The relationship between the youth-led "Fridays for Future" climate movement and voting, politician and media behavior in Germany

Marc Fabel[1], Matthias Flückiger[2], Markus Ludwig[3], Helmut Rainer[4], Maria Waldinger[5], and Sebastian Wichert[6]

[1]ottonova, Munich, Germany
[2]Department of Economics and Related Studies, University of York, UK
[3]Department of Economics, Technical University Braunschweig, Germany, CESifo
[4]Department of Economics, University of Munich, Center for Labor and Demographic Economics, ifo Institute, Germany, CESifo
[5]*Corresponding author, Center for Labor and Demographic Economics, ifo Institute, Germany, CESifo (waldinger@ifo.de)
[6]LMU-ifo Economics & Business Data Center, University of Munich, ifo Institute, Germany, CESifo

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Abstract

We study the relationship between the Fridays for Future climate protest movement in Germany and citizen political behavior. In 2019, crowds of young protesters, mostly under voting age, demanded immediate climate action. Exploiting cell phone-based mobility data and hand-collected information on nearly 4,000 climate protests, we create a highly disaggregated measure of protest participation. Using this measure, we show that Green Party vote shares increased more in counties with higher protest participation (n = 960). To address the possibility of nonrandom protest participation, we use various empirical strategies. Examining mechanisms, we find evidence for three relevant factors: reverse intergenerational transmission of pro-environmental attitudes from children to parents (n = 76,563), stronger climate-related social media presence by Green Party politicians (n = 197,830), and increased local media coverage of environmental issues (n = 47,060). Our findings suggest that youth protests may initiate the societal change needed to overcome the climate crisis.

1 Main text

1.1 Introduction

Children and youth will bear the brunt of the effects of climate change over the coming decades. They also constitute the generation with the highest stakes in climate action, as today's responses to climate change will directly affect the rest of their lives [1]. And yet, being too young to vote and hold office, children and youth face limited options to translate their climate change concerns into sustained influence on political decision-making.

Over the course of 2019, Greta Thunberg, the Swedish teen climate activist, inspired young people around the globe to stage some of the largest environmental protests in history. Imitating Thunberg's "School Strike for Climate" in front of the Swedish parliament, students skipped classes, mostly on Fridays, to participate in mass protests over climate change inaction. The declared mission of the "Fridays for Future" movement (henceforth FFF) was to push both adult voters and politicians past "business as usual" and toward prioritizing adequate climate action.

We examine the relationship between the FFF protest movement in Germany and citizen political behavior, politicians, and the media. While it is known that mass protests can change political attitudes and behaviors, FFF differs from other social movements in the scale of its demands and the intergenerational trade-offs involved in them. The young FFF activists belong to a politically marginalized group whose future well-being is at imminent threat from further delay in climate action [2]. However, whereas a large portion of the benefits of mitigation efforts would accrue to their future selves, the costs would have to be incurred now, impacting prices and consumption beyond what adult voters and economic actors appear willing to bear. This is evidenced, for example, by not-in-my-backyard reactions and opposition from organized groups that surface when climate change policies are about to be implemented [3]. Understanding whether FFF managed to shift this resistance offers broader lessons about the political economy of climate change [4].

The main question we address is whether adults vote for "Green" political parties if local youth are more active in the FFF movement. A key challenge our analysis faces is to measure the degree of local engagement in the FFF protest movement. While rallies are often organized in some central location (e.g., the main city of a region), its participants typically come from both within and outside that location (e.g., neighboring or more distant counties). In addition, information on the number of protest participants is not consistently available.

We overcome these obstacles by creating a spatially and temporally highly disaggregated measure of protest participation. This measure combines hand-collected information on nearly 4,000 climate protests with cell phone-based data on daily population flows within and between German counties origin-destination county pairs (260,000 pairs in total).

Using this measure, we find strong evidence that adults vote for the "Green" political party in counties where local youth are more active in the FFF movement. The *Alliance 90/The Greens* is perceived by voters as the party with the highest level of climate competency [5]. Their vote share increases by roughly 0.76 percentage points (P<0.001, 95% CI= 0.5283 to 0.989) in counties with a one-standard-deviation higher local protest activity. Evaluated at the average vote share of the Greens — 15.4% — this amounts to 0.5%. Voter turnout is on average higher in counties with higher local protest participation, however, the results are not statistically significant and the coefficient size is small. Instead, the climate protest movement has shifted voters away from other major political parties and toward the Greens.

A concern is that counties with strong pro-environmental attitudes are those in which youth strongly engage in climate protests and adults tend to vote green. We address the possibility of nonrandom protest participation using various empirical strategies. We start with a simple first-differencing model that accounts for time-invariant differences in county-level characteristics and a battery of time-varying county-level controls. Second, we document the absence of pre-trends. Finally, we draw on the related literature [e.g., 6] and use local rainfall shocks as an instrumental variable (IV) for protest participation. Together, the approaches suggest that any bias from omitted variables is likely to be very small.

We then explore three possible mechanisms: reverse intergenerational transmission of pro-environmental attitudes from children to parents, stronger climate-related social media presence by Green Party politicians, and increased local media coverage of environmental issues.

A unique feature of the FFF movement has been that young people set out to convince older generations to act on climate change. We, therefore, explore whether the relationship between FFF and voting behaviour may partly be explained by "reverse intergenerational value transmission": The more youth involved in the FFF movement, the more their parents are concerned about climate change, and thus the higher their proclivity to vote for the Greens. Although a direct test of this mechanism is not possible due to data limitations, we find strong suggestive evidence for its relevance. Using survey data on adults' political attitudes and voting intentions, we demonstrate that the relationship between protest participation and voting behaviour exists exclusively among parents with children of FFF-relevant ages.

We examine two complementary mechanisms that might explain our results. The first builds on the idea that the FFF movement might affect how political candidates publicly position themselves toward climate change, and this has influenced voters' evaluation of candidates and, ultimately, their vote decision. Based on a politician$\times$day panel linking Twitter activity of German federal parliament members to climate protest activity in their constituency, we show that the latter was primarily associated with more posts of climate change -related content from the Greens' members. In quantitative terms, a one-standard-deviation increase in protest activity increases the likelihood of a Green politician posting climate-related content by 18% evaluated at the mean (beta=1.052, P=0.006, 95% CI= 0.490 to 1.614).

Media sources have been shown to influence the electorate through the content of their reports. Consequently, increased media coverage of climate change is another possible mechanism through which the FFF-induced vote gains of the Greens might be explained. Drawing upon the content of 281 German print media outlets, we show that local newspapers indeed report more on climate change if protest activity is higher in their area of circulation. Evaluated at the mean, climate-related newspaper content is 9% higher in counties with a one-standard-deviation higher protest participation (beta=0.148, P=0.001, 95% CI=0.061 to 0.235).

Where do these results leave us? Besley and Persson [4] have recently coined the notion of a "climate trap". In their model, a transition to a low-pollution economy is technologically feasible, but it does not materialize because it is not jointly optimal for consumers, policymakers, and economic actors to push for change. Comparative statics show that an enhanced influence of environmentalists can propel society toward a new dynamic path where a green transformation materializes. Our empirical findings suggest that environmental activism by those too young to vote may provide some of the impetus needed to overcome the climate trap. In particular, youth participation in FFF is associated with their parents' political behavior, as well as how politicians publicly position themselves toward climate change, and the intensity of media reporting on environmental issues.

1.2 Results

1.2.1 Background

In Germany, the first climate protests occurred in late 2018 [7], but the movement gathered momentum in early 2019. By late January, protests had occurred in around 50 locations involving approximately 50,000 protesters. FFF experienced a further boost in March when Greta Thunberg attended rallies in Berlin and Hamburg. March 15 saw the first global climate protest, with an estimated 300,000 people taking to the streets of Germany. Figure 1 visualizes the temporal dynamics of the FFF protests in Germany over the course of 2019. The solid black line represents the cumulative number of protests across time. Figure 2 visualizes the geographic spread of protests across Germany.

Drawing on survey data, we provide descriptive evidence that FFF raised public awareness of climate issues and changed public attitudes [21, 27]. The share of interviewees who mentioned environmental protection as one of the most pressing political issues in Germany jumped from around 10% to almost 60% over the course of 2019 (grey line in Figure 1). Foreshadowing our regression results, a positive correlation between FFF protest activity and climate concern is clearly visible (beta= 0.008, P<0.001, 95% CI= 0.004 to 0.011). Finally, the inset figure highlights that climate change awareness only gained prominence in 2019 after hovering around 4%

between 2000 and 2018. Supplementary Figures 1 and 2 show that this is not the case for other priority topics of the Green party that are not related to climate.

We study the vote share of the *Alliance 90/The Greens* (henceforth, the Greens) as our main outcome as voters perceive it as the party with the highest level of climate competency [5]. Our analysis incorporates results from European parliament elections, German federal, and state elections. For each county and type of election, we compute the difference between the proportion of votes received in the latest election (i.e., after the start of FFF) and the preceding one. We provide further details on FFF in Germany and the German political landscape in Supplementary Material Sections A and B.

We measure local protest participation based on information on nearly 4,000 climate protests combined with proprietary cell phone-based mobility data on daily population flows within and between German counties, amounting to a total of 260,000 origin-destination county pairs. We identify daily excess population flows between each county pair and match these to the location and date of climate protests. We compute protest participation for a given county and day as the sum of all excess flows from that county to all counties (including their own) where protests occur. For any given day, our measure of local protest participation predicts how many individuals from a given county participate in FFF protests held either within the county or outside of it. We describe the measure in full detail in Section 2.3.

1.2.2 Identification

We first examine the relationship between the FFF movement in Germany and election outcomes. The following first-difference model serves as the baseline for the subsequent empirical analysis:

$$\Delta(\text{Share Greens}_{i,\tilde{t}}) = \beta \, \mathrm{P}_{i\tilde{t}} + \tau_{s,\tilde{t}} + \mu \mathbf{X}_{i,\tilde{t}} + \xi_{i,\tilde{t}}, \tag{1}$$

where $\Delta(\text{Share Greens}_{i,\tilde{t}})$ is the change in the vote share of the Greens in county i over the last election cycle. Our main independent variable is $\mathrm{P}_{i\tilde{t}}$, the cumulative protest participation in county i up to the day preceding the election $\tilde{t}$. The state×election fixed effects, $\tau_{s,\tilde{t}}$, which are equivalent to trends in our first-difference model, absorb any state- and election-specific shifts in voter behaviour.

The main threat to the validity of our empirical strategy is that there may be unobserved factors that influence both local protest participation and election outcomes, biasing our estimates. Our first-difference method accounts for time-invariant disparities in county-level characteristics, such as historical voting patterns. However, time-varying correlated factors continue to be a source of concern that we address using three complementary approaches. First, we account for a set of time-varying county-level controls (symbolized by $\mathbf{X}_{i,\tilde{t}}$ in regression equation (1)). Second, we document the absence of pre-trends (see Figure 3 and Section 2.5.1). Third, we employ rainfall shocks as an instrumental variable for protest participation (see Section 1.2.4).

1.2.3 Results on the vote share of the Green Party

In Table 1, we examine the relationship between increased local participation in climate protests and the vote share of the Greens. We start by running a parsimonious version of our first-difference regression model in which we account for state×election fixed effects and a set of baseline demographic controls (entered as first differences). Column 1 of panel A shows that there is a strong positive relationship between strike participation and voting for the Green Party. According to the point estimate, a one-standard-deviation increase in protest activity is statistically significantly correlated with an increase in the vote share of 0.76 percentage points ($P<0.001$, 95% CI= 0.5283 to 0.989). Evaluated at the average level of support for the Greens—15.4% in the preceding election cycle—this implies that the vote share was approximately 0.5% higher in counties with a one-standard-deviation higher local protest activity. We control for a comprehensive set of county-level controls, including demographic and economic characteristics of the counties. The point estimate remain almost unchanged (column 2).

In addition, we examine whether FFF may have affected the vote share of the Green party by increasing voter turnout. However, we do not find a significant relationship between local protest participation and voter turnout in most specifications (columns 3 and 4). In addition, the size of the coefficient is small. Evaluated at the average voter turnout over the latest election cycle of 67%, the coefficient of 0.138 ($P= 0.054$, 95% CI= -0.002 to 0.278) represents a 0.2% increase. Furthermore, we find that the coefficients in columns 1 and 2 remain virtually unchanged if we rerun the regressions while additionally controlling for changes in voter turnout (see Supplementary Table 6). We return to the discussions about mechanisms below and show that protest participation influenced vote share through vote switching rather than through mobilization.

1.2.4 Rainfall shocks

We next explore whether the relationship between protest participation and election outcomes can be interpreted as causal. To this end, we use county-level rainfall levels (in mm) on the first Global Strike Day (15 March 2019) as an exogenous shifter of protest participation. Similar to Collins and Margo [6], the intuition is that increases in precipitation levels deter participation on this first crucial day of coordinated strike action. This, in turn, should also affect future involvement in the movement resulting in fewer people participating in subsequent climate protests and lowering cumulative strike participation. Based on this argument, we use an instrumental variable approach, utilizing rainfall shocks as a predictor for protest participation.

Instrumental variable approach

Due to the fact that both rainfall—our instrument—and changes in the vote share of the Green party—our dependent variable–are spatially correlated, simple two-stage least squares (2SLS) estimates are likely upwards biased due to spatial feedback effects. To account for this, we follow [8] and estimate a Spatial Auto Regressive with additional Auto Regressive error structure model (SARAR) using a two-step Generalised Method of Moments (GMM) estimator, initially described by [9].

To be precise we estimate the following model:

$$\Delta(\text{Share Greens}_{i,\tilde{t}}) = \beta\, \hat{\mathrm{P}}_{i\tilde{t}} + \lambda \sum_{j\neq i}^{N} W_{i,j}\, \Delta(\text{Share Greens}_{j,\tilde{t}}) + \zeta \bar{r}_i + \tau_{s,\tilde{t}} + \mu \mathbf{X}_{i,\tilde{t}} + u_{i,\tilde{t}}, \tag{2}$$

$$u_{i,\tilde{t}} = \rho \sum_{j\neq i}^{N} W_{i,j}\, u_{j,\tilde{t}} + \epsilon_i \tag{3}$$

with λ and ρ the parameters that reflect the intensity of the spatial interdependence in the outcome variable and the error term and that need to be estimated. $W_{i,j}$ is the exogenous weight matrix that governs the structure of the spatial relationship in outcome and error term. In our case, the weight matrix consists of the bilateral inverse distances between counties in our sample. ϵ_i is an idiosyncratic error term. $\hat{\mathrm{P}}_{i\tilde{t}}$ represents protest participation instrumented with rainfall level on the first Global Strike Day (15 March 2019). To account for the possibility that prevailing rainfall patterns are correlated with (unobserved) county characteristics which themselves influence outcomes, we control for the average amount of rain (in mm) that fell on 15 March in the years 2006–2018. This ensures that we only exploit the random component of rainfall on the first Global Strike Day. The historical rainfall is represented as $\bar{r}_i$. All additional covariates in equation (2) are identical to the ones used in our main regression model and described in equation (1). The validity of our IV approach relies on the assumption that abnormal rainfall on 15 March 2019 affects outcomes solely through its impact on the number of protest participants. As with all instrumental variable methodologies, we acknowledge the inability to directly test this exclusion restriction.

Table 2 reports the results of our IV estimates. Due to the fact that we estimate the non-linear model (2) with a GMM estimator, an explicit first-stage regression does not exist. Columns 1 and 2, therefore, show 'relevance' tests, indicating that rainfall on the day of the first global climate strike indeed strongly predicts (i) protest participation on this day and (ii) cumulative protest participation. Column 3 depicts the results of the reduced-form relationship between rainfall and the vote share of the Greens. Consistent with our prior, higher precipitation levels on the day of the first Global Climate Strike reduces support for the Greens significantly. In column 4, we quantify the effects of our strike participation measure using the two-step GMM-IV approach. The statistically significant point estimate implies that a one standard deviation increase in protest participation leads to a 0.428 percentage points (P= 0.047, 95% CI= 0.007 to 0.850) gain for the Greens. Compared to the OLS results in Table 1, the GMM-IV results are somewhat smaller but statistically indistinguishable. This lends further support to the plausibility of our OLS estimates in Table 1. For completeness, Supplementary Table 9 shows the corresponding standard 2SLS estimates, which are not statistically significant (beta= 2.339, P= 0.065, 95% CI= -0.150 to 4.829). This discrepancy may be due to the less efficient estimation of the 2SLS method compared to the GMM-IV approach. Additionally, we re-estimate our two-step GMM-IV model using protest participation per capita (beta= 0.407, P= 0.006, 95% CI= 0.118 to 0.695) as the endogenous variable (column 11 of Supplementary Table 8). The results align with the model in which we use absolute protest numbers as endogenous variable.

1.2.5 Results on mechanisms

In democratic societies, voters reveal their political preferences by voting for the party that best represents these preferences. The question here is how the FFF movement may have contributed to the electoral shift towards the Green Party. We investigate the viability of three mechanisms: reverse intergenerational transmission of pro-environmental attitudes from children to parents, shifts in politicians' public stance on climate issues, and increased newspaper coverage of climate change.

Reverse Intergenerational Transmission

Evaluations of environmental education school programs show that children can foster climate change concerns among their parents [see, e.g., 10]. We hypothesize that this might also be an important mechanism in out context. Those who engaged in the climate movement were often not yet eligible to vote. However, their participation in climate protests may have forced their parents to engage with environmental issues, ultimately shaping their demand for green policies.

In the first step, we test this mechanism by examining whether the relationship between protest participation and voting behaviour differs for voters with and without children using individual-level survey data from the forsa Institute for Social Research and Statistical Analysis (n = 76,563). This daily poll elicits information on respondents' political preferences along with basic socio-economic characteristics. Crucially, respondents are asked which party they voted for in the last federal election and which party they would vote for if general elections occurred the Sunday following the interview. We match each respondent with the cumulative level of local protest participation in their county of residence up to the date of the interview. The key effects we are interested in are the interactions between local protest participation and whether a respondent lives with children under the age of 18 or not.

To get at these, we run the following regression:

$$V_{r,i,t} = \theta_p \, \mathrm{P}_{i,\tilde{t}} \times \mathrm{Kids} + \theta_n \, \mathrm{P}_{i,\tilde{t}} \times (1 - \mathrm{Kids}) + \delta_i + \tau_t + \mu \mathbf{X}_{r,i,t} + \xi_{r,i,t}. \tag{4}$$

The dependent variable, $V_{r,i,t}$, is the voting intention of respondent r who resides in county i and is interviewed on day t. The main coefficients of interest are the separate-slope parameters θ_p and θ_n, which capture the relationship between local protest participation up to the day of the interview ($\mathrm{P}_{i\tilde{t}}$) and voting intentions for parents ($Kids = 1$) and non-parents ($Kids = 0$), respectively. We condition all our regressions on county fixed effects (δ_i) and time fixed effects (τ_t), as well as a set of respondent-specific characteristics (including the *Kids* dummy). We compare voting intentions of parents and non-parents living in the same county who were interviewed at different times (i.e., having experienced varying levels of protest participation prior to the interview) while controlling for time-invariant local characteristics.

Table 3 reports results. The dependent variable in column 1 is a dummy for not having voted for the Greens in the previous general election but intending to do so at the time of the interview. On average, 15% of respondents state an intention to switch to the Green Party. A one-standard-deviation increase in local protest activity is associated with an increase in switching intention by 0.46 percentage points (P<0.001, 95% CI= 0.277 to 0.640) among respondents with children. However, there is no significant relationship between respondents' switching intentions without children. We show that this result is driven by parents in the age bracket that are most likely to have school-aged, i.e. FFF-aged, children (see Section 2.4.2), that parents switched mostly from the main parties (see Section 2.4.3, and that the relationship between protest participation and election outcomes is present for both protest participation in the home county and away from home (see Section 2.4.4). For the latter, political preferences are more likely to be influenced through protest participants sharing their views within their social and familial networks.

Politicians

The vote decision depends on *inter alia* how the electorate evaluates party candidates on specific public policy issues, which in turn depends on how politicians publicly position themselves toward them. Substantial shifts in votes from one election to the next may be attributed to changes in politicians' orientations toward key issues. In the context of our study, the question arises whether the FFF movement caused political candidates of different parties to differentially adjust their public stance on environmental issues. This might happen directly, via the FFF movement changing politicians' own convictions, or indirectly, by the movement affecting politicians' beliefs about what voters want.

We test the plausibility of this mechanism using our politician×day panel that combines Twitter activity of the members of German Federal Parliament (henceforth, MPs) with protest participation in their electoral district. Specifically, we run the panel regression:

$$S_{p,c,t} = \gamma \mathrm{P}_{c,t} + \psi_p + \zeta_{s,t} + \varepsilon_{p,c,t}, \tag{5}$$

where $S_{p,c,t}$ is the share of climate tweets in total tweets posted by politician p representing constituency c on day t. $\mathrm{P}_{c,t}$ is the local protest participation in constituency c on day t as defined in equation (10). Throughout, we control for politician fixed effects, ψ_p. These dummies absorb any time-invariant disparities in MPs tweeting behavior. Furthermore, they also account for constituency-level differences in average protest crowd sizes. We thus only compare the tweeting behavior of the same politician on days with high and days with low strike participation in their constituency. The state×day dummies, $\zeta_{s,t}$, control for any general temporal fluctuations in tweeting activity or protest participation. $\varepsilon_{p,c,t}$ is the error term and clustered simultaneously by politician and State×date [see, e.g., 11].

Table 4 presents the results. Column 1 shows that MPs are significantly more likely to tweet about climate change when the protest activity in their electoral district is high. A one-standard-deviation increase in a constituency's protest activity raises the share of climate tweets by MPs by 0.4 percentage points (P= 0.001, 95% CI=0.159 to 0.658) or 7% of the mean.

This relationship likely masks heterogeneities across MPs from different political parties. In particular, if politicians' public engagement with climate change explains the Green Party's FFF-related vote gains, then we would expect to see that MPs of the Greens are more responsive to protest activity in their constituency than MPs of other parties. We test for this in column 2 by estimating separate slope coefficients for politicians of each party. This exercise reveals that Green MPs are more than twice as likely to respond on social media than those from other political parties. We discuss the other for politicians of the remaining parties results in Section 2.4.5.

Newspapers

The political effects of the media have long been documented. Media sources such as newspapers may influence the electorate through the content of their reports [12]. Therefore, if the FFF protests increase coverage of climate-related topics, this could have led to changes in voting behaviour. To explore this possibility, we draw on our newspaper×day panel which links the content of local newspapers to climate protest activity in their area of circulation. In the first step, we employ the following panel regression approach:

$$A_{n,r,t} = \gamma \mathrm{P}_{r,t-1} + \psi_{n,r} + \zeta_t + \varepsilon_{n,r,t}, \tag{6}$$

The dependent variable, $A_{n,r,t}$, is the number of articles published in newspaper n with area of circulation r on day t that contain at least one climate change-related keyword. $\mathrm{P}_{r,t-1}$ is our daily protest participation measure, computed for each newspaper's circulation area. We lag the explanatory variable since our data capture print media content. In all regressions, we control for newspaper fixed effects, $\psi_{n,r}$, and date dummies, ζ_t. The error term is represented by $\varepsilon_{n,r,t}$ and clustered simultaneously by newspaper and date [11]. The main parameter of interest, γ, captures the relationship between FFF strike participation and newspaper content.

We also examine whether local protest activity is associated with a permanent shift in newspaper coverage of climate issues. We accomplish this by employing the first-difference model described below:

$$\Delta A_{n,r,} = \alpha + \theta \mathrm{P}_{r,\tilde{t}} + \epsilon_{n,r}. \tag{7}$$

The dependent variable $\Delta A_{n,r}$ represents the difference in the total number of climate change articles published between 1 January and 31 December 2019 (i.e., after FFF started) and the same period in 2018 (i.e., before FFF took off). Thus, the coefficient θ captures whether newspapers are more likely to continue reporting on climate issues after being exposed to strike activity.

Column 1 of Table 5 shows the relationship between local protest participation and newspaper content. A one-standard-deviation increase in protest activity is associated with 0.15 additional articles (P= 0.001, 95% CI= 0.061 to 0.236) containing climate change keywords. Compared to the sample mean of 1.65 articles, this represents a 9% increase. As previously discussed, this relationship is a composite of reporting on protest activity and reporting on climate change-related topics.

Then, we estimate the relationship between local protest participation and long-term changes in newspaper content. In equation (7), we proceed to our first-difference specification in equation (7). Column 2 displays the results. In 2019, newspapers publish on average 590 more climate-related articles compared to 2018. A one-standard-deviation higher local protest participation is associated with almost 128 (P$<$ 0.001, 95% CI= 60.806 to 194.886), or 22%, more articles.

1.3 Discussion

It is widely accepted that keeping global warming within 2°C would avoid more economic losses globally than the cost of achieving the goal [1]. There is also scientific agreement that climate action is needed now, as each additional year of delay in implementing mitigation measures is estimated to cost an additional 0.3–0.9 trillion dollars in total (discounted) future mitigation costs, if the 2°C target is to be ultimately met [13]. However, continued climate inaction has left many observers pessimistic about avoiding the worst damage from climate change.

Perhaps such pessimism is not entirely warranted. When society is close to a tipping point, where either continued climate inaction or a green transformation are possible future outcomes, even small exogenous shocks can determine the dynamic path it takes. In the model of Besley and Persson [4], one shock that can provide a push towards a transformation are demonstrations by citizens that prominently highlight the full scope of the climate crisis. In seeking to garner votes, politicians would react by implementing climate-aligned measures aimed at fostering green investments and consumption. This, in turn, would reorient technological change away from high-carbon and toward low-carbon technologies. Ultimately, environmentally-friendly values would emerge, putting an end to the climate trap.

Our paper addresses the first link in this chain. Using the FFF protest movement in Germany, we show evidence on the relationship between youth engagement in demand of climate action and political outcomes. This effect can be explained by voter movements to the Greens from other major political parties with a less climate-focused political agenda. One key mechanism appears to be intergenerational transmission of pro-environmental attitudes from children to parents: support for the Greens increases only among voters with children of FFF-relevant ages. We also find evidence for two other mechanisms. First, Green Party candidates with strong protest activity in their constituency increase their climate-related social media presence, which can be related to voters' relative evaluation of candidates and vote decision. Second, building on the idea that media may influence voters through the content they cover, we demonstrate that local newspapers report more on climate change when FFF engagement in their area of circulation is high.

Since the FFF protests first occurred, other climate movements such as "Last Generation" and "Extinction Rebellion" have gained prominence. Until now, however, they have had less support in the general population mainly due to their use of disruptive means of protests. While we cannot make predictions on the influence of these movements based on our results, these examples illustrate that each movement's distinct characteristics, such as the means of protest they use, may affect their acceptance in the broader population.

Our study investigates the relationship between FFF protest participation in 2019 and electoral outcomes in the context of Germany. Various factors may have contributed to FFF's influence that are specific to Germany, such as the proportional representation of political parties in the German parliament that allows smaller parties to grow, and a relatively high level of climate change awareness in the general population. Local Green party infrastructure, in particular, is present in many cities and may have benefited FFF protests. We do not account for this directly, as we do not have data on local party membership of the Green party or another measure for support of FFF protests by local Green party members. We also study the FFF movement in 2019, not at a later time, when leaders also voiced opinions on non-climate issues. Hence, the relationships between FFF protest participation and outcomes have to be interpreted conditional on local political, economic, and social conditions. In other words, the same FFF protest participation may not have produced the same results in different settings. That being said, the outcomes and channels we study are plausible in other settings, for example, effects of protest movements on election results [14, 8], the transmission of climate change awareness from children to parents [15, 10], and an effect of protests on political speech on social media [16].

Our study also offers a contribution to measuring how engagement in large social movements evolves spatially and temporally. Many such movements center around large protests or demonstrations in central locations. However, information on protest location and size alone is not sufficient to inform us where support for a movement comes from. Using cell-phone based mobility data, we have developed and cross-validated a measure of protest participation that approximates the geographic distribution of participants at thousands of FFF rallies. We believe this approach could be a useful tool for mapping out the evolution of social mass movements in future studies. It could also be applied to other contexts in which movements and gatherings of large numbers of people matter, such as in political uprisings or revolutions.

2 Methods

2.1 Research ethics

Our research project complies with all relevant ethical and legal regulations. In this research project we mostly use secondary data which was legally and ethically collected by third parties, either research institutions, public administration, or commercial providers. Additionally, all our data is fully anonymized and/or aggregated on geographical area and therefore privacy of individuals is not at risk. Only the Twitter posts from members of parliament have been collected by us which are publicly available and we aggregated them (see Section 2.2 for details on data collection and processing). Hence we have no active human participants in our research processes. Before conducting this research, we performed a thorough ethics self-assessment to identify potential risks as suggested by the German Data Forum's working group on research ethics [17]. This self-assessment indicated that neither researchers nor the objects in our study (i.e. protest participants, mobile phone users, members of parliament) could be plausibly harmed by our research making a formal ethics review unnecessary.

2.2 Data sources

For our analyses, we create four datasets. First, we compile a county×election-level dataset containing information on election outcomes, protest participation, and a range of county characteristics. German counties ('Landkreise') are the third level of administrative division, corresponding to districts in England or counties in the US. Second, we connect daily repeated cross-sectional survey data on citizens' political preferences and voting intentions to protest participation in their home county. Third, we construct a politician×day panel that combines Twitter activity of the members of the German federal parliament ('Bundestag') with protest participation in their electoral district. Fourth, we create a newspaper×day panel dataset that relates reporting on climate change to protest participation in the newspapers' area of circulation.

We compile these four datasets using the following six primary sources: (i) cell phone-based mobility data provided by Teralytics, (ii) hand-collected information on location and day of climate protests, (iii) county-level election results reported by local authorities, (iv) individual-level survey data from the forsa Institute for Social Research and Statistical Analysis, (v) the universe of tweets of all members of the German Bundestag extracted via the Twitter API, and (vi) newspaper content from the GENIOS Online Press Archive. We now describe the content of these data sources in detail, with summary statistics for each of them provided in the supplementary materials. Specific information on individual data providers and access to these sources is detailed in the Data Availability Statement in Section 3.

2.2.1 Cell Phone-Based Mobility Data

We acquired proprietary cell phone-based mobility data from Teralytics (https://teralytics.net, product code DELDD1). This database reports the daily number of journeys between all region pairs for the year 2019. The regions—i.e., the origins and destinations—are congruent with German counties for 355 out of 401 German counties, except for 46 large metropolitan areas that are split into subunits, with a maximum of five subunits per county for the largest metropolitan counties. The mobility data include information on journeys that occur within as well as between the regions.

To identify these journeys, Teralytics utilizes mobile device tracking data from the universe of O_2 Telefonica mobile network customers, more specifically, their SIM cards. This data captures the movements of mobile devices between cell towers. To be tracked, a device has to be switched on but not necessarily actively used. Due to strict data protection regulations, Teralytics itself only receives anonymized and aggregated data from O_2 Telefonica for separate 24-hour windows and only provides data for region pairs with a minimum of 5 journeys. Hence tracking of single individuals, persons called, or trips that last more than 24 hours is not possible. According to Teralytics, data loss due to this anonymization is negligible. Since individual level data is already professionally anonymized at Telefonica before Teralytics receives any data, no informed constent from Telefonica's mobile phone users is required according to the GDPR. However, Telefonica offers the possibility to opt out from their anonymous data processing (More information on the O_2 Telefonica data and the anonymization procedure can be found at https://www.telefonica.de/partners/wholesale/enabling-services/mobility-insights.html.). Teralytics aggregates the tracking data to journeys between and within regions for a given day using machine learning algorithms, where a journey is defined as a movement if a mobile device remains at the destination for a minimum of 30 minutes. The machine learning algorithms take into account the mobile technology of the device and the antenna, as well as the size and shape of the cell tower catchment area. As with most proprietary data, the data provider (Teralytics) does not offer a more detailed description of the methodology used in order to protect trade secrets.

In 2019, O_2 Telefonica had several sub-brands and has a market share of 31%. There are only two other major mobile network carriers in Germany (i.e. Telekom and Vodafone) and to the best of our knowledge, only Telekom transforms its data to mobility patterns and provides similar services as Teralytics does. The German federal statistical office provides quality and representativeness assessments of these data sources [18]. To obtain mobility patterns representative of the total population, Teralytics extrapolates measured mobility based on O_2's local time-varying market share and official population statistics.

Our final mobility dataset contains 64.4 billion journeys between county pairs made in 2019.

2.2.2 Climate Protest Data

Data on climate protests is hand-collected and drawn from three sources: local authorities, social media, and the website of FFF Germany. Local authorities (e.g., city councils, the police) must be notified of public gatherings, such as rallies and demonstrations at least two weeks in advance. We contacted all relevant authorities and requested a complete list of climate protests registered in their jurisdictions during 2019. A total of 44% of the authorities responded to our request, providing precise information on the location and time of 1,938 protests. To fill in existing gaps and ensure that we consider marches that were not registered with authorities, we supplement the protest data with information on protest location and date extracted from social media posts (Twitter, Facebook, and Instagram), and protest activity reported on the official website of FFF Germany. These sources provided us with an additional 1,968 strikes. Of these, 1,583 additional strikes were retrieved from the website of FFF Germany, and 385 from social media posts. After combining all data sources and dropping duplicates, we manually geocoded the location of the strikes. Our final strike dataset for 2019 encompasses 3,906 protests which occurred in 373 separate counties on 186 dates. Panel (a) of Figure 2 showcases the widespread nature of the protests, with 93% of all counties witnessing at least one protest during 2019. Panel (b) shows that the protest activity was continuous throughout the year. Furthermore, regular spikes in the number of protests are discernible on Fridays as well as on the four global climate events in March, May, September and November.

For robustness checks, we use the sources and methodology listed above to collect information on location and date of FFF strikes that took place in 2018 and early 2020, prior to the onset of the COVID-19 pandemic.

2.2.3 Election Data

Our analysis incorporates results from three types of elections: European parliament elections, state elections, and German federal elections. For each county and type of election, we compute the difference between the proportion of votes received by different parties in the latest election (i.e., after the start of FFF) and the previous one. Our main dependent variable is the *change* in the vote share of the Green Party.

The European parliament and the state elections take place approximately every five years. Results of the European Parliament (EP) elections are taken from the Federal Statistical Office and the Statistical Offices of the Länder. The EP election dates for our analysis are May 26, 2019 versus May 24, 2014. For state elections, we use data from the State Returning Officers (*Landeswahlleiter)* and the Statistical Offices of the Länder. The state elections in our sample and their dates are: Bremen (26 May 2019 versus 10 May 2015), Saxony (1 September 2019 versus 31 August 2014), Brandenburg and Thuringia (27 October 2019 versus 14 September 2014), Hamburg (23 February 2020 versus 15 February 2015), Baden-Württemberg and Rhineland-Palatinate (14 March 2021 versus 13 March 2016), Saxony-Anhalt (6 June 2021 versus 13 March 2016), Mecklenburg-Western Pomerania (26 September

2021 versus 4 September 2016), and Berlin (26 September 2021 versus 18 September 2016). A Federal Returning Officer (*Bundeswahlleiter*) reports the results of federal elections. Unlike European and state elections, the federal elections occur every four years, and we will analyse if the protests of 2019 induced changes in the Greens' vote share between the federal elections in September 26, 2021, and September 24, 2017. In total, our election dataset encompasses 960 observation at the county×election level. In robustness tests, we use vote shares from earlier election cycles which we draw from the sources listed above. Summary statistics of the key variables are reported in Supplementary Table 1. European Parliament elections, state elections, and federal elections occurred on different dates. Hence, the value of $P_{i\tilde{t}}$ varies with the county *and* the election.

2.2.4 Rainfall Data

We extract information on rainfall from Germany's National Meteorological Service (DWD, https://opendata.dwd.de/climate_environment/CDC/grids_germany/hourly/radolan/historical/asc/). Supplementary Figure 4 presents descriptive, reduced-form evidence on the role that rainfall on the first Global Strike Day played for changes in the Greens' vote share between the 2015 and 2019 EU elections. Panel (a) presents the geographical variation of the change in the Greens' vote share between the 2015 and 2019 EU elections. In Panel (b), we display the spatial variation in the amount of rainfall on March 15, 2019. Regions in the South-East and West witnessed the strongest rainfall on that day, and many of these regions also saw some of the lowest increases in the Greens' vote share in the 2019 EU election. The binscatter plot in Panel (c) confirms that there is indeed a strong negative correlation between rainfall on the day of the first global climate protest and the Green Party's electoral fortunes in the EU election (beta= -0.116, P= 0.020, 95% CI= -0.214 to -0.018).

2.2.5 Voting Intentions Survey

The Forsa Bus survey (n = 76,563) is conducted by the forsa Institute for Social Research and Statistical Analysis, a commercial, long-established German market research, opinion polling, and election survey company [19]. The Forsa Bus survey is a daily repeated cross-sectional telephone survey (CATI) that is voluntary and representative of Germany. Each day (in 2019), 500 (new) German-speaking participants answer 40 questions mostly regarding social attitudes, (realized/hypothetical) voting behavior, political preferences, and basic demographic variables such as household size, age, gender, number of children, and education. Additionally, the survey contains respondents' county of residence which enables us to link the survey to our protest participation data (see Supplementary Table 2 for key summary statistics).

2.2.6 Twitter Data

We proceed in four steps to create the daily panel data on politicians' Twitter activity. First, we identify the members of the German parliament ('Bundestag') that have an official Twitter account and are affiliated with a political party. This is the case for 499 politicians (out of 736 parliament members). Second, we use Twitter's API to collect all tweets (original and retweets) posted by these parliament members between January 4, 2019, and December 31, 2019. This results in a database of 288,490 individual tweets. Third, we apply a keyword search to identify which tweets refer to climate change-related topics. Tweets are climate change-related if they contain at least one of the phrases listed in Supplementary Table 3. Finally, we aggregate the data at the politician×day level, yielding a dataset with a total of 197,830 observations. We use the share of climate tweets in total tweets posted by a politician on a given day as our main dependent variable. Supplementary Table 4 provides key summary statistics.

2.2.7 Newspaper Data

We obtain newspaper content from the GENIOS Online Press Archive (https://www.genios.de). This archive gives access to articles from 281 German print media outlets. (We use the terms 'media outlet', 'outlet', and 'newspaper' interchangeably.) Using keyword searches, we identify the number of articles for each outlet and publication date featuring climate change-related content using the keywords listed in Supplementary Table 3.

We link protest participation to media content using the area of circulation of the newspapers. To this end, we first match each newspaper with information on its readership's geographical distribution. The readership data is provided by the German Audit Bureau of Circulation (IVW, https://www.ivw.de/print/va/verbreitungsanalyse-tageszeitungen-va), but is only available for a subset of outlets in the GENIOS archive. In total, we can identify the area of circulation of 130 newspapers and magazines. For each news outlet, we construct a variable capturing its area of circulation. Meanwhile, for each news outlet, we rank all German counties according to readership numbers and define area of circulation as counties that account for 75% of total circulation. Our results are not sensitive to the exact choice of cut-off. Our final newspaper×day dataset encompasses 130 news outlets and covers the year 2019. Supplementary Table 5 provides summary statistics.

2.2.8 Control Variables

We construct various county-level controls for our analysis. These include demographic variables (total population, average age, and share of minors) and economic ones (GDP per capita, labor productivity, and unemployment share). In a robustness check we additionally use the local COVID-19 incidence. In analogy to our dependent variables, we first-difference the controls; that is, we compute the difference between 2019 and 2014. For illustration, we additionally use geographical information on Germany's country, state and county borders.

2.2.9 Social & Political Opionion Survey Data

We use the Politbarometer survey to measure the importance of environmental and other topics in the public debate in Germany [20, 21]. It is conducted by the Research Group for Elections (Forschungsgruppe Wahlen) for the Second German Television (ZDF) since 1977. The Politbarometer is a repeated cross-sectional survey representative of the voting age population in Germany with approximately 1250 respondents who are interviewed by telephone every second to third week to determine their current attitudes towards various political and social issues.

To validate our strike participation measure, we use information on all soccer matches in the first and second Bundesliga in 2019 that comes from Fussballmafia, a sports data provider (`https://www.fussballmafia.de/`). It includes the date of the match, the location of the stadium, the origin of the away team, the number of away fans.

2.3 Measuring Local Engagement in Fridays for Future

Our analysis aims to investigate how the local strength of engagement in FFF protest activity influences the electorate's behavior. However, information on the number of participants in FFF protests is very limited and information on the origin of participants does not exist. Many types of protest, however, occur in some central locations, such as the main city of a region, with its participants originating both from within and outside that location (e.g., neighboring or most distant counties). To address this measurement issue, we combine cell phone-based mobility data with our climate protest database to predict the number of people who originate in a specific county and participate in climate protests on a given day.

2.3.1 County$\times$Day-Level Protest Participation Measure

To construct our local protest participation measure, we proceed in two steps. First, we identify excess mobility between region pairs. Second, we match these flows to the location and date of climate protests and compute the protest participation measure for a given county and day as the sum of all excess flows from that county to all counties where protests occur. This procedure is outlined in detail below.

Excess mobility is identified by estimating a standard gravity equation. This enables us to calculate the expected (i.e., average) mobility between any region-pair and day. The difference between observed and expected mobility, that is, the residuals, is then used to calculate excess mobility. We begin by running the following regression equation, where the units of analysis are region-pairs as defined by Teralytics.

$$\text{journeys}_{r(i)r(j)t} = \vartheta_{r(i)r(j)}\ NS_{r(i)r(j)t} + \varphi_t + \varepsilon_{r(i)r(j)t}. \tag{8}$$

We denote the number of journeys between origin $r(i)$ and destination $r(j)$ on day t as $\text{journeys}_{r(i)r(j)t}$. As outlined in Section 2.2 the Teralytics regions are equivalent to counties or subdivisions thereof. The mapping of regions to counties is captured by $r(\cdot)$. That is, $r(i)$ represents the region of origin equivalent to (or part of) county i and $r(j)$ is the destination region congruent with (or lying in) county j. The origin-destination fixed effects ($\vartheta_{r(i)r(j)}$) absorb any time-invariant differences in the level of mobility across pairs, including structural differences between within and cross-region movements. These fixed effects estimates represent the mean values of journeys between region pairs, i.e., the average number of journeys between regions. The indicator variables $NS_{r(i)r(j)t}$ is equal to one if there is no FFF event in neither $r(i)$ or $r(j)$. The inclusion of this indicator implies that we are only including non-strike days in the estimation of the average—i.e., typical—bilateral mobility pattern.Including strike days in the estimation of $\vartheta_{r(i)r(j)}$ typically 'mechanically' increases average flows, making detection of smaller protests more difficult. To account for temporal variation in mobility patterns, we include date fixed effects (φ_t).

The parsimonious regression equation (8) explains a very high proportion of the variance in the mobility flows, as measured by an R-squared of 0.97. As indicated earlier, the remaining unexplained variation (i.e. the residuals) constitutes the basis for our strike participation measure. The residuals capture how many more journeys are made from origin $r(i)$ to destination $r(j)$ than expected. For the subsequent analysis, we aggregate these excess flows—i.e., the positive residuals—at the county-pair level. Formally, this can be represented as follows:

$$e_{ijt} = \sum_{r(j)\in j} \sum_{r(i)\in i} (\text{journeys}_{r(i)r(j)t} - \widehat{\vartheta_{r(i)r(j)}} - \widehat{\varphi}_t), \tag{9}$$

where e_{ijt} is the excess mobility from county i into county j on day t.

To predict protest participation of a given county, we match the residuals to our climate protest database (Section 2.2.2). This enables us to identify which excess flows reflect journeys to climate protest. For each county and day, we then compute its total protest participation as the sum of excess journeys to counties where a climate protest occurs. Formally, we predict:

$$\mathrm{P}_{it} = \sum_{j=1}^{J} \mathrm{I}_{j,t}\ e_{ijt}. \tag{10}$$

The total protest participation of county i on day t is symbolized by P_{it}. The indicator variable $\mathrm{I}_{j,t}$ takes the value of 1 if a strike occurs in county j on day t, and 0 otherwise.

Extended Data Figure 1 visualizes our strike participation measure for a climate protest in Berlin that occurred on March 29, 2019. Greta Thunberg attended this protest, which drew a large crowd. The figure illustrates that protest participants predominantly originate from within Berlin and the surrounding counties. This pattern of participation holds true in general. A county's total protest participation can be decomposed into two parts: participation in protests that occur in the own (i.e., home) county and participation in protests that occur in other counties. This decomposition is represented as:

$$\mathrm{P}_{it} = \sum_{j=1}^{J} \mathrm{I}_{j,t}\, e_{ijt} = \underbrace{\underbrace{\mathrm{I}_{i,t}\, e_{iit}}_{\mathrm{P}_{it}^{H}}}_{\substack{\text{protest participation}\\ \text{in home county}}} + \underbrace{\underbrace{\sum_{j\neq i}^{J} \mathrm{I}_{j,t}\, e_{ijt}}_{\mathrm{P}_{it}^{F}}}_{\substack{\text{protest participation}\\ \text{in other counties}}}. \tag{11}$$

The first term of the decomposition, P_{it}^{H}, represents participation in protests that occur in the home county. That is, the number of excess journeys that start and end in the home county on protest days. Naturally, within-county protest participation is 0 on days on which there are no protests in the home county i. The second term (P_{it}^{F}) reflects journeys to protests that occur in other counties. Fluctuation in total protest participation is overwhelmingly driven by participation in marches that occur in the home county; 96% of the variation in total strike participation P_{it} is due to variation in P_{it}^{H}.

2.3.2 Cumulative County-Level Protest Participation Measure

Some of the analysis is not conducted at the daily but at a higher level of temporal aggregation. Primarily, this applies to our main analysis of election outcomes. Here, we aggregate local protest participation over time. The aggregation process can be written as:

$$\mathrm{P}_{i\tilde{t}} = \sum_{t=1}^{\tilde{t}} \sum_{j=1}^{J} \mathrm{I}_{j,t}\, e_{ijt} = \underbrace{\underbrace{\sum_{t=1}^{\tilde{t}} \mathrm{I}_{i,t}\, e_{iit}}_{\mathrm{P}_{i\tilde{t}}^{H}}}_{\substack{\text{protest participation}\\ \text{in home county}}} + \underbrace{\underbrace{\sum_{t=1}^{\tilde{t}} \sum_{j\neq i}^{J} \mathrm{I}_{j,t}\, e_{ijt}}_{\mathrm{P}_{i\tilde{t}}^{F}}}_{\substack{\text{protest participation}\\ \text{in other counties}}}, \tag{12}$$

where $\tilde{t}$ represents the day before the election. For elections that occurred in 2019, the cumulative protest participation measure is the sum of daily protest participation between January 1, 2019, and the day preceding the election. For the elections in our sample that took place after 2019, the total daily protest participation for the entire year 2019 is defined as the cumulative protest participation measure. This assignment is based on the fact that the COVID-19 pandemic and related mobility restrictions prohibited large-scale gatherings, including FFF protests, for much of 2020 and 2021. As a result, the movement ground largely to a halt (see Supplementary Section A). Robustness checks will distinguish between the FFF effect in the short run (i.e., on 2019 election outcomes) and the longer run (i.e., on post-2019 election outcomes), and the potential concern that different counties' exposure to the COVID-19 pandemic may bias our results. As with the daily data, the overwhelming part of the total cumulative protest participation ($\mathrm{P}_{i\tilde{t}}$) variation is driven by participation in marches held in the home county ($\mathrm{P}^{H}_{i\tilde{t}}$).

One possible concern is that protests may influence movements by non-protesters. If non-protesters made fewer journeys to avoid travel disruptions on protest days, we would under-estimate the number of protesters. If non-protesters made more journeys to avoid the protests we would over-estimate the number of protesters. While we do not directly observe the intention of travelers, we know that protests often took place at a central location without through-traffic (e.g. a market square), necessitating only the locking of few streets. In addition, the protests did not take place at peak traffic times.

In Supplementary Material Section C, we provide two pieces of evidence showing that our approach to predicting protest participation successfully captures variation in the total number and origin of protesters. Supplementary Figure 6 uses the subset of climate protests in our sample for which local authorities have provided information on the number of participants, and shows that there is a strong correlation between observed and predicted protest participation. Supplementary Figure 7 exploits professional soccer matches (i.e., information on the number of away team supporters at these matches) to demonstrate that our method can forecast the number of people who leave a given county to attend a large-scale public event in another county.

2.4 Additional results

2.4.1 Protest participation and election outcomes for other parties

In Section 1.2.3, we examine the relationship between increased local participation in climate protests and the vote share of the Greens. A natural follow-up question is how protest participation influences the vote share of the remaining major political parties. Supplementary Table 7 illustrates that parties on both the left and the right political spectrum experience losses in vote shares associated with protest participation. Specifically, the Left party, FDP, and AfD see a reduction in support, whereas the estimates are not statistically significant for the Union and the SPD. These findings indicate that the protests are not merely reflecting a shift in support among left parties, nor that they lead to increased political polarization. But rather that the Greens draw support from across the entire political spectrum. In Section 1.2.5, we complement these findings by presenting an analysis of individual-level party-switching decisions.

2.4.2 The relationship between protest participation and voting intentions by age of parents

The Forsa Bus survey does not elicit information on the age of children. This would have allowed us to test if the relationship documented above is specifically driven by parents whose children are school-aged and, consequently, much more likely to participate in the protest movement. However, we can investigate whether the relationship between local FFF participation and voting behaviour differs depending on the age of the respondents. Supplementary Figure 5 shows that the relationships documented in Table 3, column 1, are exclusively driven by respondents aged 31–55 who live in households with children. Protests neither shift voting intentions of the young (aged 18–30) nor the old (aged 55 and above) interviewees, irrespective of whether they live with children. Among the group of respondents, the middle-aged are the most likely to have school-aged children participating in FFF protests. Conversely, young respondents typically have no or very young children who are not engaged in the climate movement. Similarly, the children of older respondents are unlikely to still live at home or participate in protests. Thus, the probability that young and old respondents are exposed to the FFF movement through the participation of their offspring is much lower compared to the middle-aged interviewees.

2.4.3 The relationship between protest participation and patterns of vote switching for parents and non-parents

In columns 2 to 6 of Table 3, we look at which parties are bringing in new voters for the Greens. We observe that the climate movement has caused parents who previously voted for Germany's two major political parties (CDU/CSU and SPD) to switch to the Greens. This is not the case, however, for respondents without children. The pattern of results for the three smaller parties is more varied. Respondents who previously supported the FDP are less likely to switch to the Greens, but only if they have no children (column 4). This may be because the views of the Greens and the FDP on how to tackle climate change are vastly different, with the former advocating tougher environmental laws and regulations and the latter calling for market-based solutions. There are no statistically significant FFF-associated changes in switching intentions among supporters of the Left or the AfD, neither for parents nor non-parents. In non-reported regressions, we also explored whether individuals who abstained from voting in the previous general election are more likely to state an intention to vote for the Greens if they resided in areas with high FFF engagement. We found no evidence of climate-related mobilization. This result is consistent with the modest association between protest participation and voter turnout documented in Table 1.

2.4.4 The relationship between away-from-home and home protest participation and voting intentions

A second, more indirect approach to dealing with the reverse intergenerational transmission hypothesis is to divide total protest participation into two dimensions: participation in protests held in one's own (home) county and in rallies held elsewhere. See Section 2.3 for more details. The idea is the following: Protest activity in the home county is directly observable by all county residents, and this may raise the public's awareness of climate change issues. However, protest activity is not as salient if children and youth leave the home county to participate in FFF protests elsewhere. Here, political preferences are more likely to be influenced through protest participants sharing their views and experiences within their social and family network. Thus, if reverse intergenerational transmission was taking place then a relationship between protest partcipiation and election outcomes would exist not only for within-county protest participation, but also for participation in rallies away from home.

Extended Table 1 demonstrates that this is indeed the case. Column 1 shows that a one-standard-deviation higher within-county protest participation is associated with an increase in the Green Party's vote share by 0.36 percentage points ($P = 0.003$, 95% CI= 0.125 to 0.591). However, away-from-home protest participation is associated with an even stronger increase in the Green support in the home county: a one-standard-deviation increase in this measure causes the Green Party's vote share to increase by 0.51 percentage points ($P < 0.001$, 95% CI= 0.275 to 0.734). This is remarkable, as differences in within-county protest participation account for the vast majority of the variation in counties' total protest activity. A back-of-the-envelope calculation suggests that every away-from-home protest participant is associated with 0.025 additional Green Party votes.

2.4.5 Protest participation and politician's social media tweets by party

Above, we showed that politicians of the Green party posted more social media tweets in counties with higher protest participation. Column 2 of Table 4 also shows that increased protest activity encourages members of the Left Party to post more climate change-related content. Relative to Green Party MPs, the size of the association is considerably smaller. The increased posting activity of AfD members likely represents their stance against climate change mitigation policies. In fact, the vast majority of tweets from AfD politicians in our sample contain negative statements about FFF activity. Coefficients are small and statistically non-significant for members of the SPD, Union, and FDP. This lack of reaction could be due to conflicts between the demands of the FFF movement and core party voters' (perceived) preferences.

2.5 Robustness

2.5.1 Pre-trends election results

As stated previously, the main threat to the validity of our empirical approach is the potential bias introduced by unobserved time-varying factors. However, the stability of the point estimates in Table 1 across regressions with both basic and extended sets of country-level controls suggests that this is unlikely to be the case (e.g., 22, 23).

As a second piece of evidence, we test for the absence of pre-trends. To this end, we expand our main dataset to incorporate the results from the preceding four election cycle: five federal elections (2005 to 2021), the European Parliament elections (1999 to 2019); and 550 elections (1999 to 2021.) We then interact our protest participation measure with election-cycle dummies and assess whether protest participation influenced the vote share of the Greens before the emergence of the FFF movement. Formally, we estimate the following regression model:

$$\text{Share Greens}_{i,z} = \beta \sum \mathrm{P}_i \times I_z + \mu \sum \mathbf{X}_i \times I_z + \theta_{s,z} + \pi_i + \psi_{i,z},$$

where Share $\text{Greens}_{i,z}$ is the vote share of the Greens in county i and election cycle z. The election-cycle-dummy-interacted protests participation is represented by $\mathrm{P}_i \times I_z$ where we use the last cycle preceding the FFF movement as the reference category. We further account for the usual (time-interacted) control variables ($\mathbf{X}_i$), election-cycle×state effects ($\theta_{s,z}$) as well as county fixed effects (π_i).

Figure 3 visualizes the results. Reassuringly, we do not observe any differential effects predating the FFF protests. Particularly notable is the absence of a significant effect two election cycles prior to the emergence of the FFF movement (labelled FFF-2). During this period, the nuclear accident in Fukushima significantly heightened the prominence of environmental issues as a policy concern (see, e.g., Böhmelt [24]). If our protest participation measure were to capture any unobserved county characteristics that consistently led to a shift in votes towards the Green party whenever environmental issues became more salient, we would expect our measure to exert a substantial effect during the election cycle FFF-2. The fact that this is not the case provides further evidence that we are specifically estimating the impact of the FFF protest movement. Consistent with our main findings, we observe a strong positive association between protest participation and the electoral support for the Greens in the most recent cycle, i.e., in elections affected by FFF. The size of the point estimate for this last election cycle is 0.63 and statistically indistinguishable from the coefficient of 0.75 produced using our main regression framework (Table 1, column 2).

2.5.2 Alternative measure of local protest activity

Returning to our main analysis, Panel B of Table 1 reproduces the results using an alternative measure of local protest activity: the cumulative number of FFF protests a county experienced up to the date of an election, standardized with mean 0 and standard deviation of 1. This addresses worries related to the possibility that the measurement error in our protest measure biases our results. The instrumental variable approach further helps tackle this concern. We continue to find a strong association between FFF protest activity and the Greens' electoral fortunes: a one-standard deviation increase in the number of FFF protests in a county increases the Greens' vote share by 0.58 to 0.59 percentage points. The fact that the point estimates in Panel B are smaller compared to Panel A suggests that our main measure based on cell phone mobility data contains more information than the measure based only on the location and number of protests.

2.5.3 Pretrends rainfall and vote shares: Reduced-form evidence

We explore the impact of abnormal rainfall on 15 March 2019 on the Greens' vote share across the last five election cycles, employing the methodology detailed in Section 2.5.1. Extended Data Figure 2 illustrates our findings. Notably, we observe a strong and statistically significant effect of rainfall shocks on the Greens' vote share in the most recent election cycle—i.e., in elections occurring after the emergence of the FFF movement. In line with our prior, counties experience diminished support for the Greens when faced with unexpectedly heavy rainfall during the first Global Strike Day. The fact that rainfall patterns on this day do not influence vote shares in preceding election cycles provides strong evidence that this specifically represents effects driven by FFF protest participation.

2.5.4 IV estimates rainfall and vote shares: further robustness

In our IV approach, we account for differences in local rainfall patterns in a simple and intuitive way by including the historical amount of rainfall on the day of the first Global Strike Day as a linear control. However, there may be some potential issues associated with this approach. One concern is that it may fail to capture non-monotonic effects of prevailing weather patterns on voting behaviour. To account for this possibility, we more flexibly control for typical rainfall using separate dummies for each decile of the average historical rainfall in the regression model [25]. A second potential issue is that average rainfall may not accurately reflect typical rainfall conditions due to the relatively short time period for which the historical rainfall data is available. Extreme weather events—e.g., floods—are assigned a high weight when computing the historical averages. We address this concern by (i) aggregating historical data by counting the number of rainy days on 15 March 2006—2018, and alternatively (ii) use more data points by extending the time window used to construct averages. We implement the latter approach by computing historical averages based on rainfall that fell between 10 March and 20 March in the years 2006–2018. A third potential issue is that climate change decreases the reliability of historical data as a predictor for current weather patterns over time. To tackle this concern, we assign higher weights to more recent years in the construction of the (now weighted) average historical rainfall on 15 March. In Supplementary Table 10, columns (2)–(5), we present the results of these alternative approaches, demonstrating that their point estimates are statistically indistinguishable from our main IV setup. In the final column of Table 10, we show that our results also remain unaltered if we control for rainfall on the two days preceding the first Global Strike Day (i.e. 13 and 14 March 2019).

2.5.5 Alternative specifications

In the Supplementary Material, we document that our results are robust to alternative estimation and data construction choices. The results in Supplementary Table 8 show that using the natural logarithm of our protest participation measure (rather than the untransformed values) as a measure of local FFF engagement yields qualitatively equivalent results (column 1). This is also true when we use the protest participation per capita as an alternative measure of protest intensity (column 2). Similarly, using a Poisson pseudo-maximum-likelihood regression approach rather than an OLS regression approach when estimating our gravity model (8) changes the result very little (column 3). Weighting observations based on population numbers also produces very similar results (column 4).

To illustrate that counties at either end of the population distribution are not driving our results, we drop the 5% counties with the smallest and largest population, respectively. Column 5 demonstrates that this has little effect on our estimate. To alleviate concerns that exposure to the COVID-19 pandemic could be correlated with our participation measure and thus bias our results, we use two complementary approaches. First, we control for the (average) local COVID-19 incidence. This effectively leaves the point estimate unchanged (column 6). Second, we provide separate estimates for elections that occurred before COVID (i.e. in 2019) and after the disease's arrival. The estimates for the two subsets of elections are very similar in size compared to our main setup and statistically indistinguishable from each other (columns 7 and 8).

These results also speak to the question whether FFF participation have merely affected election results through their impact on climate change topic salience (Crawley et al., 2021; Dennison, 2019; Lavine et al., 1996) or whether they have affected underlying climate change attitudes. In the first case, we would expect the association between FFF protests and election results to decrease or vanish after other topics increase in relative importance. In 2020 and 2021, Covid-19 and economic recovery were top of the political agenda. Results in columns 7 and 8 affirm that the association between FFF protests and election results did not vanish with the emergence of these new topics, but persists over at least two years. This also indicates that such association is not only immediate, but persists for at least two years.

Column 9 documents that controlling for the change in the vote share of the Greens during the preceding election cycle leaves our estimate virtually unchanged. This provides further evidence that our protest participation is unlikely to pick up any county-specific trends in support for the Greens. In column 10 we extend our secondary FFF exposure measure—cumulative number of FFF protests—to also incorporate protests that took place in 2018 and early 2020, before the start of the COVID-19 pandemic. Due to the fact that we only have mobility data for the year 2019, we cannot incorporate the protests of 2018 or 2020 in the construction of our main protest participation. Compared to the measure computed solely based on the protests of 2019, the extended version produces extremely similar estimates.

Finally, we demonstrate that our results are unlikely to be the result of chance. To that end, we permute protest participation across counties at random and then re-run model (1). We repeat this exercise 1,000 times and present the results in Supplementary Figure 3. Point estimates are centered around 0 and orders of magnitude smaller than the coefficients reported in Table 1 (column 2).

3 Data Availability Statement

Some data sources used in this study are freely available and/or self-collected, while others are only available through third-party providers and are proprietary and/or subject to license agreements. Hence, we are not allowed to make a full replication package freely available. However, a replication package including the data and code necessary to replicate all analysis results is available on request at the secure workstations in the LMU-ifo Economics & Business Data Center, ifo's accredited research data center in Munich, Germany (https://www.ifo.de/ebdc). Meta data describing the replication package and access requirements can be found here: https://doi.org/10.7805/5087.5. Here we mainly provide information about the original sources and how to access/acquire them, while detailed content and usage information is available in the methods section of the text.

- Proprietary cell phone-based mobility data can be acquired from Teralytics (https://teralytics.net, product code DELDD1).
- Data on climate protests from end of 2018 until spring 2020 is hand-collected, geo-coded and drawn from three sources: enquiries with local authorities, social media (Twitter, Facebook, and Instagram), and the (archived) website of FFF Germany (https://fridaysforfuture.de/ and https://web.archive.org/web/20190801000000*/https://fridaysforfuture.de/).
- Data on European parliament elections and German federal elections is provided by the Federal Returning Officer and the Federal Statistical Office (https://www-genesis.destatis.de/, https://www.bundeswahlleiter.de/). Data on state elections comes from the State Returning Officers, the statistical offices of the Länder and the regional database of the Statistical Offices of the Federation and the Federal States (https://www.regionalstatistik.de).
- Survey data on the opinions and attitudes towards current societal/political issues comes from the Politbarometer survey which is conducted by the Research Group for Elections (Forschungsgruppe Wahlen) for the Second German Television (ZDF) and is available through the GESIS Research Data Center Elections and the GESIS Data Archive [20, 21].
- Survey data on voting intentions is drawn from the Forsa Bus survey which is conducted by the forsa Institute for Social Research and Statistical Analysis, a commercial, long-established German market research, opinion polling, and election survey company, and is available through the GESIS Research Data Center Elections and GESIS Data Archive [19].
- Twitter data was freely available at the time of collection, but now has to be acquired through the (proprietary)Twitter/X API (https://developer.x.com/en/products/twitter-api).
- Rainfall data can obtained from the Germany's National Meteorological Service (DWD, https://opendata.dwd.de/climate_environment/CDC/grids_germany/hourly/radolan/historical/asc/).
- Newspaper data can be acquired through GENIOS (https://www.genios.de) and newspaper circulation data is available for purchase through the

ABC Audit Bureau of Circulations (IVW, https://www.ivw.de/print/va/ausweisung-der-ivw-va-tageszeitungen).

- Regional control variables can be obtained from the "Regionaldatenbank Deutschland" which is provided by the regional database of the Statistical Offices of the Federation and the Federal States (https://www.regionalstatistik.de).
- Information on all soccer matches in the first and second Bundesliga in 2019 comes from https://www.fussballmafia.de/.
- Data about local COVID-19 incidence is drawn from the Robert Koch Institut, Germany's national public health agency (https://github.com/robert-koch-institut/SARS-CoV-2-Infektionen_in_Deutschland).
- Data on administrative state and county boundaries comes from the Database of Global Administrative Areas (GADM, https://gadm.org/data.html).

4 Code Availability Statement

Replication code to generate all analysis results - given one has all the necessary data sets - is publicly available through the LMU-ifo Economics & Business Data Center's data repository (https://www.ifo.de/en/ebdc). It can be accessed at: https://doi.org/10.7805/5087.5. Data has been analyzed with Python 3.12, R4.3 and Stata 17/18.

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6 Author contributions

Mark F., Matthias F., M.L., H.R., M.W., and S.W. contributed equally to the conceptualization, formal analysis, and writing of the study.

7 Competing interests

The authors report no competing interests.

8 Additional information

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Main Article - Tables and Figures

Table 1. Protest participation, vote share of the Green Party, and voter turnout

Dependent variable:	Δ Vote share Green Party		Δ Voter turnout	
	(1)	(2)	(3)	(4)
Panel A: Cumulative protest participation index				
Participation Index (SD)	0.759**	0.745**	0.110	0.138
	(0.117)	(0.118)	(0.070)	(0.071)
	[<0.001]	[<0.001]	[0.121]	[0.054]
Panel B: Cumulative Number of Days with Strikes				
Number of days with strikes (SD)	0.584**	0.575**	0.101	0.123*
	(0.090)	(0.090)	(0.058)	(0.057)
	[<0.001]	[<0.001]	[0.084]	[0.031]
State×election FE	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
Economic controls	-	✓	-	✓
Mean dependent variable	5.943	5.943	6.223	6.223
Observations	960	960	960	960

Notes: 'Participation index (SD)' is the standardized cumulative participation index, as defined by equation (12), computed up to the day before the respective election in 2019. For elections held in 2020 and 2021, the measure is defined as total cumulative participation of 2019. 'Cumulative number of days with strikes (SD)' is the standardized cumulative number of protests in a county, as described in Section (2.2.2), computed up to the day before the respective election in 2019. For elections held in 2020 and 2021, the measure the standardized cumulative number of days with strikes of 2019. 'Δ Vote share Green Party' is the change in Greens' vote share between current election cycles. 'Δ Voter turnout' is the change in the share of eligible citizens that vote between current election cycles. Demographic controls' include changes between election cycles in: log total population, average age, share minors, log number of pupils and share of high school students. 'Economic controls' encompass changes between election cycles in: log GDP per capita, log labour productivity, unemployment share.
Significance levels: * $p < 0.05$, ** $p < 0.01$. The p-value of a two-sided test of the null hypothesis that the coefficient is zero is reported in square brackets. Standard errors clustered at the county level are reported in parentheses.

Table 2. Instrumental variables results

Dependent variable:	Participation index 15.03.19 (SD)	Participation index (SD)	Δ Vote share Green Party	
	'Relevance'		Reduced form	IV
	(1)	(2)	(3)	(4)
Participation index (SD)				0.428*
				(0.215)
				[0.047]
Rainfall 15.03.19 (SD)	-0.130**	-0.082**	-0.134	
	(0.031)	(0.022)	(0.080)	
	[<0.001]	[<0.001]	[0.092]	
Long-run average	0.080*	0.053	-0.079	-0.136
	(0.040)	(0.027)	(0.081)	(0.072)
	[0.048]	[0.050]	[0.334]	[0.058]
λ	2.451**	2.643**	1.445**	0.388**
	(0.353)	(0.405)	(0.092)	(0.091)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]
ρ	-2.808	-1.827**	0.966*	1.005*
	(2.364)	(0.264)	(0.422)	(0.412)
	[0.235]	[<0.001]	[0.022]	[0.015]
State×election FE	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
Economic controls	✓	✓	✓	✓
Mean dependent variable	0	0	5.942	5.942
Observations	960	960	960	960

Notes: Results are from two-step GMM regressions of a Spatial Auto Regressive with additional Auto Regressive error structure model (SARAR). λ and ρ show the spatial autocorrelation parameters for the outcome and the error term. Heteroskedasticity robust standard errors are reported in parentheses (). The protest participation index is standardized so that the mean is 0 and the standard deviation is 1. All control variables are entered as first differences, symbolized by 'Δ'. * $p < 0.05$, ** $p < 0.01$. The p-value of a two-sided test of the null hypothesis that the coefficient is zero is reported in square brackets.

Table 3. Protest participation and voting intentions: parents versus non-parents

Dependent Variable:	Switch to Greens	Switch Union to Greens	Switch SPD to Greens	Switch FDP to Greens	Switch The Left to Greens	Switch AfD to Greens
	(1)	(2)	(3)	(4)	(5)	(6)
HH with children ×	0.459**	0.821*	1.033*	1.568	-0.944	-0.303
Participation index (SD)	(0.090)	(0.372)	(0.479)	(1.323)	(0.767)	(0.233)
	[<0.001]	[0.032]	[0.036]	[0.241]	[0.224]	[0.199]
HH without children ×	-0.157	0.318	-0.288	-1.773*	0.298	0.264
Participation index (SD)	(0.192)	(0.393)	(0.309)	(0.852)	(0.329)	(0.169)
	[0.419]	[0.423]	[0.356]	[0.043]	[0.368]	[0.124]
County FE	✓	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓	✓
Previous party	fixed effects	Union	SPD	FDP	The Left	AfD
Individual FE	✓	✓	✓	✓	✓	✓
Mean dependent variable	14.754	11.976	25.388	10.805	14.992	1.389
Observations	76,563	30,245	18,440	6,514	6,439	5,171

Notes: Results from ordinary least squared regressions, with two-way clustered standard errors at the county and week dimension reported in parentheses. The p-value of a two-sided test of the null hypothesis that the coefficient is zero is reported in square brackets. The protest participation index is standardized so that the mean is 0 and the standard deviation is 1. 'Previous party fixed effects' are dummies capturing which party the respondent voted for in the previous federal election. 'Individual FE' include fixed effects for age, education, number of children in household, employment, income bracket, and gender. * $p < 0.05$, ** $p < 0.01$. The p-value of a two-sided test of the null hypothesis that the coefficient is zero is reported in square brackets.

Table 4. Protest participation and politicians' social media presence

Dependent variable:	Share climate tweet	
	(1)	(2)
Participation index (SD)	0.409**	
	(0.127)	
	[0.001]	
Union ×		0.041
Participation index (SD)		(0.126)
		[0.749]
SPD ×		0.169
Participation index (SD)		(0.118)
		[0.152]
Greens ×		1.052**
Participation index (SD)		(0.286)
		[<0.001]
FDP ×		0.232
Participation index (SD)		(0.201)
		[0.414]
Left ×		0.651**
Participation index (SD)		(0.237)
		[0.006]
AfD ×		0.379
Participation index (SD)		(0.194)
		[0.051]
Politician FE	✓	✓
State×date FE	✓	✓
Mean dependent variable	5.889	5.889
Observations	197,830	197,830

Notes: Results are from ordinary least squared regressions, with two-way clustered standard errors at the politician and state×date dimension reported in parentheses. The p-value of a two-sided test of the null hypothesis that the coefficient is zero is reported in square brackets. The protest participation index is standardized so that the mean is 0 and the standard deviation is * $p < 0.05$, ** $p < 0.01$. The p-value of a two-sided test of the null hypothesis that the coefficient is zero is reported in square brackets.

Table 5. Protest participation and newspaper content

Dependent variable:	# articles with climate keywords	
	Daily Panel	Long difference
	(1)	(2)
Participation index (SD)	0.148**	127.846**
	(0.044)	(33.881)
	[0.001]	[<0.001]
Newspaper FE	✓	✓
Time FE	✓	✓
Mean dependent variable	1.660	590.830
Observations	47,060	130

Notes: Results in column 1 are from ordinary least squared regression, with two-way clustered standard errors at the newspaper and day dimension reported in parentheses. The p-value of a two-sided test of the null hypothesis that the coefficient is zero is reported in square brackets. Results in column 2 are from ordinary least squared regression, with White-Huber standard errors reported in parentheses. The protest participation index is standardized so that the mean is 0 and the standard deviation is 1. * $p < 0.05$, ** $p < 0.01$. The p-value of a two-sided test of the null hypothesis that the coefficient is zero is reported in square brackets.

Figure 1. Protest activity and public opinion

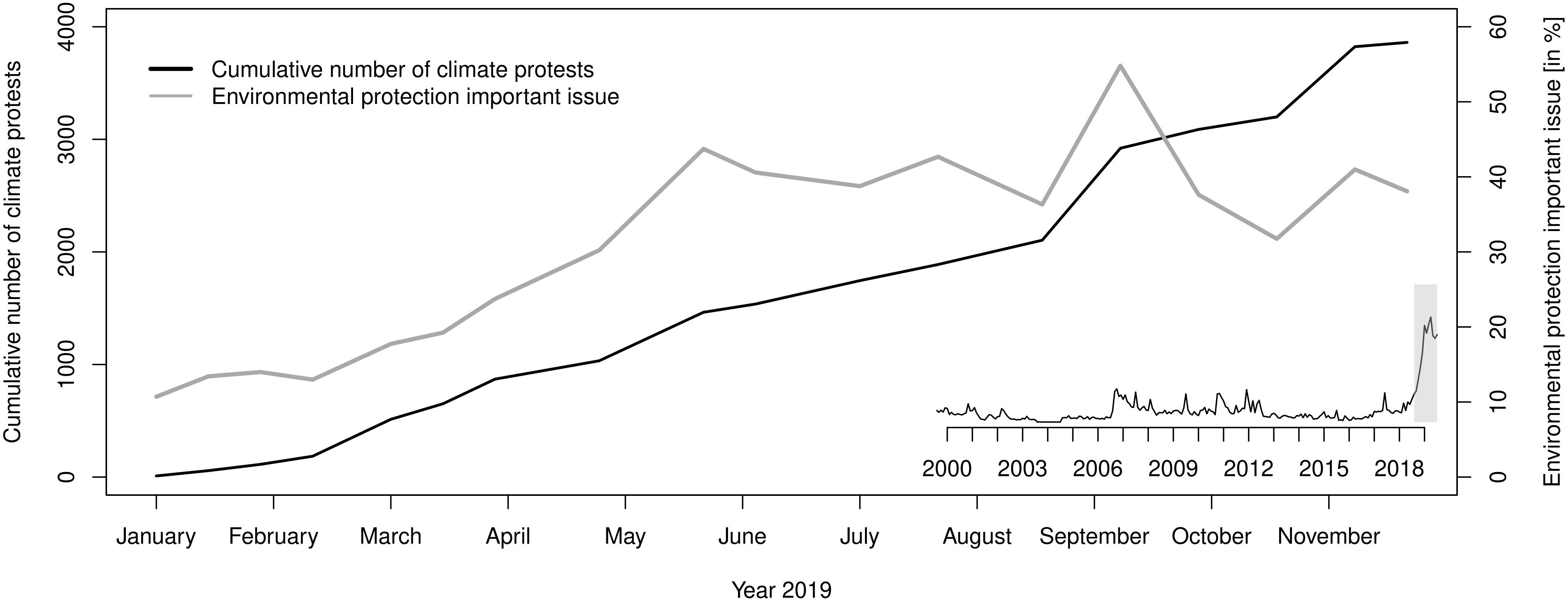
The black line depicts the cumulative number of climate protests in Germany in 2019 (black line). Protest data are hand-collected from various sources (see Section 2.2 for details). The grey line represents the proportion of individuals naming environmental protection as one of the most pressing issues in Germany over the course of 2019. n=18 unique observations. The inset plot depicts the same proportion over the time period 2000-2019. Grey shading represents the year 2019. n=240 unique observations.

Figure 2. Locations of climate strikes in 2019

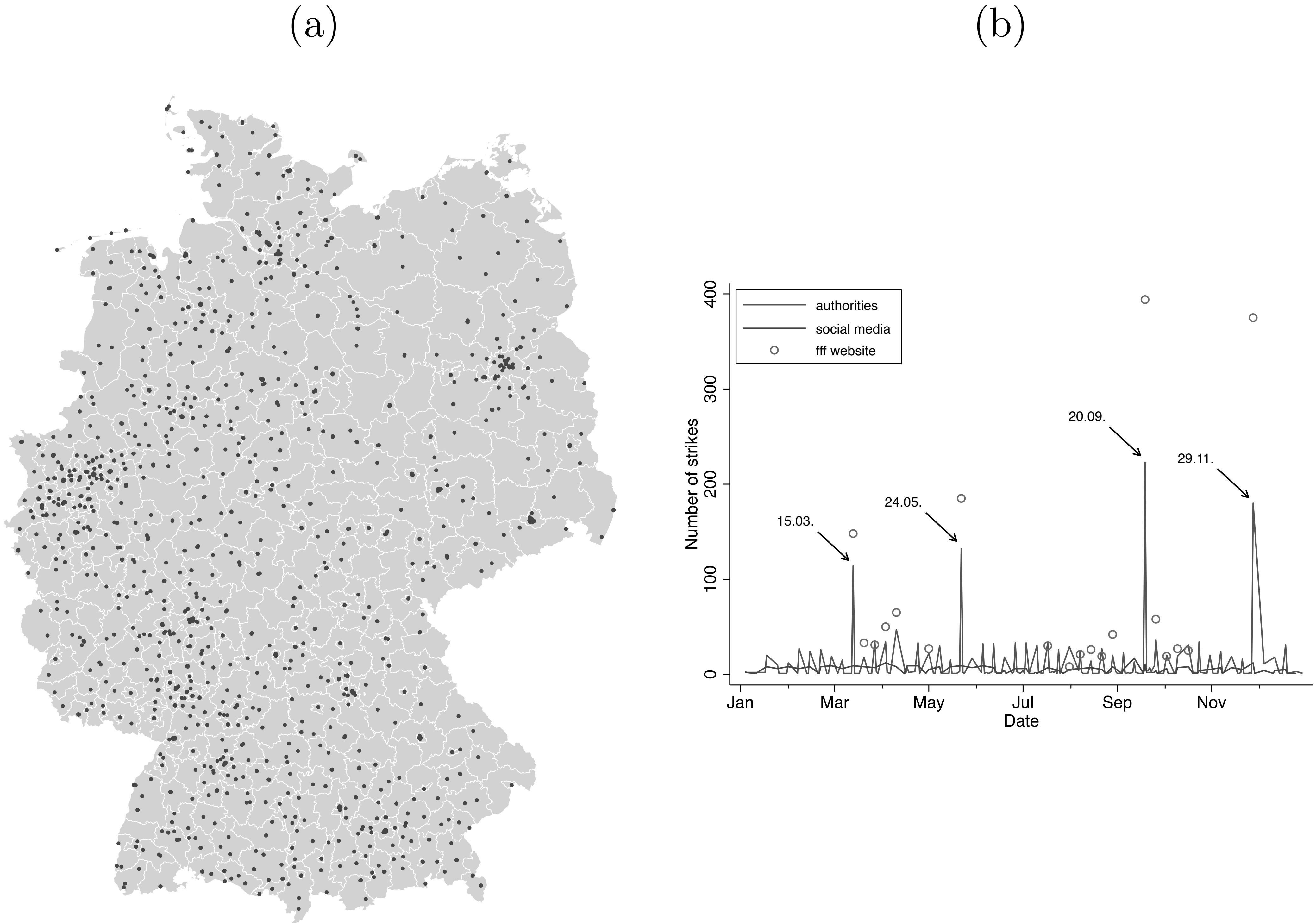
Panel (a): Map depicts the location of climate strikes (red dots) for year 2019. The bold white lines represent state boundaries whereas the thin white lines represent county borders. n=401 unique observations. Panel (b): Figure depicts the daily number of strikes by data source. The indicated dates above the spikes mark the four global climate strikes. n=3,906 unique observations.

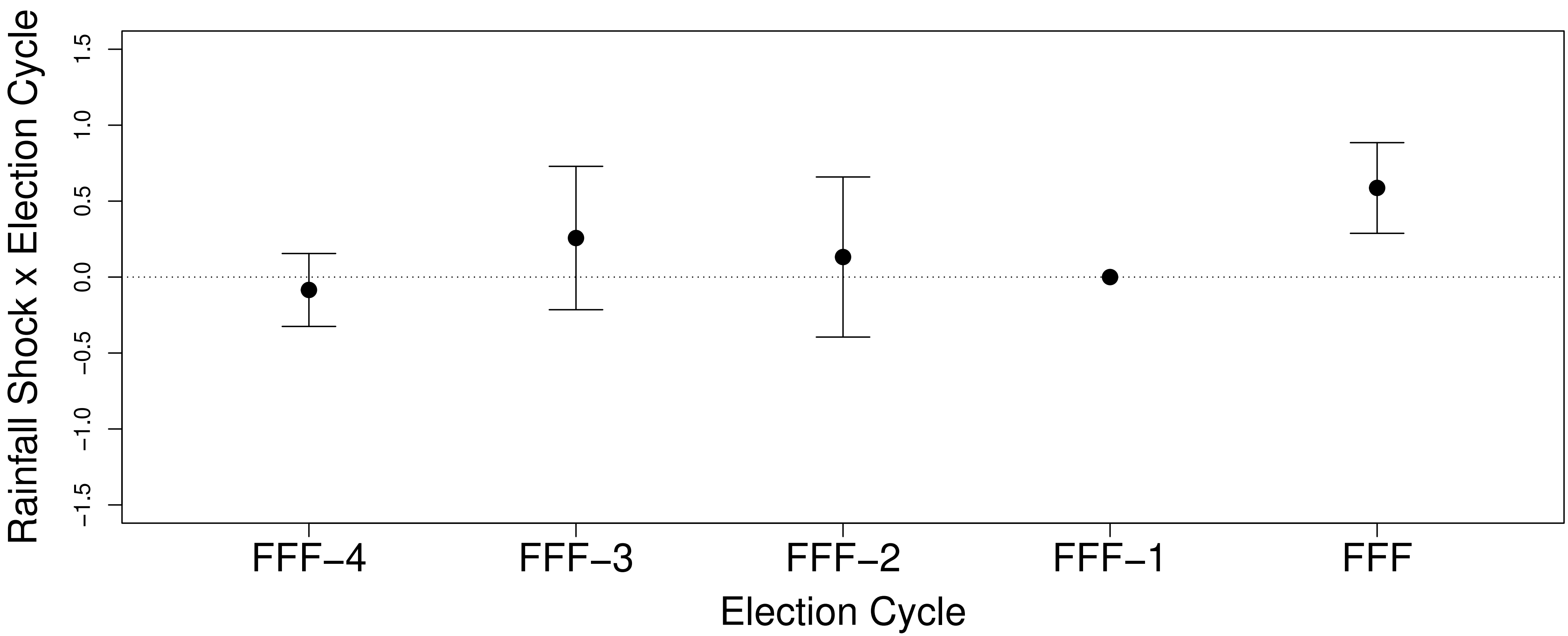
Figure 3. Pre-trends

Figure depicts point estimates (dots) and 95% confidence intervals (capped horizontal bars) of the election-cycle interacted effect of protest participation. Protest participation is standardized so that the mean is 0 and the standard deviation is 1. Dependent variable is the vote share of the Green party. FFF denotes the election cycle after the emergence of the FFF movement whereas $FFF - z$ denotes the preceding z election cycles. n=3,979 unique observations. Measure of center: average,
Statistics: FFF-4 (beta= -0.084, P= 0.444, 95% CI= -0.325 to 0.155), FFF-3 (beta= 0.257, P= 0.249, 95% CI= -0.215 to 0.729), FFF-2 (beta= 0.131, P= 0.586, 95% CI= -0.395 to 0.658), FFF-1 (baseline), FFF (beta= 0.586, P= 0.002, 95% CI= 0.288 to 0.885).

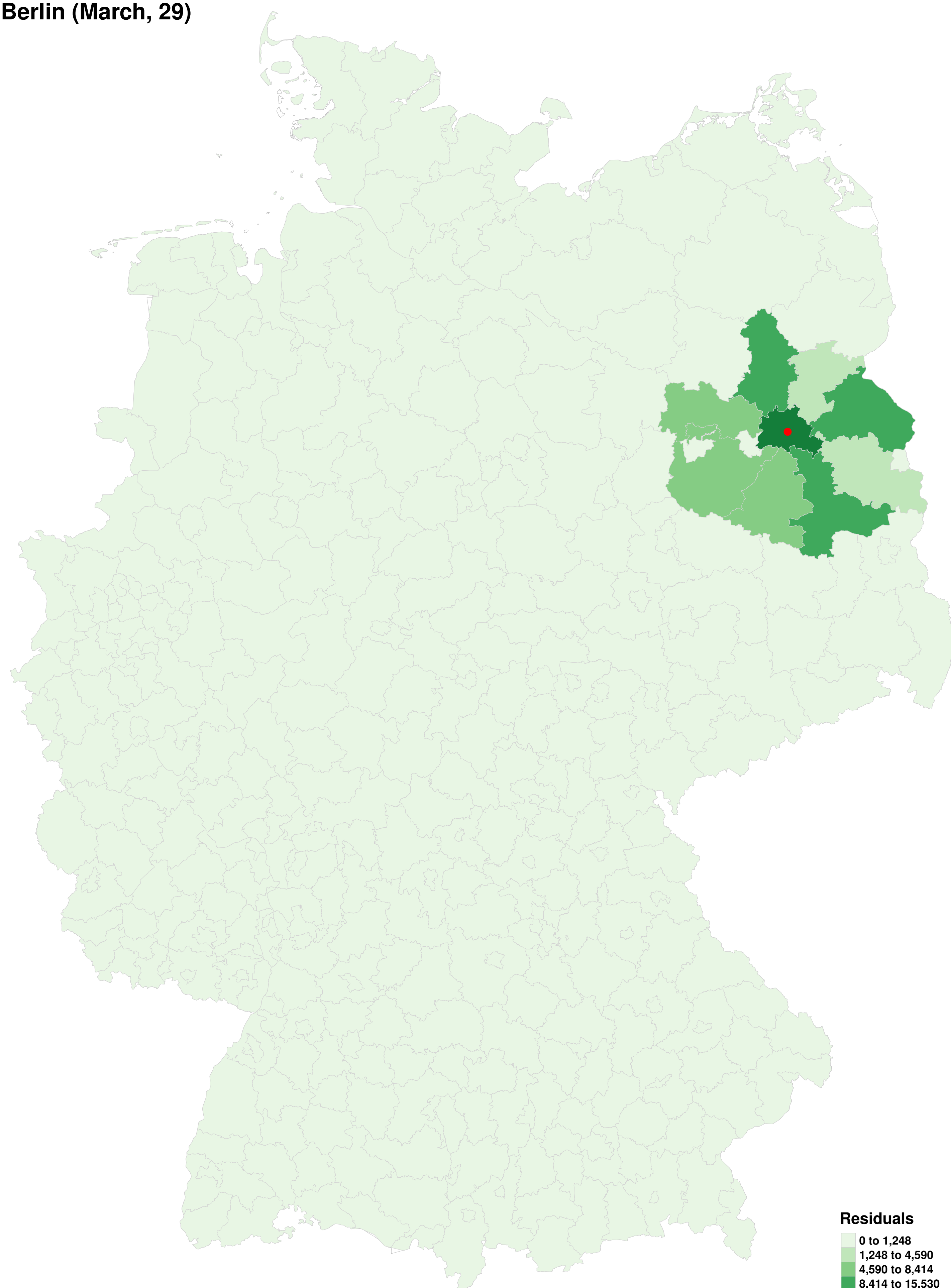


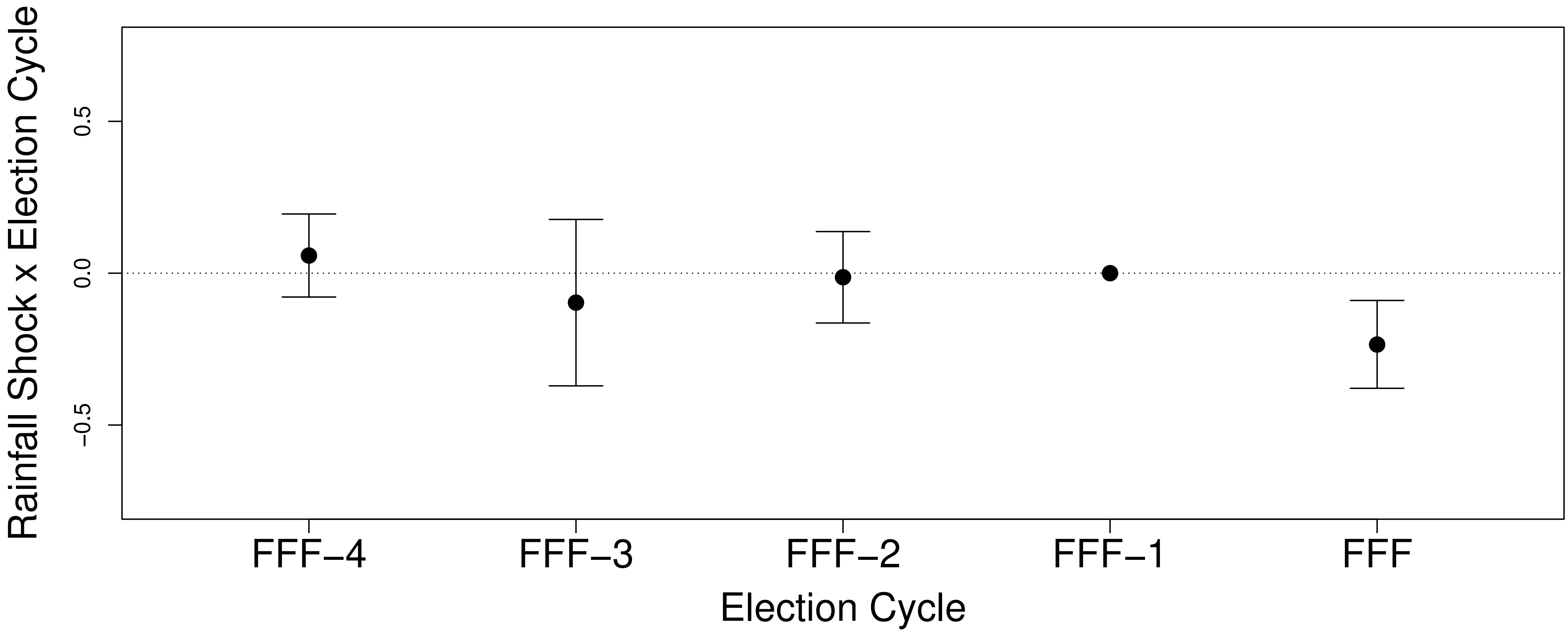
Cumulative number of climate protests
Environmental protection important issue
0
1000
2000
3000
4000
Cumulative number of climate protests
0
10
20
30
40
50
60
Environmental protection important issue [in %]
2000
2003
2006
2009
2012
2015
2018
January
February
March
April
May
June
July
August
September
October
November
Year 2019


(a)
(b)
authorities
social media
fff website
Number of strikes
0
100
200
300
400
Date
Jan
Mar
May
Jul
Sep
Nov
15.03.
24.05.
20.09.
29.11.


Rainfall Shock x Election Cycle
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
FFF−4
FFF−3
FFF−2
FFF−1
FFF
Election Cycle

Berlin (March, 29)





Rainfall Shock x Election Cycle
0.5
0.0
−0.5
FFF−4
FFF−3
FFF−2
FFF−1
FFF
Election Cycle

Extended Data Table 1. Protest participation in home county and in away counties

Dependent Variable:	Δ Vote share Green Party	Δ Voter turnout
	(1)	(2)
Participation index in home county (SD)	0.358**	0.084
	(0.119)	(0.077)
	[0.003]	[0.274]
Participation index in away counties (SD)	0.505**	0.072
	(0.117)	(0.081)
	[<0.001]	[0.374]
State ×Election FE	✓	✓
Demographic controls	✓	✓
Economic controls	✓	✓
Mean dependent variable	5.943	6.223
Observations	960	960

Notes: 'Participation index (SD)' is the standardized cumulative participation index, as defined by equation (12), computed up to the day before the respective election in 2019. For elections held in 2020 and 2021, the measure is defined as total cumulative participation of 2019. 'Cumulative number of days with strikes (SD)' is the standardized cumulative number of protests in a county, as described in Section (2.2.2), computed up to the day before the respective election in 2019. For elections held in 2020 and 2021, the measure the standardized cumulative number of days with strikes of 2019. 'Participation index (SD) in home county (SD)' is the standardized cumulative participation index in the home county, as defined by equation (12), computed up to the day before the respective election in 2019. For elections held in 2020 and 2021, the measure is defined as total cumulative participation of 2019. 'Participation index (SD) in away county (SD)' is the standardized cumulative participation index in the non-home county, as defined by equation (12), computed up to the day before the respective election in 2019. For elections held in 2020 and 2021, the measure is defined as total cumulative participation of 2019. 'Δ Vote share Green Party' is the change in Greens' vote share between current election cycles. 'Δ Voter turnout' is the change in the share of eligible citizens that vote between current election cycles. 'Demographic controls' include changes between election cycles in: log total population, average age, and share minors. 'Economic controls' encompass changes between election cycles in: log GDP per capita, labour productivity, unemployment share.
* $p < 0.05$, ** $p < 0.01$. The p-value of a two-sided test of the null hypothesis that the coefficient is zero is reported in square brackets. Standard errors clustered at the county level are reported in parentheses.