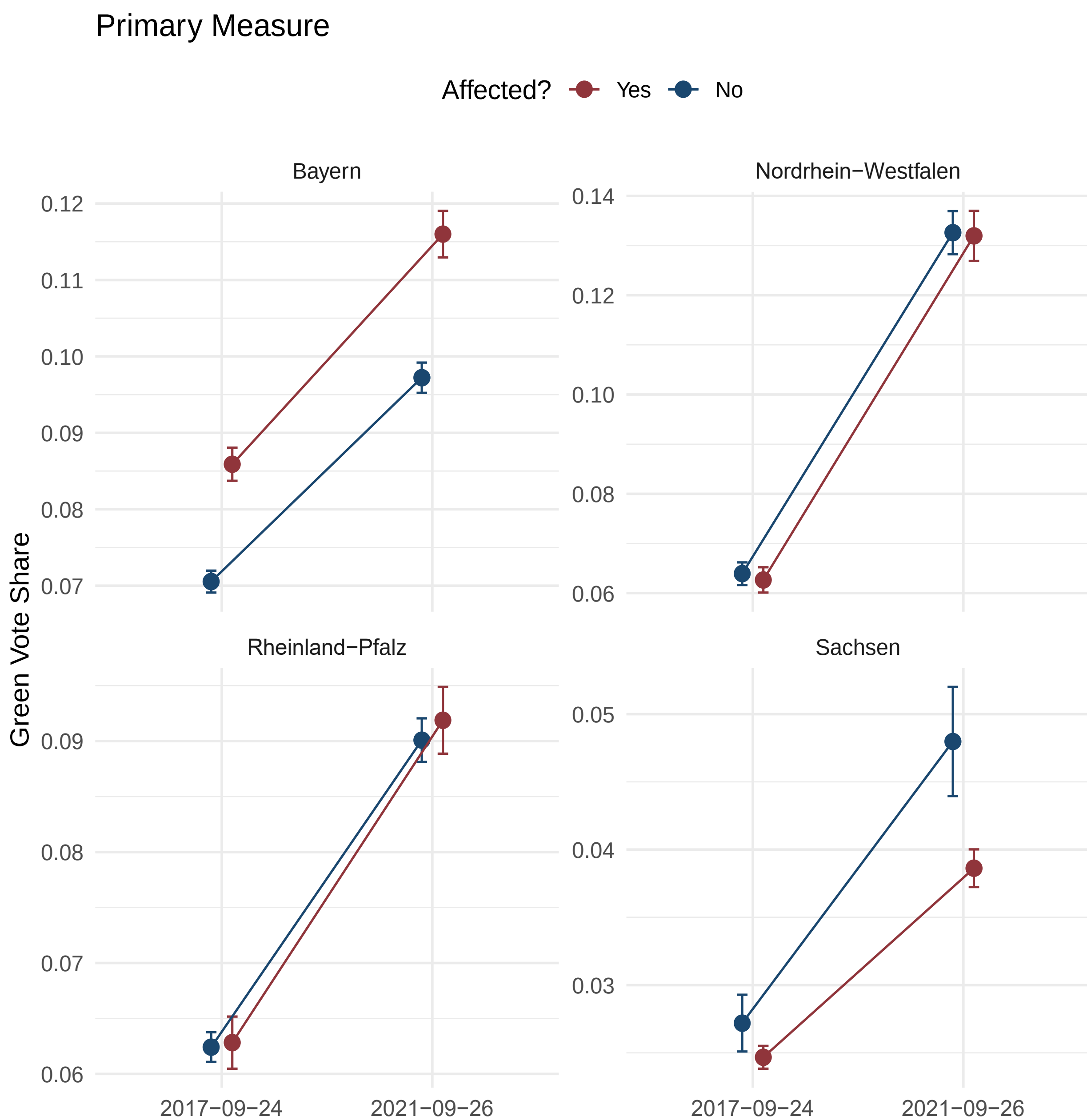

Figure 10: Green Party vote share change between the 2017 and 2021 German federal elections for the four states affected by the 2021 floods. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte").

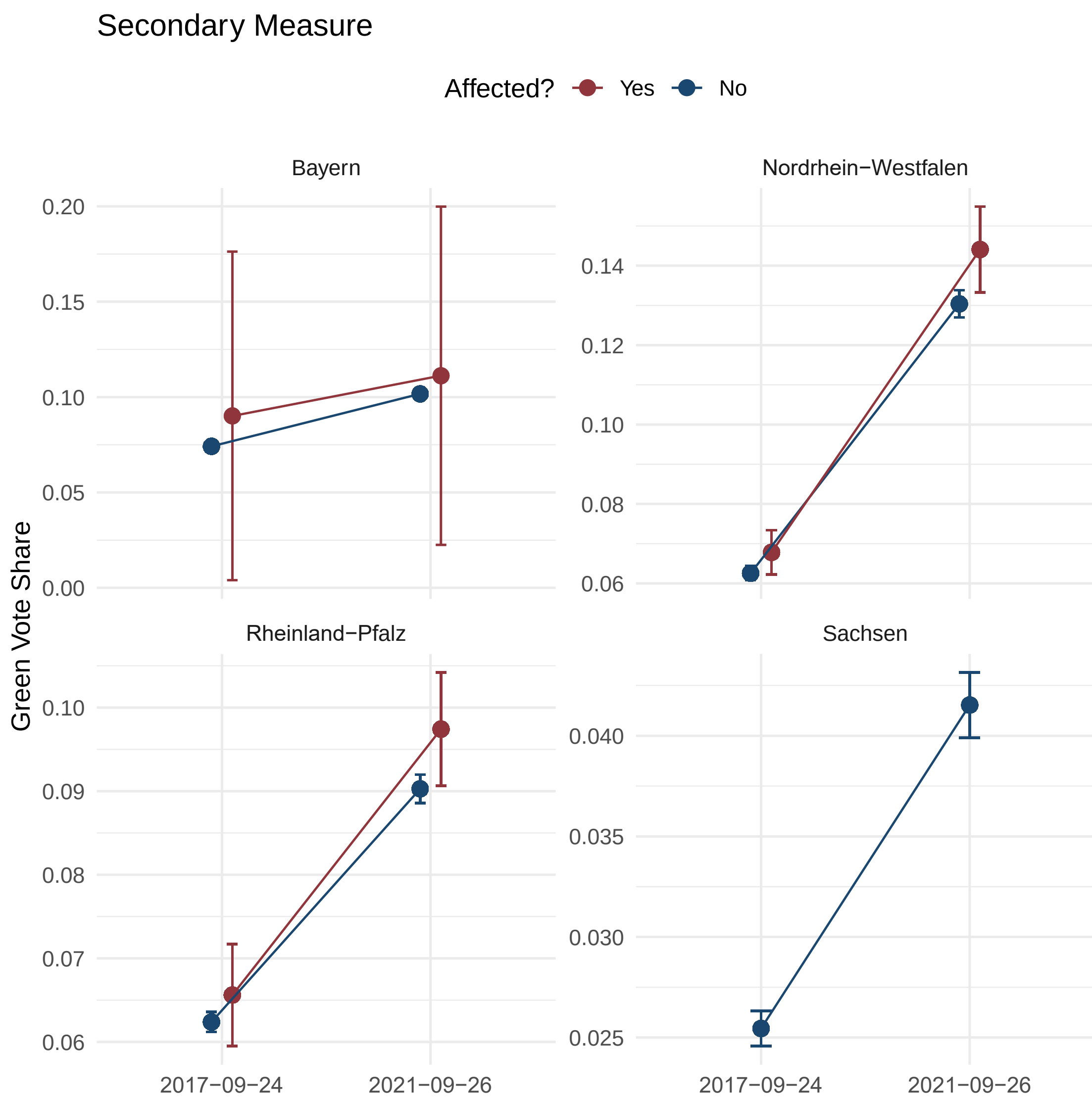

Figure 11: Green Party vote share change between the 2017 and 2021 German federal elections for the four states affected by the 2021 floods. The secondary measure of flood exposure is based on satellite-based flood mapping from the Copernicus Emergency Management Service (EMS).

Direct Effects by State

Direct Effects: By State	Primary Measure				Secondary Measure		
	RP	NW	BY	SN	RP	NW	BY
Post Period	0.029*** (0.002)	0.066*** (0.004)	0.029*** (0.001)	0.024*** (0.002)	0.030*** (0.002)	0.064*** (0.003)	0.030*** (0.001)
Post x Flooded	0.003 (0.002)	-0.0004 (0.002)	0.001 (0.001)	-0.005*** (0.001)	0.006† (0.004)	0.007* (0.003)	-0.006*** (0.001)
FE	✔	✔	✔	✔	✔	✔	✔
N Obs.	4,297	786	4,112	837	4,297	786	4,112
Adj. R^2	0.615	0.926	0.917	0.795	0.615	0.927	0.916

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 10: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election by state for the core sample of the four affected states: Rhineland-Palatinate (RP), North Rhine-Westphalia (NW), Bavaria (BY) and Saxony (SN). The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Results for Saxony (SN) are omitted from the secondary measure as there no municipalities in this state are classed as flooded under this measure. All results are for the fully controlled model with covariates. Except for Saxony, no state has experienced a change of incumbent status for the Green Party, so the corresponding covariate has been dropped. Heteroscedasticity-consistent standard errors clustered by municipality.

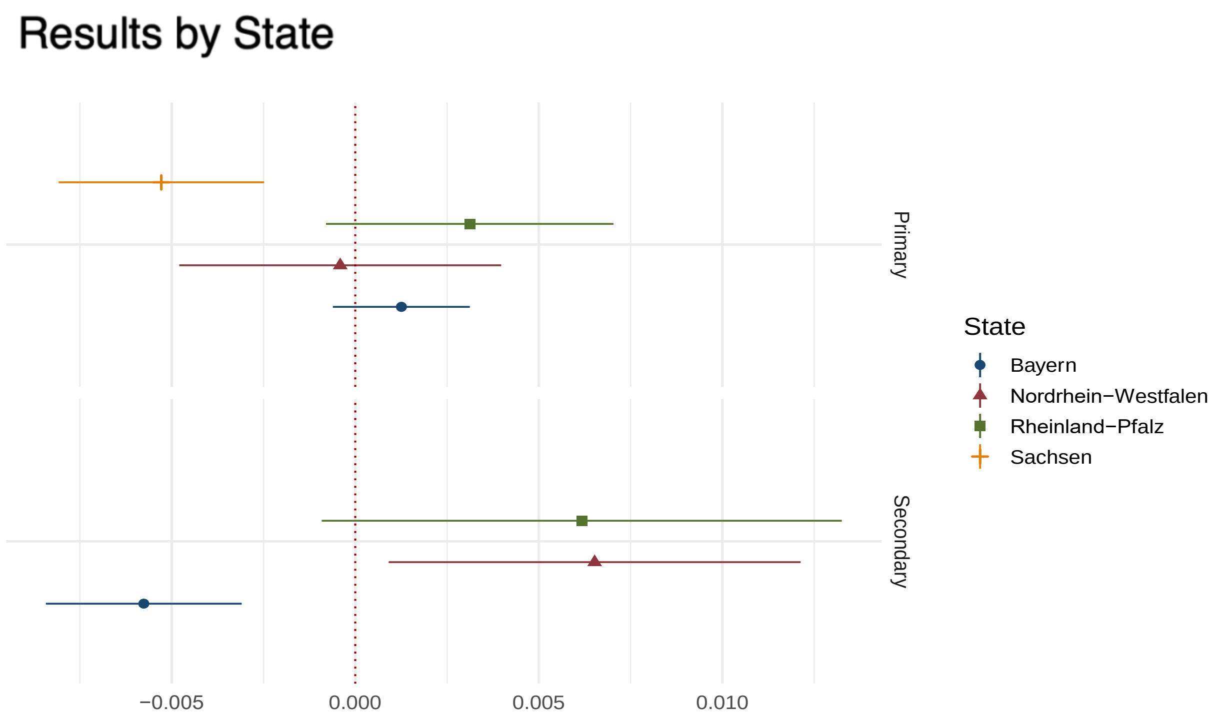

Figure 12: Estimated effects of flood exposure on municipality-level Green Party second vote share in the 2021 federal election by state for each of the core four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). Each dot represents a point estimate, and each bar represents the corresponding 95% confidence interval. All results are based on full models with controls. Blue circle = estimated effect for Bavaria (Bayern). Red triangle = estimated effect for North Rhine-Westphalia (Nordrhein-Westfalen). Green square = estimated effect for Rhineland-Palatinate (Rheinland-Pfalz). Yellow cross = estimated effect for Saxony (Sachsen). Note that except for Saxony, no state has experienced a change of incumbent status for the Green Party, so the corresponding covariate has been dropped from models with these states.

Differential Effects by State

Differential Effects: By State	Primary Measure			Secondary Measure	
	RP	NW	BY	RP	NW
Post Period	0.029*** (0.002)	0.066*** (0.004)	0.030*** (0.001)	0.030*** (0.002)	0.063*** (0.003)
Post x Low	0.006** (0.002)	-0.002 (0.002)	0.002* (0.001)	0.005 (0.016)	0.009* (0.004)
Post x High	0.0003 (0.003)	0.005 (0.004)	-0.003* (0.002)	0.006† (0.004)	0.004 (0.003)
FE	✔	✔	✔	✔	✔
N Obs.	4,297	786	4,112	4,297	786
Adj. R^2	0.615	0.927	0.917	0.614	0.927

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 11: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election by state for the core sample of the four affected states: Rhineland-Palatinate (RP), North Rhine-Westphalia (NW), Bavaria (BY) and Saxony (SN). The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. "High" indicates the subset of severely affected municipalities which lie within counties which declared a flooding catastrophe (Federal Ministry of the Interior and Finance Ministry, 2021). "Low" indicates the other affected municipalities which do not lie within these counties. Results for Saxony (SN) are omitted from the secondary measure as there no municipalities in this state are classed as flooded under this measure. All results are for the fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

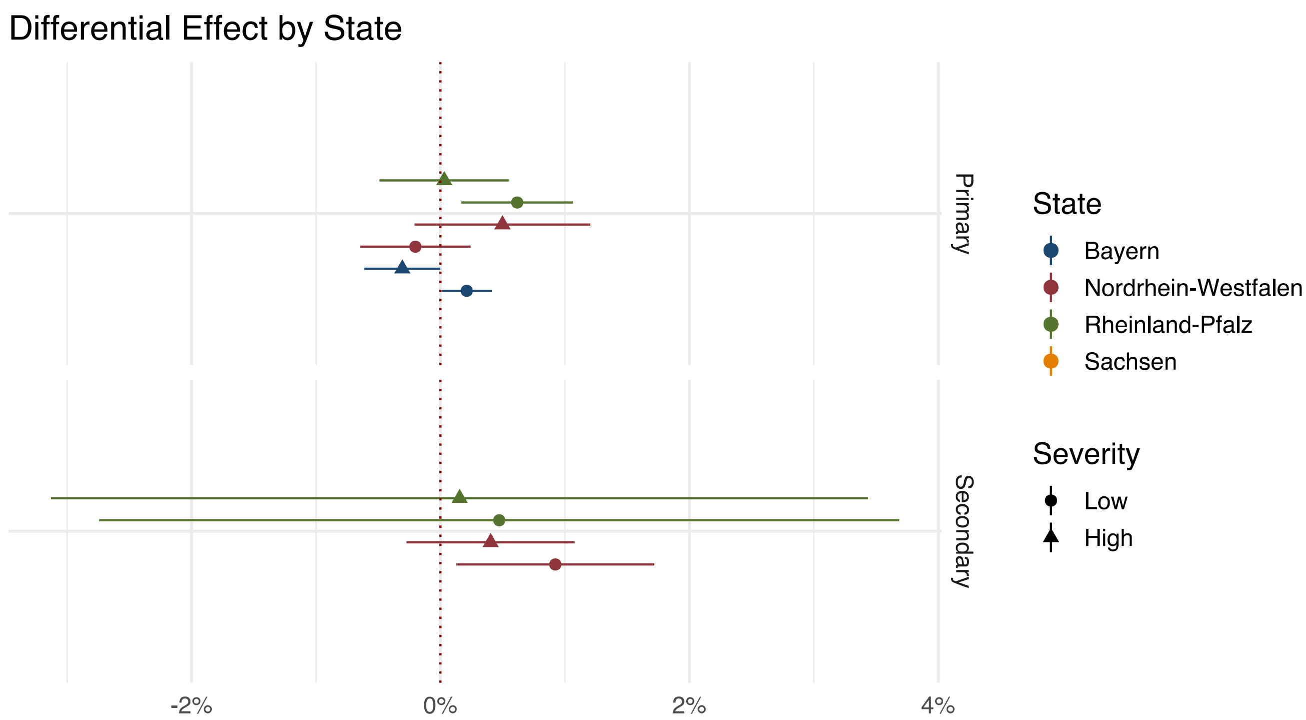

Figure 13: Estimated effects of flood exposure on municipality-level Green Party second vote share in the 2021 federal election by level of severity in each state of the core sample of four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). Each dot represents a point estimate, and each bar represents the corresponding 95% confidence interval. All results are based on full models with controls. The reference category is the municipalities that have not been affected by the flood. Blue = estimated effect for Bavaria (Bayern). Red = estimated effect for North Rhine-Westphalia (Nordrhein-Westfalen). Green = estimated effect for Rhineland-Palatinate (Rheinland-Pfalz). Yellow = estimated effect for Saxony (Sachsen). Circle = estimated effect for the less affected municipalities. Triangle = estimated effect for the more affected municipalities. Note that Saxony has no severely affected municipalities under both primary and secondary measures and Bavaria has too few severely affected municipalities (N=4) under the secondary measure so the effect cannot be identified in this case.

Population Density

Figure 14 shows the correlation between change in Green vote share (2017-2021 federal elections) for municipalities in North Rhein-Westphalia which were affected by the floods. We observe that major cities with high population densities (which do not lie within severely affected counties which declared flooding catastrophes) make up the municipalities with the largest increases in Green vote share.

Figure 14: This graph shows the correlation between change in Green vote share between the 2017 and 2021 federal elections for flood-affected municipalities in North Rhein- Westphalia.

Climate Change Concern

To investigate possible mechanisms through which the Green vote could be affected by the floods, we examine whether citizens in flood-affected areas demonstrate increased issue prioritisation of climate change after the floods. We expect to find that citizens living in flood-affected areas demonstrate increased issue prioritisation of climate change after experiencing the floods. To test this, we draw on survey data from the German Longitudinal Election Survey (GLES) and use two measures of climate concern: one measuring citizen's positions on climate change and the other measuring how salient they find the issue. Our measures of climate change position and climate change salience are drawn from questions in the 2021 GLES cross-section pre-election survey and compared with similar questions from the 2017 pre-election survey. For 2021 the survey has a sample size of 5,220 and uses a multi-stage register sample, with respondents randomly selected from a sample of 162 municipalities. The two pairs of most-similar questions are as follows:

Climate Position:

2021: "What position do you take on the fight against climate change?" on an 11-point scale, ranging from "1- Politics should do much more to combat climate change" to "11- Politics to combat climate change have already gone way too far".

2017: "What position do you take on the fight against climate change and economic growth?", with answers on an 11-point scale, ranging from "1- Fight against climate change should take precedence, even if it impairs economic growth" to "11- Economic growth should take precedence, even if it impairs the fight against climate change".

Climate Salience:

2021: "How important is the issue of combating climate change to you?", with answers on a 5-point scale from (very important, somewhat important, in between, not very important, not important at all).

2017: "How important is the topic of climate change and economic growth to you?", with answers on a 5-point scale from (very important, somewhat important, in between, not very important, not important at all).

The GLES survey data does not allow us to test for divergences in trends between affected and unaffected constituencies within affected states, so we instead check for systematic differences in trends across affected and unaffected states and find no considerable divergences (see Figure 15). Here we use a question from Eurobarometer survey rounds (2009-2021) which asks "How serious a problem do you think climate change is at this moment?" Answers are coded on a scale from 1 to 10, with '1' meaning it is "not at all a serious problem" and '10' meaning it is "an extremely serious problem".

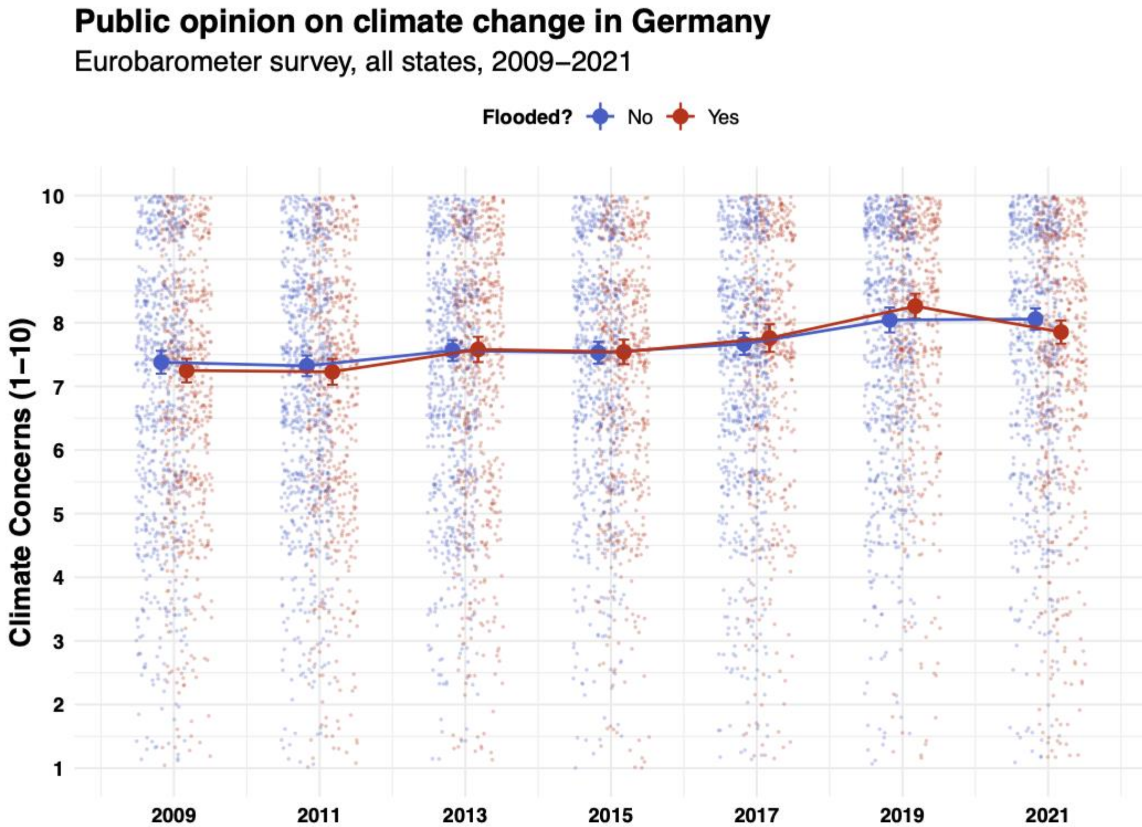

Figure 15: Pre-trends in climate change concern in affected and unaffected states (2009-2021).

Results are show in Table 12 and Figure 16. Note that results are reported at the constituency level and in the fully controlled models, we aggregate our municipality-level covariates to the constituency level.

We find no evidence that citizens living in affected constituencies demonstrate increased issue prioritisation of climate change after experiencing the floods. This is the case both for attitudes towards the fight against climate change and on the issue salience of climate change. We conjecture that this null finding may be in part due to ceiling effects in the survey answers, whereby many respondents already reported high levels of climate concern in the 2017 survey round, leaving little room for observable increase.

Climate Concern Effect	**Climate Position**				**Issue Salience**			
	Primary		Secondary		Primary		Secondary	
	Base	**Full**	**Base**	**Full**	**Base**	**Full**	**Base**	**Full**
Post Period	0.336 (0.247)	0.549 (0.970)	0.303 (0.187)	0.594 (0.925)	0.104 (0.065)	0.218 (0.331)	0.054 (0.055)	0.207 (0.339)
Post x Flooded	0.094 (0.335)	0.609 (0.410)	0.338 (0.435)	0.620 (0.535)	-0.110 (0.096)	-0.088 0.120	0.010 (0.117)	-0.121 (0.136)
FE	✓	✓	✓	✓	✓	✓	✓	✓
N Obs.	100	100	100	100	100	100	100	100
Adj. R^2	0.363	0.386	0.371	0.375	0.330	0.314	0.313	0.315

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 12: This table shows the effects of the 2021 Germany floods on constituency-level concern for the core sample of the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). The climate position variable is composed of measures from survey questions in the 2017 and 2021 German Longitudinal Election Survey (GLES) cross-section pre-election survey rounds which ask respondents about the position they take on the fight against climate change. The issue salience variable asks respondents how important they consider climate change to be. The secondary measure of flood exposure combines the primary measure – which is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) and maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte") – with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Base = baseline model without controls. Full = fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

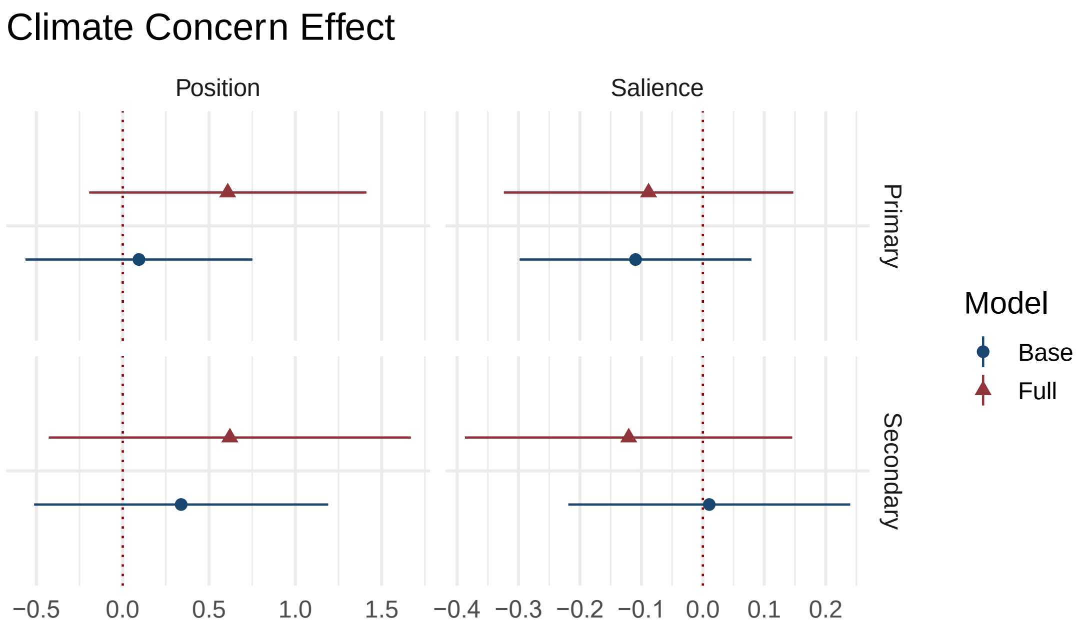

Figure 16: Estimated effects of flood exposure on constituency-level climate concern in the 2021 GLES cross-section pre-election survey. Using the core sample of four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). Each dot represents a point estimate, and each bar represents the corresponding 95% confidence interval. The left panel shows results using respondents' self-reported position on climate change as the measure of concern. The right panel shows results using respondents' perceived importance of climate issues as the measure of concern. Blue circle = baseline model estimate without controls. Red triangle = full model estimate with controls.

Mobilisation and Persuasion Mechanisms

We test two competing mechanisms to explain the observed increase in Green vote share: a *mobilisation* and a *persuasion* effect. We jointly test for these effects by examining whether there are systematic differences in treated and untreated municipalities, in terms of: (a) the correlation between actual turnout and pro-Green vote (Table 13 and Figure 17); and (b) the reported votes in the last and the intended votes in the present elections by respondents of the 2021 GLES Cross-Section Pre-Election Survey (Table 15 and Figure 18). The results of our mediation analysis are displayed in Table 14.

Mobilisation Effect

Mobilisation Effect	**Primary Measure**	**Secondary Measure**
Flooded	0.186*** (0.024)	0.487*** (0.070)
Not Flooded	0.173*** (0.017)	0.171*** (0.014)

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 13: This table shows the correlation between municipality Green Party second vote share in the 2021 federal election and turnout for the core sample of the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect.

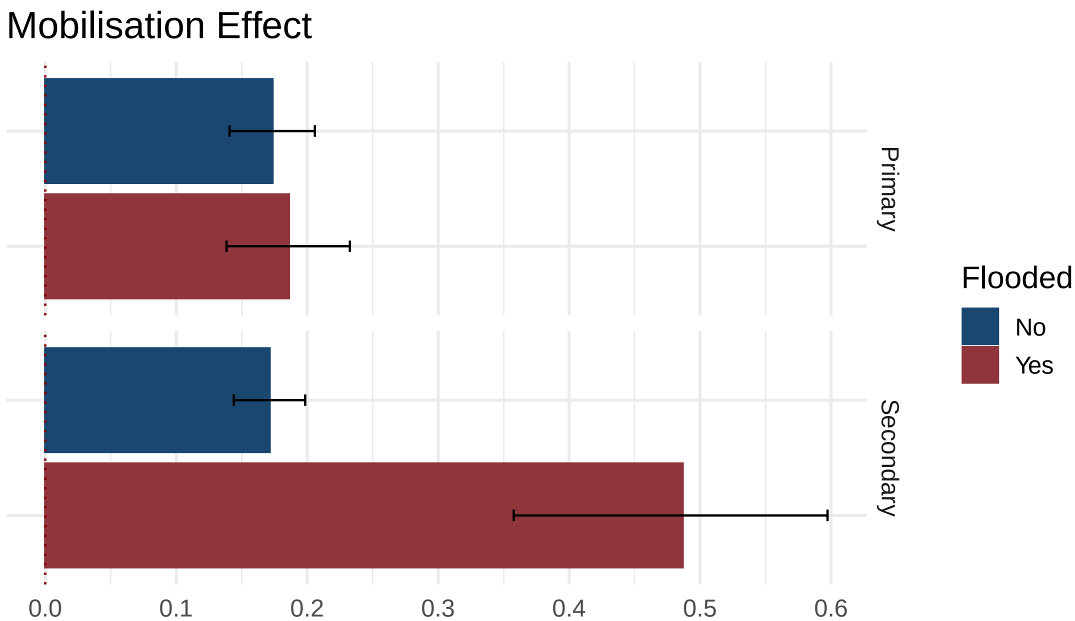

Figure 17: This graph shows the correlation between municipality-level turnout and Green Party second vote share in the 2021 federal election, by status of flood exposure for the core sample of four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). Each horizontal bar represents a correlation (Pearson's product-moment correlation coefficient), and each black error bar at the end represents the corresponding 95% confidence interval. Red bar = result for municipalities that have not been affected by the flood. Blue bar = result for municipalities that have been affected by the flood.

Mediation Analysis

We run a mediation analysis to more formally examine whether turnout (itself an intermediary outcome of the flood treatment) has been a plausible mediator for the effect of flood exposure on Green vote share.

Mediation	**Primary Measure**	**Secondary Measure**
Mediator Model		
Flooded	0.008 (0.006)	0.041* (0.017)
Outcome Model		
Flooded	0.004*** (0.001)	0.004 (0.003)

Turnout	0.001 (0.002)	0.001 (0.002)
Full Model		
ACME	0.000 [0.000, 0.00]	0.000 [-0.0002, 0.00]
ADE	0.004*** [0.002, 0.01]	0.004 [-0.004, 0.01]
Total Effect	0.004*** [0.002, 0.01]	0.004 [-0.004, 0.01]
Prop. Mediated	0.001 [-0.012,0.02]	0.003 [-0.22, 0.23]
N obs.	4,932	4,932

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 14: This table shows the results of mediation analysis of the effect of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election for the core sample of the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Base = baseline model without controls. Mediator = turnout. Outcome = Green Party second vote share. First-difference model estimates with heteroscedasticity-consistent standard errors. Causal effect estimates based on 1000 simulations.

Persuasion Effect

Persuasion Effect	Primary Measure		Secondary Measure	
	Base	**Full**	**Base**	**Full**
Intercept	0.029* (0.014)	0.185 (0.103)	0.040** (0.013)	0.188 (0.102)
Flooded	0.027 (0.026)	0.017 (0.029)	0.005 (0.036)	-0.008 (0.040)
FE	✔	✔	✔	✔
N Obs.	1,072	876	1,072	876
Adj. R^2	0.0004	0.003	-0.0009	0.003

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 15: This table shows the effects of the 2021 Germany floods on individual-level self-reported propensity to switch their second vote choice to the Green Party at the 2021 federal election. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Base = baseline model without controls. Full = fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

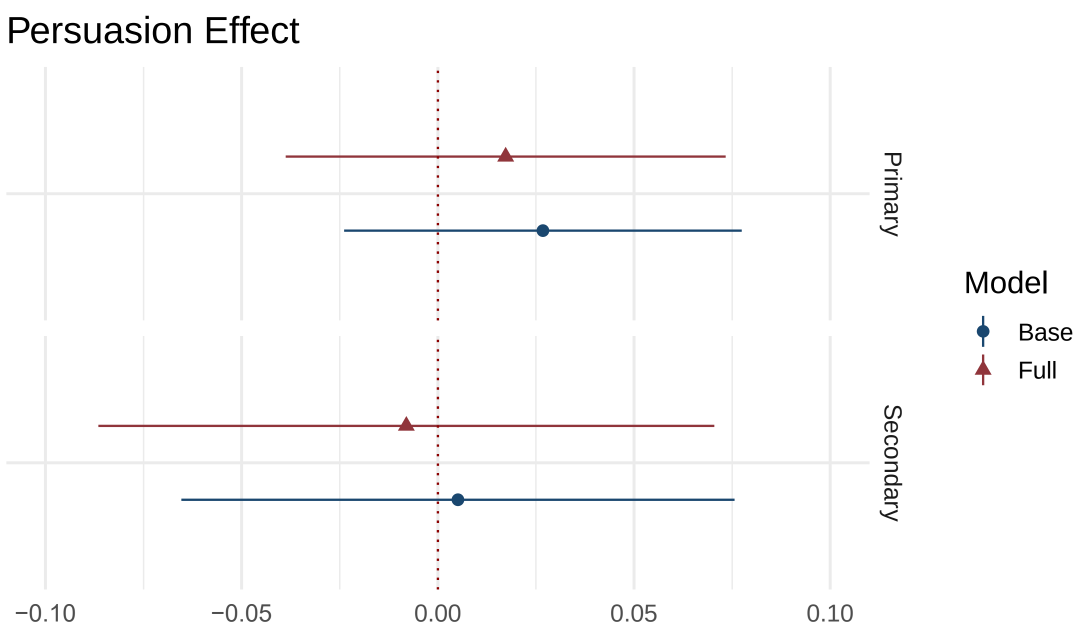

Figure 18: Estimated effects of flood exposure on individual-level self-reported propensity to vote for the Green Party in vote in the 2021 federal election in the 2021 GLES cross-section pre-election survey for the core sample of four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). Each dot represents a point estimate, and each bar represents the corresponding 95% confidence interval. Blue circle = baseline model estimate without controls. Red triangle = full model estimate with controls.

Reported Vote Change[2]

Whilst the above test focuses on the behaviour of all partisan voters; here informed by our SUR analysis results (see appendix section "Seemingly Unrelated Regression (SUR) Model"), we focus more specifically on main party (the CDU/CSU and the SPD) voters and examine whether flood exposure has had particular effects on these voters to vote for the Greens. We construct three dummies for self-reported CDU/CSU, SPD, and Green voters in the 2017 election and test for the flood's effect conditional on such voting record using a linear probability model (LPM).[3] Table 16 displays the results. In line with results seen in the SUR test, we see that there is a small to moderate effect on switching to the Green Party among the two main party supporters in the previous election: the estimated effect is about

[2] Note that this analysis is additional: it was not pre-registered in our registered report or Pre-Analysis Plan.
[3] We only use the primary flooding measure as the secondary measure does not scale as well at the aggregated, constituency level.

10% for ex-CDU/CSU voters and 15% for ex-SPD voters, both significant at the 10% level. Based on the extended results here, we might tentatively infer that the flood has more of a persuasion than mobilisation effect in boosting Green support. The fact that the flood does not appear to have strengthened Green loyalty among the party's old supporters (given the highly imprecisely estimated coefficient for the corresponding term in the table) also supports this interpretation from a different perspective.

Voter Change - OLS	**Primary Measure**
2017 CDU/CSU	-0.090* (0.040)
2017 Greens	0.575*** (0.054)
2017 SPD	-0.017 (0.051)
2017 CDU/CSU x Flooded	0.097† (0.056)
2017 Greens x Flooded	-0.094 (0.076)
2017 SPD x Flooded	0.145† (0.074)
FE	✔
N Obs.	876
Adj. R^2	0.417

Table 16: This table shows propensities for survey respondents who reported voting for the CDU/CSU, Greens and SPD in the previous elections to report intention to vote Green in the 2021 election. Results shown are for the core sample of the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). We compare survey respondents living in flooded and unflooded constituencies under the primary measure of flood exposure which maps flooding at the level of counties ("Landkreise/Kreisfreie Städte").

We also re-run the above vote swing test with logistic regression (Table 17). The results are substantively similar, though more precisely estimated.

Voter Change - Logit	**Primary Measure**
2017 CDU/CSU	-1.67* (0.700)
2017 Greens	3.386*** (0.520)
2017 SPD	-0.173 (0.523)
2017 CDU/CSU x Flooded	1.797* (0.866)
2017 Greens x Flooded	-0.281 (0.771)
2017 SPD x Flooded	1.345† (0.735)
FE	✓
N Obs.	762
Adj. Pseudo R^2	0.342

Table 17: This table shows propensities for survey respondents who reported voting for the CDU/CSU, Greens and SPD in the previous elections to report intention to vote Green in the 2021 election. Results shown are for the core sample of the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). We compare survey respondents living in flooded and unflooded constituencies under both of our measure of flood exposure. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte").

Robustness Checks

A set of post-estimation checks examine and ensure the robustness of our estimates:

Interaction of Covariates with Post-Treatment Indicator

For hypothesis **H1**, we interact all covariates with our post-treatment indicator and compare changes under this more saturated specification against our main estimate. The results are displayed in Table 18. The results do not differ substantially from our main results, so we therefore do not consider it necessary to use the covariates at their baseline values in interaction with the post-treatment indicator as more reliable controls.

Covariates Interaction	**Primary Measure**	**Secondary Measure**
Post	0.033*** (0.001)	0.034*** 0.001
Flooded x Post	0.003 (0.002)	0.017** 0.006
FE	✓	✓
N Obs.	10,032	10,032
Adj. R^2	0.780	0.781

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 18: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election for the core sample of the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). The model controls for two-way interactions of all covariates with the treatment variable. Heteroscedasticity-consistent standard errors clustered by municipality.

Seemingly Unrelated Regression (SUR) Model

To rule out possible scenarios of a more widespread boost in support for the Greens as well as some other parties, we run a seemingly unrelated regression (SUR) model which simultaneously examines the effect of the flood treatment on all parties' vote shares. We use the SUR model to allow for correlations within municipalities that might lead to particular support for one or several parties. The results are shown in Figure 19 and Table 19.

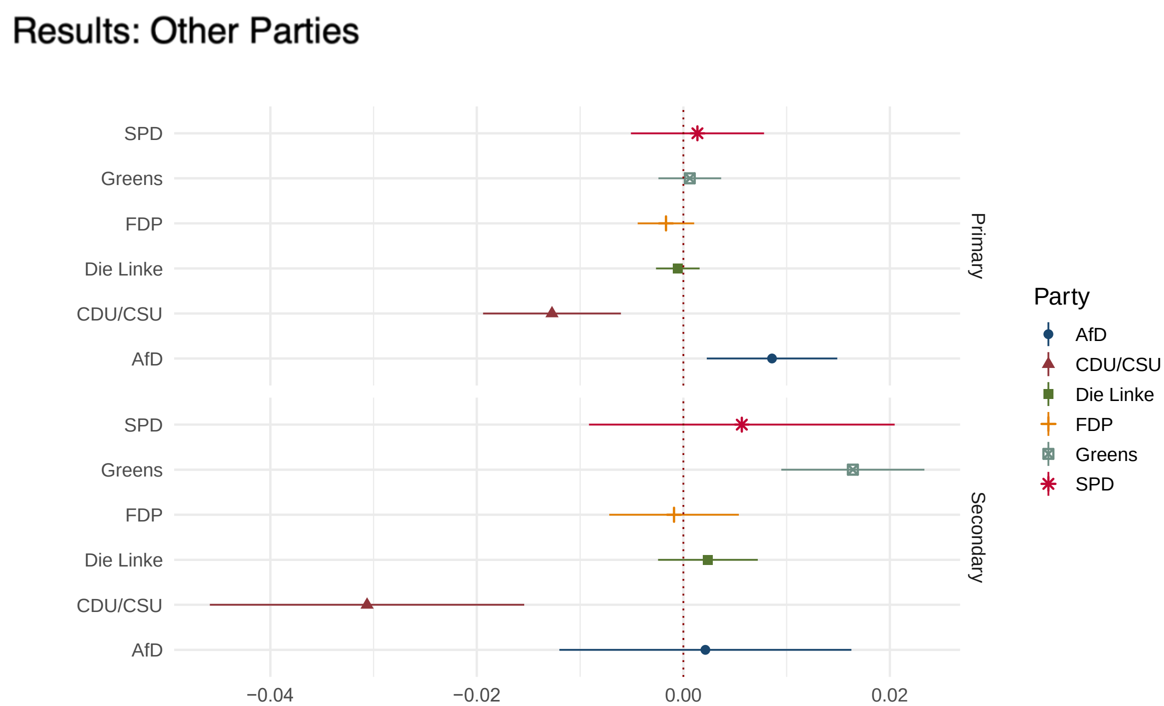

Figure 19: Estimated effects of flood exposure on municipality-level second vote share for all parties in the 2021 federal election for the core sample of four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). Each dot represents a point estimate, and each bar represents the corresponding 95% confidence interval. All results are based on full models with controls, using seemingly uncorrelated regression (SUR) estimation. Blue circle = estimated effect for the Alternative for Germany (AfD) party. Red triangle = estimated effect for the Christian Democratic/Social Union (CDU/CSU) parties. Green square = estimated effect for the Left (Die Linke) party. Yellow cross = estimated effect for the Free Democratic Party (FDP). Teal box = estimated effect for the Green (Greens) party. Red star = estimated effect for the Social Democratic Party (SPD).

SUR	**Primary Measure**	**Secondary Measure**
CDU/CSU	-0.013*** (0.003)	-0.031*** (0.008)
SPD	0.001 (0.003)	0.006 (0.008)
AfD	0.009** (0.003)	0.002 (0.007)
FDP	-0.002 (0.001)	-0.001 (0.003)
Die Linke	-0.001* (0.001)	0.002 (0.002)
Greens	0.001 (0.002)	0.016*** (0.004)

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 19: This table shows the effects of the 2021 Germany floods on municipality-level second vote share in the 2021 federal election for six parties for the core sample of the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). The leftmost column displays the name of the party whose second vote share is used as the dependent variable in the corresponding model within the system of models. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Seemingly uncorrelated regression estimates.

We also replicate the SUR model on the four state-specific subsamples and present the results below (Figure 20).

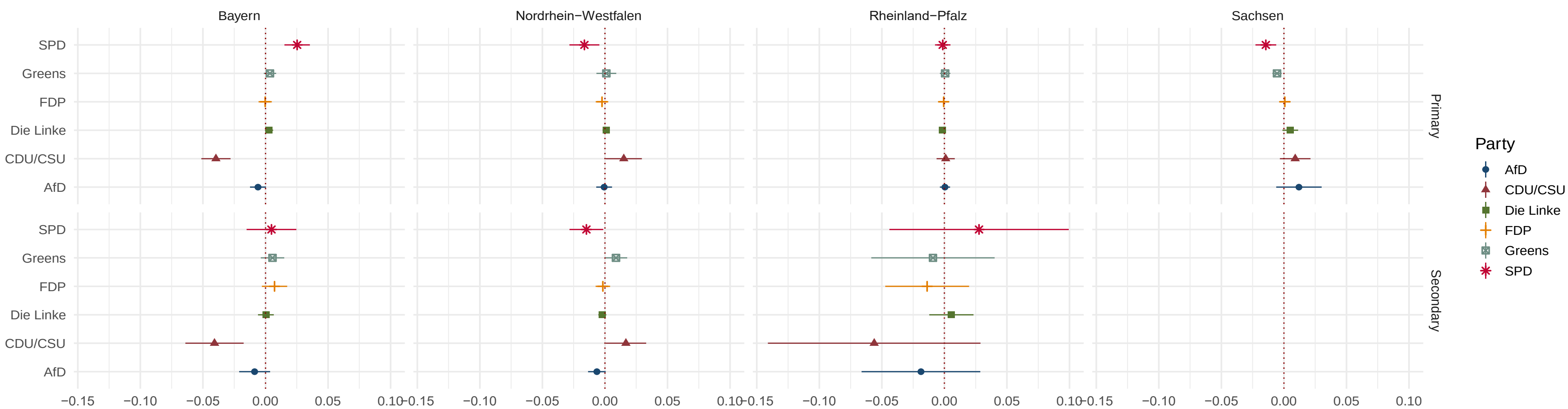

Figure 20: Estimated effects of flood exposure on municipality-level second vote share for all parties in the 2021 federal election for each of the core sample of four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). Each dot represents a point estimate, and each bar represents the corresponding 95% confidence interval. All results are based on full models with controls, using seemingly uncorrelated regression (SUR) estimation. Blue circle = estimated effect for the Alternative for Germany (AfD) party. Red triangle = estimated effect for the Christian Democratic/Social Union (CDU/CSU) parties. Green square = estimated effect for the Left (Die Linke) party. Yellow cross = estimated effect for the Free Democratic Party (FDP). Teal box = estimated effect for the Green (Greens) party. Red star = estimated effect for the Social Democratic Party (SPD).

Full Sample Results

In our full sample we exclude the 52 municipalities in Saarland where the Green Party was banned from the from the second ballot by the Federal Election Committee. This constitutes a trivial reduction of the full sample (< 0.5%). **In these results we note little substantive difference from our core sample results.**

Full Sample Direct Effects

Direct Effect: Full Sample	**Primary Measure**		**Secondary Measure**	
	Base	**Full**	**Base**	**Full**
Post Period	0.029*** (0.0003)	0.030*** (0.0007)	0.029*** (0.0003)	0.031*** (0.0006)
Post x Flooded	0.003*** (0.0008)	0.008*** (0.0009)	0.019 *** (0.003)	0.021*** (0.003)
FE	✔	✔	✔	✔
N Obs.	21,279	21,055	21,279	21,055
Adj. R^2	0.826	0.840	0.826941	0.840

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 20: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election for the full sample of all German states. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Base = baseline model without controls. Full = fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

Full Sample Differential Effects by Severity

Differential Effect: Full Sample	Primary Measure		Secondary Measure	
	Base	**Full**	**Base**	**Full**
Post Period	0.029*** (0.0003)	0.030*** (0.0007)	0.029*** (0.0003)	0.031*** (0.0006)
Post x Low	0.003*** (0.0008)	0.009*** (0.0009)	0.041*** (0.006)	0.042*** (0.005)
Post x High	0.002 (0.002)	0.006** (0.002)	0.013*** (0.003)	0.015*** (0.003)
FE	✓	✓	✓	✓
N Obs.	21,279	21,055	21,279	21,055
Adj. R^2	0.826	0.840	0.827	0.840

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 21: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election for the full sample of all German states. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. High indicates the subset of severely affected municipalities which lie within counties which declared a flooding catastrophe (Federal Ministry of the Interior and Finance Ministry, 2021). Low indicates the other affected municipalities which do not lie within these counties. Base = baseline model without controls. Full = fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

Full Sample Indirect Effects

Indirect Effect: Full Sample	**Secondary Measure**	
	Base	**Full**
Post Period	0.029*** (0.0003)	0.031*** (0.0006)
Post x Direct	0.019*** (0.003)	0.021*** (0.003)
Post x Indirect	-0.005 (0.005)	-0.007 (0.005)
FE	✓	✓
N Obs.	21,279	21,055
Adj. R^2	0.827	0.840

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 22: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election for the full sample of all German states. Direct indicates first-order exposure to the flood. Indirect indicates second-order exposure to the flood via neighbouring municipalities. Neighbourliness is measured with the K-nearest neighbour metric (K=5). The secondary measure of flood exposure combines the primary measure, (which is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) and maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte") with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Base = baseline model without controls. Full = fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

Full Sample Perception-Induced Effect Heterogeneity

Perception Effect: Position, Full Sample	**Primary Measure**		**Secondary Measure**	
	Base	**Full**	**Base**	**Full**
Post Period	0.003	0.077***	-0.011	0.075***
	(0.030)	(0.020)	(0.029)	(0.019)
Post x Flooded	-0.038	-0.020	0.134*	0.019
	(0.073)	(0.027)	(0.058)	(0.032)
Post x Pre-Position	0.008*	-0.002	0.009*	-0.001
	(0.004)	(0.002)	(0.004)	(0.002)
Post x Flooded x Pre-Position	0.006	0.004	-0.011	0.001
	(0.009)	(0.004)	(0.007)	(0.004)
FE	✓	✓	✓	✓
N Obs.	232	232	232	232
Adj. R^2	0.854	0.965	0.876	0.968

Table 23: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election the full sample of all German states. Pre-position indicates pre-treatment positions on climate change based on German Longitudinal Election Study (GLES) survey data. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Base = baseline model without controls. Full = fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

Perception Effect: Salience, Full Sample	**Primary Measure**		**Secondary Measure**	
	Base	**Full**	**Base**	**Full**
Post Period	-0.029 (0.055)	0.086** (0.031)	-0.031 (0.052)	0.082** (0.028)
Post x Flooded	-0.047 (0.159)	0.086 (0.031)	0.130 (0.146)	0.023 (0.075)
Post x Pre-Salience	0.022 (0.013)	-0.006 (0.007)	0.022† (0.013)	-0.004 (0.006)
Post x Flooded x Pre-Salience	0.013 (0.038)	0.010 (0.012)	-0.019 (0.034)	0.0009 (0.017)
FE	✔	✔	✔	✔
N Obs.	116	116	232	232
Adj. R^2	0.851	0.965	0.872	0.968

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 24: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election for the core sample of the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). Pre-salience indicates pre-treatment salience of climate change based on German Longitudinal Election Study (GLES) survey data. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Base = baseline model without controls. Full = fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

Full Sample Climate Concern Effects

Climate Concern: Full Sample	Climate Position				Issue Salience			
	Primary		Secondary		Primary		Secondary	
	Base	**Full**	**Base**	**Full**	**Base**	**Full**	**Base**	**Full**
Post Period	0.362** (0.111)	0.448 (0.537)	0.347*** (0.102)	0.548 (0.512)	0.090** (0.034)	0.155 (0.164)	0.073* (0.032)	0.120 (0.164)
Post x Flooded	0.069 (0.250)	0.315 (0.310)	0.295 (0.401)	0.406 (0.494)	-0.096 (0.078)	-0.112 (0.096)	-0.009 (0.107)	-0.061 (0.138)
FE	✓	✓	✓	✓	✓	✓	✓	✓
N Obs.	232	232	232	232	232	232	232	232
Adj. R^2	0.426	0.477	0.429	0.476	0.287	0.283	0.278	0.275

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 25: This table shows the effects of the 2021 Germany floods on constituency-level concern for the full sample of all German states. The climate position variable is composed of measures from survey questions in the 2017 and 2021 German Longitudinal Election Survey (GLES) cross-section pre-election survey rounds which ask respondents about the position they take on the fight against climate change. The issue salience variable asks respondents how important they consider climate change to be. The secondary measure of flood exposure combines the primary measure – which is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) and maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte") – with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Base = baseline model without controls. Full = fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

Full Sample Mobilisation Effects

Mobilisation: Full Sample	**Primary Measure**	**Secondary Measure**
Flooded	0.186*** (0.024)	0.487*** (0.070)
Not Flooded	0.204*** (0.010)	0.196*** (0.010)

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 26: This table shows the correlation between municipality Green Party second vote share for the full sample of all German states. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect.

Full Sample Persuasion Effects

Persuasion: Full Sample	**Primary Measure**		**Secondary Measure**	
	Base	**Full**	**Base**	**Full**
Intercept	0.018* (0.008)	0.143* (0.067)	0.023** (0.008)	0.148* (0.067)
Flooded	0.037 (0.023)	0.034 (0.028)	0.021 (0.034)	0.010 (0.041)
FE	✔	✔	✔	✔
N Obs.	2,564	2,066	2,564	2,066
Adj. R^2	0.001	0.004	-0.0001	0.003

*** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 27: This table shows the effects of the 2021 Germany floods on individual-level self-reported propensity to switch their second vote choice to the Green Party at the 2021 federal election. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Base = baseline model without controls. Full = fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

Full Sample Interaction of Covariates with Post-Treatment Indicator

Covariates Interaction: Full Sample	**Primary Measure**	**Secondary Measure**
Post	0.030*** (0.0007)	0.031*** (0.0006)
Flooded x Post	0.006*** (0.0018)	0.019*** (0.006)
FE	✔	✔
N Obs.	21,055	21,055
Adj. R^2	0.841	0.840

*** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 28: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election for the full sample of all German states. The model controls for two-way interactions of all covariates with the treatment variable. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Heteroscedasticity-consistent standard errors clustered by municipality.

Full Sample Mediation Analysis

Mediation: Full Sample	**Primary Measure**	**Secondary Measure**
Mediator Model		
Flooded	0.041*** (0.005)	0.097*** (0.014)
Outcome Model		
Flooded	0.0003 (0.0009)	0.003 (0.003)
Turnout	0.005* (0.002)	0.005* (0.002)
Full Model		
ACME	0.0002* [0.00004, 0.00]	0.0005* [0.00004, 0.00]
ADE	0.0004 [-0.001, 0.00]	0.003 [-0.005, 0.01]
Total Effect	0.0006 [-0.001, 0.00]	0.004 [-0.005, 0.01]
Prop. Mediated	0.137 [-2.23, 4.46]	0.07 [-1.10, 1.04]
N obs.	10359	10359

Table 29: This table shows the results of mediation analysis of the effect of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election for the full sample of all German states. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Base = baseline model without controls. Mediator = turnout. Outcome = Green Party second vote share. First-difference model estimates with heteroscedasticity-consistent standard errors. Causal effect estimates based on 1000 simulations.

Full Sample Seemingly Unrelated Regression (SUR)

SUR: Full Sample	**Primary Measure**	**Secondary Measure**
CDU/CSU	-0.013*** (0.003)	-0.031*** (0.008)
SPD	-0.001 (0.003)	-0.008 (0.008)
AfD	0.009 ** (0.003)	0.002 (0.007)
FDP	-0.002 (0.001)	-0.001** (0.003)
Die Linke	0.001 (0.001)	0.002 (0.002)
Greens	-0.001 (0.002)	0.016*** (0.004)

*** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 30: This table shows the effects of the 2021 Germany floods on municipality-level second vote share in the 2021 federal election for six parties f for the full sample of all German states. The leftmost column displays the name of the party whose second vote share is used as the dependent variable in the corresponding model within the system of models. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Seemingly uncorrelated regression estimates.

Genetic Matching

We use genetic matching techniques to construct a subset of units that are most similar across our covariate conditions, and re-estimate our treatment effects on this matched subsample, to check for potential estimation bias from our core sample due to selection and confounding. We notice little substantive change between the current results and those based on our core sample.

Matched Sample Direct Effects

Direct Effect: Matched Sample	**Primary Measure**	**Secondary Measure**
Post Period	0.033*** (0.002)	0.034*** (0.002)
Post x Flooded	0.003 (0.001)	0.015* (0.006)
FE	✔	✔
N Obs.	4,120	1,498
Adj. R^2	0.767	0.796

*** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 31: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election for our matched sample in the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Results shown are for the fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

Matched Sample Differential Effects by Severity

Differential Effect: Matched Sample	**Primary Measure**
Post Period	0.037*** (0.003)
Post x Low	-0.004 (0.005)
Post x High	(-0.004) (0.007)
FE	✓
N Obs.	576
Adj. R^2	0.762

*** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 32: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election for our matched sample in the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. High indicates the subset of severely affected municipalities which lie within constituencies which declared a flooding catastrophe (Federal Ministry of the Interior and Finance Ministry, 2021). Low indicates the other affected municipalities which do not lie within these constituencies. Results shown are for the fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

Matched Sample Indirect Effects

Indirect Effect: Matched Sample	**Secondary Measure**
Post Period	0.034*** (0.002)
Post x Direct	0.008 (0.007)
Post x Indirect	0.047* (0.020)
FE	✔
N Obs.	1,498
Adj. R^2	0.799

*** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 33: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share for our matched sample in the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). Direct indicates first-order exposure to the flood. Indirect indicates second-order exposure to the flood via neighbouring municipalities. Neighbourliness is measured with the K-nearest neighbour metric (K=5). The secondary measure of flood exposure combines the primary measure, (which is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) and maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte") with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Results shown are for the fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

Matched Sample Climate Concern Effects

Climate Concern Effect: Matched Sample	**Climate Position**		**Issue Salience**	
	Primary	Secondary	Primary	Secondary
Post Period	0.473 (1.020)	0.716 (1.259)	0.232 (0.332)	0.287 (0.448)
Post x Flooded	0.647 (0.420)	0.734 (0.537)	-0.056 (0.123)	0.020 (0.194)
FE	✔	✔	✔	✔
N Obs.	88	44	88	44
Adj. R^2	0.363	0.086	0.331	-0.251

*** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 34: This table shows the effects of the 2021 Germany floods on constituency-level concern for our matched sample in the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). The climate position variable is composed of measures from survey questions in the 2017 and 2021 German Longitudinal Election Survey (GLES) cross-section pre-election survey rounds which ask respondents about the position they take on the fight against climate change. The issue salience variable asks respondents how important they consider climate change to be. The secondary measure of flood exposure combines the primary measure – which is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) and maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte") – with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Results shown are for the fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

Matched Sample Mobilisation Effects

Mobilisation Effect: Matched Sampled	**Primary Measure**	**Secondary Measure**
Flooded	0.198*** (0.038)	0.589** (0.163)
Not Flooded	0.181*** (0.026)	0.239*** (0.015)

*** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 35: This table shows the correlation between municipality Green Party second vote share in the 2021 federal election and turnout for our matched sample in the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect.

Matched Sample Persuasion Effects

Persuasion Effect: Matched Sample	**Primary Measure**	**Secondary Measure**
Intercept	0.341* (0.134)	0.515* (0.195)
Flooded	-0.012 (0.042)	-0.040 (0.078)
FE	✔	✔
N Obs.	474	185
Adj. R^2	0.017	0.016

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 36: This table shows the effects of the 2021 Germany floods on individual-level self-reported propensity to switch their second vote choice to the Green Party at the 2021 federal election for our matched sample in the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Results shown are for the fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

Flood Risk

We restrict our analyses to the subset of municipalities considered to be of high flood risk by using a newly released dataset on European flood risk which is available from the European Commission's Joint Research Centre Data Catalogue (Dottori et al., 2021). This nets out any long-term differences in the propensity to flood exposure among regions and any resulting confounds on our main relationship of interest.

Flood Risk Sample Direct Effects

Direct Effect: Risk	**Primary Measure**	**Secondary Measure**
Post Period	0.041*** (0.002)	0.041*** (0.002)
Post x Flooded	0.004* (0.002)	0.020*** (0.004)
FE	✔	✔
N Obs.	2,362	2,362
Adj. R^2	0.847	0.852

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 37: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election for the subset of municipalities in the core sample of the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony) which are of high flood risk. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. The flood risk measure is based on a newly released dataset on European flood risk available from the European Commission's Joint Research Centre Data Catalogue. Heteroscedasticity-consistent standard errors clustered by municipality.

Flood Risk Sample Differential Effects by Severity

Differential Effect – Risk	**Primary Measure**	**Secondary Measure**
Post Period	0.041*** (0.002)	0.041*** (0.002)
Post x Low	0.004† (0.002)	0.031*** (0.006)
Post x High	0.009* (0.004)	0.012** (0.005)
FE	✔	✔
N Obs.	2,362	2,362
Adj. R^2	0.848	0.853

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 38: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election for the subset of municipalities in the core sample of the four affected states which are of high flood risk. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. The flood risk measure is based on a newly released dataset on European flood risk available from the European Commission's Joint Research Centre Data Catalogue. High indicates the subset of severely affected municipalities which lie within counties which declared a flooding catastrophe (Federal Ministry of the Interior and Finance Ministry, 2021). Low indicates the other affected municipalities which do not lie within these counties. Heteroscedasticity-consistent standard errors clustered by municipality.

Flood Risk Sample Indirect Effects

Indirect Effect – Risk	**Secondary Measure**
Post Period	0.040*** (0.002)
Post x Direct	0.009 (0.009)
Post x Indirect	0.032† (0.017)
FE	✔
N Obs.	2,362
Adj. R^2	0.853

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 39: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election for the subset of municipalities in the core sample of the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony) that are of high flood risk. Direct indicates first-order exposure to the flood. Indirect indicates second-order exposure to the flood via neighbouring municipalities. Neighbourliness is measured with the K-nearest neighbour metric (K=5). The secondary measure of flood exposure combines the primary measure, (which is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) and maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte") with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. The flood risk measure is based on a newly released dataset on European flood risk available from the European Commission's Joint Research Centre Data Catalogue. Heteroscedasticity-consistent standard errors clustered by municipality.

Flood Risk Sample Climate Concern Effects

Climate Concern Effect – Risk	**Climate Position**		**Issue Salience**	
	Primary	Secondary	Primary	Secondary
Post Period	-0.837 (0.583)	-0.619 (0.626)	-0.473† (0.246)	-0.473† (0.240)
Post x Flooded	1.058** (0.344)	0.845† (0.498)	0.048 (0.091)	-0.095 (0.104)
FE	✔	✔	✔	✔
N Obs.	92	92	92	92
Adj. R^2	0.531	0.470	0.513	0.525

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 40: This table shows the effects of the 2021 Germany floods on constituency-level concern for the subset of municipalities in the core sample of the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony) that are considered to be of high flood risk. The climate position variable is composed of measures from survey questions in the 2017 and 2021 German Longitudinal Election Survey (GLES) cross-section pre-election survey rounds which ask respondents about the position they take on the fight against climate change. The issue salience variable asks respondents how important they consider climate change to be. The secondary measure of flood exposure combines the primary measure – which is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) and maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte") – with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. The flood risk measure is based on a newly released dataset on European flood risk available from the European Commission's Joint Research Centre Data Catalogue. Heteroscedasticity-consistent standard errors clustered by municipality.

Flood Risk Sample Mobilisation Effects

Mobilisation Effect – Risk	**Primary Measure**	**Secondary Measure**
Flooded	0.119* (0.052)	0.524*** (0.111)
Not Flooded	0.179*** (0.035)	0.133*** (0.030)

Table 41: This table shows the correlation between municipality Green Party second vote share in the 2021 federal election and turnout for the subset of municipalities in the core sample of the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony) that are considered to be of high flood risk. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. The flood risk measure is based on a newly released dataset on European flood risk available from the European Commission's Joint Research Centre Data Catalogue.

Flood Risk Sample Persuasion Effects

Persuasion Effect – Risk	**Primary Measure**	**Secondary Measure**
Intercept	0.235* (0.100)	0.247* (0.098)
Flooded	0.033 (0.031)	0.004 (0.040)
FE	✔	✔
N Obs.	837	837
Adj. R^2	-0.004	-0.006

Table 42: This table shows the effects of the 2021 Germany floods on individual-level self-reported propensity to switch their second vote choice to the Green Party at the 2021 federal election for the subset of municipalities in the core sample of the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony) that are considered to be of high flood risk. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. The flood risk measure is based on a newly released dataset on European flood risk available from the European Commission's Joint Research Centre Data Catalogue. Heteroscedasticity-consistent standard errors clustered by municipality.

First Vote Results

We reproduce our main results replacing the outcome variable with the Green Party vote share in the first vote ("*Erststimme*"). Whereas the second vote is used to elect a party list in each state, the first vote is for an individual constituency candidate.

First Vote Direct Effects

Direct Effect: First Vote	**Primary Measure**	**Secondary Measure**
Post Period	0.026*** (0.0007)	0.030*** (0.0007)
Post x Flooded	0.018*** (0.001)	0.040*** (0.003)
FE	✔	✔
N Obs.	21,110	21,110
Adj. R^2	0.808	0.806

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 43: This table shows the effects of the 2021 Germany floods on municipality-level Green Party first vote share in the 2021 federal election for the full sample of all German states. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Heteroscedasticity-consistent standard errors clustered by municipality.

First Vote Differential Effects by Severity

Differential Effect: First Vote	**Primary Measure**	**Secondary Measure**
Post Period	0.027*** (0.0007)	0.030*** (0.0007)
Post x Low	0.013*** (0.001)	0.045*** (0.007)
Post x High	0.030*** (0.002)	0.039*** (0.003)
FE	✓	✓
N Obs.	21,110	21,110
Adj. R^2	0.810	0.806

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 44: This table shows the effects of the 2021 Germany floods on municipality-level Green Party first vote share in the 2021 federal election for the full sample of all German states. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. "High" indicates the subset of severely affected municipalities which lie within counties which declared a flooding catastrophe (Federal Ministry of the Interior and Finance Ministry, 2021). "Low" indicates the other affected municipalities which do not lie within these counties. Heteroscedasticity-consistent standard errors clustered by municipality.

First Vote Indirect Effects

Indirect Effect: First Vote	**Secondary Measure**
Post Period	0.029*** (0.0007)
Post x Direct	0.003 (0.005)
Post x Indirect	0.089*** (0.008)
FE	✔
N Obs.	21,110
Adj. R^2	0.811

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 45: This table shows the effects of the 2021 Germany floods on municipality-level Green Party first vote share in the 2021 federal for the full sample of all German states. Direct indicates first-order exposure to the flood. Indirect indicates second-order exposure to the flood via neighbouring municipalities. Neighbourliness is measured with the K-nearest neighbour metric (K=5). The secondary measure of flood exposure combines the primary measure, (which is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) and maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte") with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Heteroscedasticity-consistent standard errors clustered by municipality.

First Vote Mobilisation Effects

Mobilisation Effect: First Vote	**Primary Measure**	**Secondary Measure**
Flooded	0.281*** (0.023)	0.562*** (0.060)
Not Flooded	0.220*** (0.010)	0.221*** (0.009)

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 46: This table shows the correlation between municipality Green Party first vote share for the full sample of all German states. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect.

First Vote Persuasion Effects

Persuasion Effect: First Vote	**Primary Measure**	**Secondary Measure**
Intercept	0.145* (0.070)	0.156* (0.070)
Flooded	0.062* (0.025)	0.046 (0.033)
FE	✓	✓
N Obs.	2,015	2,015
Adj. R^2	0.024	0.020

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 47: This table shows the effects of the 2021 Germany floods on individual-level self-reported propensity to switch their first vote choice to the Green Party at the 2021 federal election. The primary measure of flood exposure is based on official reporting from the Federal Office for Civil Protection and Disaster Assistance (BKK) which maps flood exposure at the level of counties ("Landkreise/Kreisfreie Städte"). The secondary measure of flood exposure combines this measure with satellite-based flood mapping from the Copernicus Emergency Management Service (EMS), coding areas as affected where the two measures intersect. Heteroscedasticity-consistent standard errors clustered by municipality.

Indirect Effects: Alternative Measure

We also use a different measure of indirect treatment (via neighbours that are treated), by redefining the spatial weight matrix with the queen metric, to check for the spatial model's sensitivity to contiguity measurement choice.

Indirect Effect: Queen Metric	**Secondary Measure**
Post Period	0.033*** (0.001)
Post x Direct	0.002 (0.005)
Post x Indirect	0.013*** (0.004)
FE	✓
N Obs.	10.032
Adj. R^2	0.783

Note: *** p < .001, ** p < .01, * p <.05, † p<0.1.

Table 48: This table shows the effects of the 2021 Germany floods on municipality-level Green Party second vote share in the 2021 federal election for the core sample of the four affected states (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria, and Saxony). Direct indicates first-order exposure to the flood. Indirect indicates second-order exposure to the flood via neighbouring municipalities. Neighbourliness is measured with the queen neighbour metric which includes both common edges and vertices as evidence for being neighbours. Results shown are for the fully controlled model with all covariates. Heteroscedasticity-consistent standard errors clustered by municipality.

Parallel Work by Hilbig and Riaz

Hilbig and Riaz (2022) also study the effects of the 2021 Germany floods on Green Party votes in the 2021 federal election, with their analysis centred on the two most affected states of Rhineland-Palatinate and North Rhine-Westphalia.[4] Their work provides a valuable and rare opportunity to consider the robustness of our results across different research designs. Our combined findings help to build cumulative knowledge, both for this specific case and for our understanding of the impact of climate events on support for environmentalist parties more generally.

Our respective designs differ in several ways including the level, unit, and scope of analysis; the measurement of flood exposure; the specification of identification models; and the different data sources and sub-analyses set-ups. The most important difference is that the studies have different operational definitions of the estimand, namely the effect of flood exposure on Green Party vote share. For Hilbig and Riaz, this is the average difference in vote share change in the two most affected states (North Rhine-Westphalia and Rhineland-Palatinate). In our paper, this is the average difference in vote share change either pooled across all four affected states for the core-sample analysis (North Rhine-Westphalia, Rhineland-Palatinate, Bavaria and Saxony), or across all German states for the full sample analysis.

Hilbig and Riaz's results echo our findings under our model specification which is the most comparable to their main analysis: the by-state analysis for Rhineland-Palatinate and North Rhine-Westphalia under our primary measure (see appendix section "Results by State"). Based on this, Hilbig and Riaz conclude that the floods had little to no effect on Green Party voting in the federal elections in Rhineland-Palatinate and North Rhine-Westphalia.

We draw our conclusions from our main analyses, as declared in our pre-registered design. At the design stage, we chose to focus on nationwide samples because of the nature of the election (which were federal elections) and the nature of the Green Party (which is a national political party). We find no evidence for the violation of our key identification assumption (parallel trends) on either the core or full samples (see appendix section "Randomisation Checks"). The consistency of our core and matched sample results lends further support for the robustness of our main results, especially against potential contentions about the comparability of units, whether by state or some other stratifying factors (see appendix section "Genetic Matching").

[4] The first version of Hilbig and Riaz's working paper was made available online on 4th October 2022, after the submission of our registered report to *Research & Politics*.

We exercise greater caution when interpreting our by-state results and take them to be mostly indicative of differences in local effects between the states which make up our core sample. Indeed, by comparison with our main results, we see greater inconsistency between the results for each measure. We see positive estimates for the Rhineland-Palatinate and North Rhine-Westphalia under the secondary measure, whilst under the primary measure, the estimate for Rhineland-Palatinate is weakly positive (but not statistically significant at the 5% level) and we see no evidence for an effect in North Rhine-Westphalia (see appendix section "Results by State"). In contrast to the secondary measure results, the small effect we observe for the primary measure in our main analysis may not be large enough to remain detectable under this model specification at a within-state level.

When considering these results in conjunction with our main results, we also note (as do Hilbig and Riaz) that the floods could have contributed towards nationwide increases in Green Party support. In the context of our design, this would render localised effects of the floods less visible since the control group becomes contaminated. Taking this logic to the state level, it is also possible — particularly in the heavily affected states of Rhineland-Palatinate and North Rhine-Westphalia — that the floods caused increases in Green Party support in untreated municipalities which were sufficient to counter the small true effect we assume from the results in our main analysis.

Hilbig and Riaz find that their conclusions remain unchanged when measuring flooding intensity at the municipality rather than county level with a measure based on satellite data. We cannot currently comment on how our secondary measure relates to the satellite-based measure used by Hilbig and Riaz, since the data used are not publicly available and their current working paper shows no visualisation of the data.

As noted in the main text, we recognise Hilbig and Riaz's valuable contribution in studying the impacts of the floods on the perceived salience of climate change and on self-reported Green Party support. Both of our studies draw conclusions that caution against overoptimism in natural disaster-driven improvements in popular support for pro-environment parties. Even in the aftermath of a major environmental disaster such as the 2021 Germany floods, the studies reveal that effects on reported attitudes and voting behaviour are limited in magnitude, short in timespan, and heavily dependent on local conditions and circumstances.

Simulation Analysis

We use the state-of-the-art software suite in the R language, DeclareDesign (DD), tailored for declaring, simulating, and diagnosing designs before implementing them in practice, for transparent and reproducible social science research with credible scientific claims. The DD suite follows the *MIDA* framework, which includes a full-stack sequence of design philosophy and practice: briefly stated, one (1) starts with an *"M"*odel which describes a relationship among investigated variables in the real world (i.e. a data generating process, or DGP), (2) specifies an *"I"*nquiry of interest or more (i.e. one or more outcomes), (3) declares a *"D"*ata strategy for collecting the sample(s) used for testing the corresponding hypothesis (i.e. a sampling strategy), and (4) finally chooses an *"A"*nswer strategy for actual hypothesis testing (i.e. one to several statistical tests).

By simulating the entire process of the research workflow, from data generation to empirical estimation, the MIDA-DD setup allows researchers to observe and diagnose issues and problems in a design prior to and independent of real data, which can effectively minimise risks of p-hacking and maximise chances of reaching credible inference. The DD suite itself offers a powerful computational toolkit to pre-test a research design without using actual data, especially in terms of estimation bias and statistical power, which offers a great way to quantify a priori strengths and weaknesses in our design.

For our study, our baseline set-up is a simple but reasonable two-period treatment-response process, where the outcome, Green Party vote share, is assumed to be a linear combination of our treatment, flood exposure, other covariates (including the more "special" ones for supposed heterogeneous processes), time and unit indicators, and their respective effects. For unit i at time t we assume:

$$Y_{it} = \eta_i + \delta_t + \tau D_{it} + X_{it}'\beta + \rho R_{it} + \sigma D_{it}^{+} + \epsilon_{it}$$

where Y is the outcome, D the time-varying binary treatment indicator (1 = Treated), X the set of covariates with potential confound, R the second-order treatment indicator representing distance-weighted average spillover among neighbouring units, and D^{+} the additional treatment indicator (1 = Extra High Intensity). η, δ and ϵ are the unit, time, and unit-time co-specific effects. τ is the average treatment effect among the treated (ATT) of main interest, ρ and σ the spatial autoregressive and extra-intensity effects, and β the (total) effect from the covariates. Notice that $Cor[D, X]$ can either be zero (random assignment) or not (nonrandom assignment with confounding). The assumed DGP includes *all* our theoretical scenarios about the true DGP and allows us to simulate virtually all possible (idealised) situations for consideration.

In the special — and most important — case where D is assumed to be random to Y and X, we assume the following set of distributional situations for the random parameters (variables) in the DGP model, without loss of generality:

$$\begin{aligned} D &\sim \mathcal{Binom}(0.3), \\ X &\sim \mathcal{N}(0,1)\ \ (Cor[D,X]=0), \\ R &= WD \text{ where } W \text{ is the spatial weights matrix}, \\ D^{+} &\sim \mathcal{Binom}(0.1) \text{ if } D=1 \text{ and } 0 \text{ otherwise}, \\ \eta,\delta,\epsilon &\sim \mathcal{N}(0,1). \end{aligned}$$

where the two probability parameters (for D, D^{+}) are assigned with values taken from our actual sample. For the scalar parameters (effects) we assume the following:

$$\tau = 1,\ \beta = 10,\ \rho = 0.5,\ \sigma = 0.1.$$

For sample size, we follow our expected sample (5,172 municipalities in the four affected states in Germany[5]), in a two-period temporal framework:

$$N = 5172, T = 2.$$

We then add to this "M" setup our "I" designation, which is τ, the AT from our four DID models introduced in the main text, the simple and fully controlled classical models (DID and DIDX), the additional treatment model (DID+), and the spatial model (SDID). Our "D" strategy is a simple inclusion of the whole sample; and our "A" strategy is the four estimators just mentioned. We then simulate this entire design 500 times, each time with a different randomly drawn sample as our data and different estimates on this sample. We obtain a simulated distribution of true and estimated effects.

We also calculate four diagnostic statistics: bias, root-mean-square error (RMSE), power, and coverage, defined in the following ways:

$$\begin{aligned} Bias &= E[\tau - \hat{\tau}], \\ RMSE &= \sqrt{E[(\tau - \hat{\tau})^2]}, \\ Power &= E[\mathbb{1}\{p(\hat{\tau} = 0) < 0.05\}], \\ Coverage &= E[\mathbb{1}\{\tau \text{ is in the 95\% CI of } \hat{\tau}\}]. \end{aligned}$$

Roughly speaking, the first two statistics quantify the ability of our design in estimating and predicting the true parameter value, and the next two its ability in detecting and covering the latter.

Overall, the code we use for setting up and implementing the design is as follows:

[5] Simulation results for the full sample ($N = 10{,}790$) are very similar. We choose to focus on the core sample for consistency and clarity. Full results available from the authors.

```
## function(N_units = 5172, N_periods = 2,
##          tau = 1, beta = 10, corr = 0,
##          p_d1 = 0.1,  tau1 = 0.1,
##          w = W, rho = 0.5) {
##    # define population
##    declare_population(
##      units = add_level(
##        N = N_units, # nobs
##        U_unit = rnorm(N), # unit fe
##        D_unit = rbinom(N, 1, 0.3), # treatment dummy (p=30%)
##        D_time = rep(N_periods, N) # treatment time (2)
##      ),
##      periods = add_level(
##        N = N_periods, # n periods
##        U_time = rnorm(N), # time fe
##        nest = FALSE
##      ),
##      unit_period = cross_levels(
##        by = join(units, periods), # unit x time
##        U = rnorm(N), # unit-time effect
##        D = if_else(D_unit == 1 & as.numeric(periods) >= D_time, 1, 0), # treatment status (def)
##        X = sim_corrv(D, rho = corr), # controls
##        D1 = sim_dplus(D, p = p_d1), # treatment +
##        R = sim_slag(D, w, periods), # indirect treatment
##        potential_outcomes(
##          Y ~ U + U_unit + U_time + D*tau + X*beta + D1*tau1 + R*rho, # y
##          conditions = list(D = c(0, 1)) # treatment status
##          )
##      )
##    ) +
##      # define estimand
##      declare_inquiries(
##        ATT = mean(Y_D_1 - Y_D_0) # att
##      ) +
##      # define measurement
##      declare_measurement(Y = reveal_outcomes(Y~D)) + # yobs
##      # define estimators
##      declare_estimator(
##        Y~D, # basic model
##        cluster = "units", # clustered se
##        fixef = c("units", "periods"), # 2wfw
##        model = fixest::feols,
##        model_summary = tidy_model,
```

```
##       inquiry = "ATT",
##       label = "DID"
##     ) +
##     declare_estimator(
##       Y~D+X, # full model
##       cluster = "units", # clustered se
##       fixef = c("units", "periods"), # 2wfw
##       model = fixest::feols,
##       model_summary = tidy_model,
##       inquiry = "ATT",
##       term = "D",
##       label = "DIDX"
##     ) +
##     declare_estimator(
##       Y~D+X+D1, # full model + treat+
##       cluster = "units", # clustered se
##       fixef = c("units", "periods"), # 2wfw
##       model = fixest::feols,
##       model_summary = tidy_model,
##       inquiry = "ATT",
##       term = "D",
##       label = "DID+"
##     ) +
##     declare_estimator(
##       Y~D+X+R, # full model + sl
##       cluster = "units", # clustered se
##       fixef = c("units", "periods"), # 2wfw
##       model = fixest::feols,
##       model_summary = tidy_model,
##       inquiry = "ATT",
##       term = "D",
##       label = "SDID"
##       )
##  }
```

A graphical illustration of the simulated DGP using the parameter setups above is shown below:

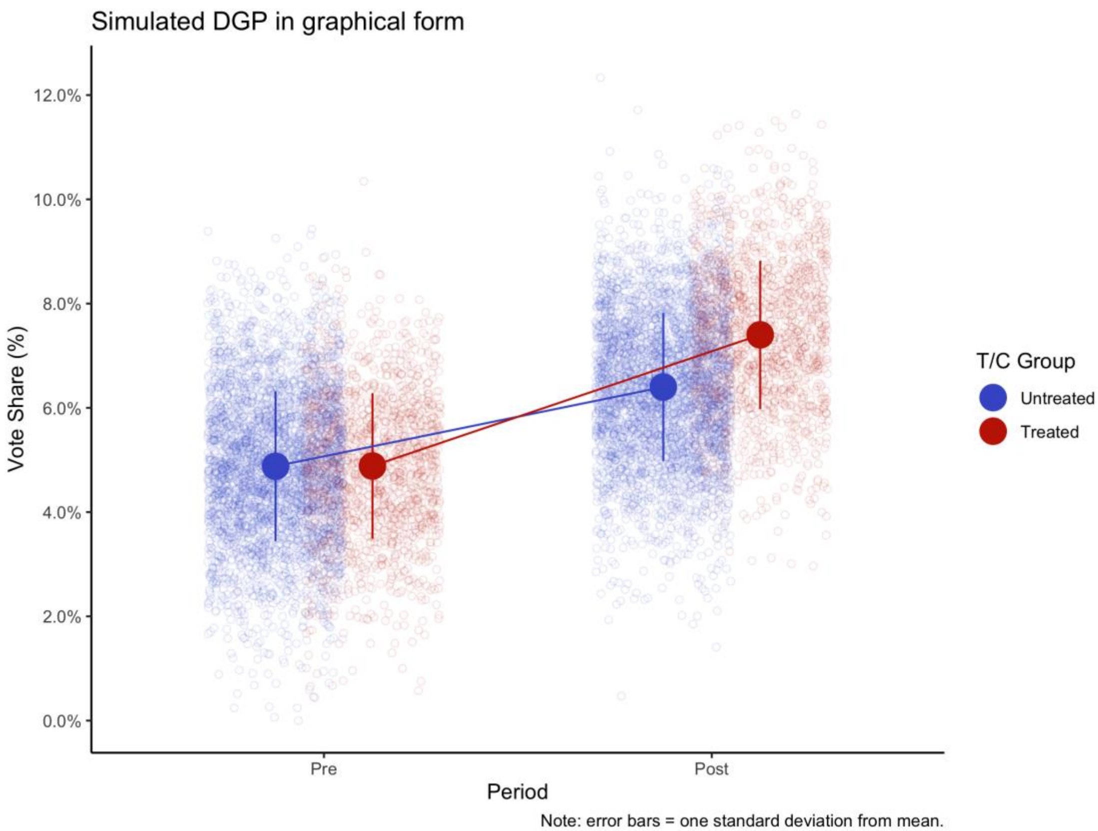

Figure 21: A graphical illustration of our baseline DGP. Treated = Red, Untreated = Blue, True ATT = +1%.

For our baseline design, we present summary results for a single simulation of this design, based on the same parameter setup as before:

Table 49: Example of true and estimated ATTs.

Term	Mean	SE
Estimand	1.000	-
Estimate (DID)	1.018	0.044
Estimate (DIDX)	1.014	0.044
Estimate (DID+)	0.992	0.045
Estimate (SDID)	1.010	0.044

Whilst the diagnostic statistics for this simulated design are as follow:

Table 50: Example of estimated diagnostic statistics.

Inquiry	Estimator	E[ATT]	E[ATT Est.]	Bias	RMSE	Power	Coverage
ATT	DID	1.000	1.005	0.005	0.042	1.000	0.960
ATT	DIDX	1.000	1.006	0.006	0.042	1.000	0.960
ATT	DID+	1.000	0.995	-0.005	0.043	1.000	0.950
ATT	SDID	1.000	1.006	0.006	0.042	1.000	0.962

And it is obvious that whilst the different models differ in their bias, precision, and coverage estimates — albeit to a very minor extent under the random assignment assumption — their statistical powers are all estimated at ≈ 100% (500 simulation draws). We are therefore not concerned about lack of power in our design, should a true positive effect be detected.

For generalisability and realism, we also look beyond the basic setup and across a broad range of parameter setups. We are interested to see if and how our estimation strategies perform under a diverse range of possible DGP scenarios, especially when (a) treatment assignment has been confounded to be non-random due to covariate influence, (b) additional treatment effects vary in their assignment likelihoods and effect magnitudes, and (c) spatial autoregressive and spillover effects change in their intensities as well. These are achieved by tweaking the parameter values above, and thus broadening our parameter space through their unique listwise comparison. We see little substantial change in key parameter estimates across these scenarios. Results are available from the authors upon request.

Appendix References

Copernicus Emergency Management Service (2021) *EMSR517:* Flood in Western Germany. https://emergency.copernicus.eu/mapping/list-of-components/EMSR517 (last accessed August 2022).

Database of Global Administrative Areas (GADM) (2021) Germany. https://gadm.org/download_country.html (last accessed August 2022).

Delgado MS and Florax RJGM (2015) Difference-in-Differences Techniques for Spatial Data: Local Autocorrelation and Spatial Interaction. *Economics Letters* 137: 123–26. DOI: 10.1016/j.econlet.2015.10.035.

Deutsche Welle (2021) German floods: Leaders agree on €30-billion reconstruction fund. https://www.dw.com/en/german-floods-leaders-agree-on-30-billion-reconstruction-fund/a-58822602 (last accessed August 2022).

Dottori F, Alfieri L, Bianchi A, Skoien, J, and Salamon P (2021) A new dataset of river flood hazard maps for Europe and the Mediterranean Basin region [Preprint]. *Hydrology and Soil Science – Hydrology*. https://doi.org/10.5194/essd-2020-313.

Federal Ministry of the Interior and Finance Ministry (2021) Zwischenbericht zur Flutkatastrophe 2021: Katastrophenhulfe, Soforthulfen und Wiederaufbau. September 2021.

Federal and State Statistical Offices (2021) Bundestagswahlen: Wahlberechtigte, Wahlbeteiligung, gültige Zweitstimmen nach ausgewählten Parteien - Wahltag - regionale Tiefe: Gemeinden (bis 2017).

GLES (2019) GLES Pre-Election Cross-Section 2017. *GESIS, Cologne. ZA6800 Data file Version 5.0.1,* https://doi.org/10.4232/1.13234.

GLES (2022) GLES Pre-Election Cross-Section 2021. *GESIS, Cologne. ZA7700 Data file Version 2.0.0,* https://doi.org/10.4232/1.13860.

Hilbig H and Riaz S (2022) Natural Disasters and Green Party Support. OSF Preprints. 22 September. DOI: 10.31219/osf.io/3k64w.

Wing C, Simon K and Bello-Gomez RA (2018) Designing Difference in Difference Studies: Best Practices for Public Health Policy Research. *Annual Review of Public Health* 39(1): 453–469. DOI: 10.1146/annurev-publhealth-040617-013507.