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The Power of Youth: Political Impacts of the “Fridays for Future” Movement

Abstract

We study the impact of the “Fridays for Future” climate protest movement in Germany on citizen political behavior and explore possible mechanisms. Over the course of 2019, large crowds of young protesters, most below voting age, skipped school to demonstrate for rapid and far-reaching measures to mitigate climate change. Based on cell phone-based mobility data and hand-collected information on almost 4,000 climate protests, we first construct a novel county ×rally-specific measure of protest participation, allowing us to map out how engagement in the climate movement evolved spatially and temporally. Then, using a variety of empirical strategies to address the issue of nonrandom protest participation, we show that the local strength of the climate movement led to more Green Party votes in state-level and national-level elections during 2019 and thereafter. We provide evidence suggesting that three mechanisms were simultaneously at play: reverse intergenerational transmission of pro-environmental attitudes from children to parents, stronger climate-related social media presence by Green Party politicians, and increased coverage of environmental issues in local media. Together our results suggest that environmental protests by those too young to vote provides some of the impetus needed to push society towards overcoming the climate trap.

JEL-Codes: D720.

Keywords: climate protest movement, citizen political behavior.

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1 Introduction

Despite the ever more visible consequences of human-induced climate change (IPCC, 2014),[1] politicians still regularly shy away from implementing long-term beneficial climate mitigation measures, fearing the short-term costs involved may hurt their reelection chances (Finnegan, 2022).[2] Many firms are hesitant to invest in low-carbon technologies because they lack certainty about the benefits it can bring. And support in the general public for climate change policies and green technologies is often mixed, especially when costs are incurred locally so that not-in-my-backyard reactions surface (Stokes, 2016). All of this chimes with what Besley and Persson (2020) have formally described as a "climate trap": while a transition to a low-pollution economy is technologically feasible, it does not materialize because policymakers, economic actors, and voters are jointly indecisive in pushing for change.

Such inaction and lack of public support is, however, diametrically opposed to the interests of young people who do not (yet) have the right to vote, as it exacerbates intergenerational injustice in the distribution of climate change damages (Dietz *et al.*, 2009). Indeed, while today's young will in any case experience the brunt of the projected impacts of climate change during the 21st century (Hersch and Viscusi, 2006), further delay in climate mitigation will with great certainty further aggravate these impacts (Stern, 2007).

This intergenerational tension may explain why children and youth have often been at the forefront of demanding climate action.[3] 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 raise awareness of the full scale of the climate crisis and to push both adult voters and politicians past "business as usual" and towards prioritizing a green transformation. The FFF movement has been especially strong in Germany, where it gained significant momentum throughout 2019, staging thousands of local climate protests across the country.

Despite the growing prevalence of youth spearheading mass protests in demand of climate action, it is still an open question whether their activism can bring about political change. This paper sheds light on this issue. We examine the impact of the FFF protest movement in Germany on citizen political behavior and explore mechanisms that may be involved. In particular, we ask whether adults are swayed to vote for "green" political parties if local youth are more active in the FFF movement. If so, can this be explained by "reverse intergenerational transmission" whereby youth raise their parents' environmental awareness and increase their demand for green politics? Do politicians publicly position themselves

[1] The last nineteen years are among the twenty hottest years ever since temperature record-keeping began in 1880 (Lenssen *et al.*, 2019). The melting of glaciers and the thermal expansion of seawater as it warms is causing a steady increase in sea levels (Church and White, 2011).

[2] The phenomenon that politicians underinvest in long-term public goods that cause short-term costs is well known from various areas of public policy. It is due to the difficulty of imposing short-term costs on voters for benefits that will arrive in the future, uncertainty about whether future benefits will materialize, and overcoming opposition from cost-bearing organized groups (Jacobs, 2011).

[3] Already in 1992, during the UN Climate Conference in Rio de Janeiro, the then 12-year old Severn Cullis-Suzuki addressed delegates by stressing that "you must change your ways, [...] losing my future is not like losing an election or a few points on the stock market."

differently towards climate change if protest activity in their constituency is high? Do higher rates of climate protest participation shape the content of local media?

To address these questions, we develop a spatially and temporally highly disaggregated measure of engagement in the FFF protest movement. For any given day, the measure captures how many individuals from a given county participate in FFF protests held either in the county itself or outside of it. Our approach combines information on location and dates of climate protests with spatio-temporal granular population flows. We hand-compiled data on the first component, FFF protests, from a variety of sources, including police forces, city councils, municipal authorities, and official FFF announcements. In total, our protest database contains almost 4,000 events, illustrating the magnitude of the FFF movement in Germany. The second component, daily population flows within and between counties, is derived from cell phone-based tracking data. It includes the daily number of journeys between 260,000 origin-destination county pairs. Employing a standard gravity equation, we use this data to estimate average population flows between each county pair. Finally, we combine the two components to compute our measure of protest participation. For a given county and day, we simply sum up the number of above-normal journeys from the county to all counties (including the own) in which FFF protests are held on the day. In contrast to commonly used measures of protest activity—such as crowd sizes or simple dummies for the occurrence of a rally—our index thus allows us to more accurately map out the degree of local engagement in the FFF protest movement.[4]

Armed with this measure of local FFF engagement, we first study its role in citizens' voting behavior in several state-level and national-level elections during 2019 and thereafter. The challenge in establishing a causal relationship between the two is to purge unobserved factors that might determine both protest participation and electoral outcomes. A concern is, for example, that counties where pro-environmental attitudes are widespread are those where youth strongly engage in climate protests and adults tend to vote green. We start with a simple first-differencing model that accounts for time-invariant differences in county-level characteristics. To address the remaining concern of time-varying correlated factors, we implement three complementary approaches. First, we control for a battery of time-varying county-level controls. Second, we illustrate by means of placebo tests the absence of differential pre-trends. Third, we use an instrumental variables-type approach that exploits local rainfall shocks as an exogenous source of variation in protest participation. Together, these approaches suggest that any bias from omitted variables is likely to be very small.

We find that the FFF protest movement has altered the political landscape in significant ways. In Germany's multiparty system, the party that puts climate highest on their agenda and regularly comes out top in nationwide surveys concerning climate competency is the *Alliance 90/The Greens*. Our first main finding is that a one-standard-deviation increase in local protest activity raises the vote share of the Greens by roughly 0.5 percentage points. This amounts to 8 percent of the Greens' average vote gain compared to preceding elections. Digging deeper into this result, voter turnout also increases with local protest participation, but the effect is too small for voter mobilization to explain the FFF-induced vote gains of the Greens. Instead, the climate protest movement seems to have caused left-leaning voters to swing from the center-left Social Democratic Party (SPD) and the socialist Left Party to the Greens.

[4] In the specific case of Germany, our approach also allows us to circumvent data availability issues. Information on protest crowd sizes, for example, are largely unavailable.

Turning to factors that may explain these results, we argue that several complementary mechanisms are plausibly at play. The first is what we label the "reverse intergenerational transmission" channel, which says that youths' engagement in the FFF movement may raise their parents' climate change concerns and hence their propensity to vote the Greens. Using survey data on adults' political attitudes and voting intentions, we demonstrate that a strong FFF effect on green party support is only present among parents with children of FFF-relevant ages.

The second mechanism we explore builds on the idea that the FFF movement might affect how political candidates publicly position themselves towards climate change, and that this has influenced voters' evaluation of candidates and, ultimately, their vote decision. Based on a politician×day panel that links Twitter activity of the members of the German federal parliament to climate protest activity in their constituency, we show that the latter induces primarily members of the Greens to post more climate change-related content. In quantitative terms, a one-standard-deviation increase in own-constituency protest activity increase the probability a member of parliament of the Greens posts climate-related content by more than 11 percent.

Media sources have been shown to influence the electorate through the content of their reports, and so increased media coverage of climate change is another possible mechanisms through which the FFF-induced vote gains of the Greens might be explained. Drawing upon the content of 281 German print media outlets, we establish that local newspapers indeed report more on climate change, both in the short- and long-term, if protest activity in their area of circulation is high. The effects are sizeable, with a one-standard-deviation increase in local protest participation raising climate-related newspaper content by up to 18 percent.

Our final result shows that the political impact of the FFF movement goes beyond vote swings towards the Greens. In particular, we find that in counties with strong protest activity, there are remarkable voter movements among Germany's right-of-center parties: the extreme-right Alternative for Germany (AfD) experiences substantial losses while support for the center-right Christian Democratic Union (CDU) increases. We provide evidence suggesting that the voter swing among the right-leaning electorate can be explained by strategic voting.

Where do these results leave us? Returning to the notion of the climate trap raised at the outset, Besley and Persson (2020) show theoretically that an enhanced influence of environmentalists, even if small, can push society over a "critical juncture" towards a new dynamic path were a green transformation materializes. Our empirical findings provide a nuanced take on this. Environmental activism by those too young to vote provides some of the impetus needed, in theory, to overcome the frictions that cause the climate trap. In particular, through their engagement in FFF, youth seem to have changed the political preferences of their parents, influenced how politicians publicly position themselves towards climate change, and impacted the intensity of media reports on environmental issues. Finally, as an unintended byproduct of the climate movement, there has been a substantial drop in far-right party support, very likely triggered by strategic voting.

Our paper touches upon several strands of literature. First, it has antecedents in a small but insightful literature that examines the impact of social and political movements. Studying the Tea Party protests in the United States, Madestam *et al.* (2013) establish that the movement has caused a shift to the right in policymaking, both directly through incumbent politicians' decision-making and indirectly through voters' selection of politicians in elections. Using daily variation in the number of protesters during Egypt's Arab Spring, Acemoglu *et al.* (2018) show that more intense protests are associated with lower stock market valuations of firms connected to politicians in power relative to unconnected firms. In addition, several papers have studied the determinants of protest participation (Finkel and Opp, 1991, Finkel and Muller, 1998, Cantoni *et al.*, 2019, Bursztyn *et al.*, forthcoming). An interesting but not directly related phenomenon is described by Depetris-Chauvin *et al.* (2020): collectively shared experiences of the type induced by mass sports events—in particular, international football games in the context of Sub-Saharan Africa—can shape identities in ways that can help build national sentiment at the expense of ethnic identification.

Second, our paper contributes to a body of work examining the influence of certain interventions for environmental awareness and behavior. Hungerman and Moorthy (2022) study the effect of the original 1970 Earth Day on environmental attitudes in communities, demonstrating that it had long-lasting impacts on support for environmental spending and local air quality. Deryugina and Shurchkov (2016) provide experimental evidence showing that information provision on the scientific consensus on climate change affects the public's beliefs about climate change in the short-run, but does not increase the view that policy action is warranted or willingness to donate toward climate change causes. A large literature, mostly outside of economics, provides correlational or qualitative evidence on the role of socio-demographic factors (Abdul-Wahab and Abdo, 2010), mass media and social media (Mallick and Bajpai, 2019, Saikia, 2017), and perceptions of the degree of scientific consensus on climate change (Ding *et al.*, 2011). Our paper is, to the best of our knowledge, the first paper to describe the role of a mass movement as a factor determining demand for climate change policies and voting behavior.

Third, our study also speaks to work on the intergenerational transmission of preferences, norms, and beliefs. While a substantial part of the literature has highlighted how older generations transmit these to younger generations (Bisin and Verdier, 2001, Fernández *et al.*, 2004, Fernández and Fogli, 2009, Figlio *et al.*, 2019), there only exist a few studies, mostly outside of economics, that has looked into the reverse intergenerational transmission. This body of work has established, *inter alia*, that younger generations influence their parents' attitudes towards a variety of controversial topics, including unhealthy consumption behaviors (Flurry and Burns, 2005), the use of modern technology (Baily, 2009), and views on sexual orientation (LaSala, 2000). A particularly relevant subset of studies has explored whether children can foster climate change concerns among their parents. Based on a controlled trial in the Seychelles, Damerell *et al.* (2013) show that adults exhibit more comprehensive knowledge of wetlands and improved water management behavior when their child has received wetland-based environmental education. In a similar vein in the United States, Lawson *et al.* (2019) present an experimental evaluation of an educational intervention program designed to build climate change concern among parents through their middle school-aged children, finding that parents of children in the treatment group expressed higher levels of climate change concern than parents in the control group.

Finally, our work relates to studies that use cell phone data to examine economically and socially important phenomena. A large part of this literature centers around the investigation of social network patterns (Onnela *et al.*, 2007, 2011, Kovanen *et al.*, 2013). Beyond this, cell phone records have recently been used to predict the spatial distribution of urban economic activity from commuting choices (Kreindler and Miyauchi, 2021) and to assess the contagion externality of mass events (Dave *et al.*, 2020). We instead exploit cell phone-based tracking data to measure the spread of a major social movement across time and space.

The remainder of the paper proceeds as follows. In Section 2, we provide background information on the FFF movement. Section 3 contains a description of the data we use. In Section 4, we lay out our methodology for measuring climate protest participation across time and space. In Section 5, we explore the role of youth environmental activism in adults' voting behavior, discussing our empirical strategy before presenting the results. Section 6 explores mechanisms that may explain our findings. The final section concludes.

2 Background

2.1 Fridays for Future

FFF is an international youth-led climate movement that demands fast and science-based action from politicians to address climate change. The key demand is that governments adhere to the target set in the 2015 Paris Agreement: to lower global greenhouse gas emissions to a level that limits global warming to 1.5 degrees compared to pre-industrial levels. To raise awareness and publicly express their demands, local FFF chapters organise regular protest marches. These typically take place on Fridays, where participating students skip classes to attend the protest (Smith and Bognar, 2019). The FFF movement is therefore also frequently referred to as 'School Strike for Climate' which is also reflected in the demographics of the activists. Protesters are overwhelmingly school- or college-age students who position themselves at the left of the political spectrum (Sommer *et al.*, 2019, De Moor *et al.*, 2020).[5]

The FFF movement was sparked by Greta Thunberg who—aged 15—started protesting in front of the Swedish parliament to call for stronger action on climate change in August 2018. From there, the movement spread across the world, gaining significant traction in 2019. During that year, FFF staged four global strikes in March, May, September, and November. Each event drew huge crowds. For the September strike—the largest of the four—FFF organized 6,000 protests in 185 countries, mobilising around 7.6 million people (De Moor *et al.*, 2020). With the emergence of COVID-19 in 2020, the FFF movement lost impetus. Large-scale public gatherings were forbidden in many countries, implying a temporary end of the protest marches.

The global temporal dynamics of the FFF movement are also reflected in Germany. While the first climate protests took place in late 2018, these were restricted to a handful of cities and few activists (Sommer *et al.*, 2019). Starting in early 2019, however, the movement gathered dramatic momentum. By late-January, protests had occurred in around 50 locations involving around 50,000 protesters in total. Engagement in FFF protest activity experienced a further boost in March when Greta Thunberg attended marches in Berlin and Hamburg. March also saw the the first global climate strike, staged on the 15th. On that day, an estimated 300,000 individuals took to German streets in demand for climate action. Climate rallies continued throughout the year (mostly on Fridays) with dramatic increases in participation numbers observable during the subsequent three global

[5] Surveys conducted among protesters in Germany suggest that around 75% are school- or college-age students (Sommer *et al.*, 2019, De Moor *et al.*, 2020).

strike days. The second—held on May 24, 2019—was strategically chosen to precede the European Parliament elections, which FFF declared as 'climate election'. More than 300 strikes with a total of 320,000 participants were recorded for Germany (Die Zeit, 2019). The largest protest crowds were observed during the third climate strike (September 20, 2019). While more than 7.6 million individuals participated in climate strikes globally, the numbers amounted to 1.4 million protesters in more than 500 locations in Germany alone (De Moor *et al.*, 2020). The fourth and last global climate protest of 2019 took place on November 29. Compared to previous global strike days, strike participation had declined; around 630,000 individuals joined protests across Germany (Zeit Online, 2019). Figure 1 visualises the temporal dynamics of the FFF protests in Germany for 2019. The solid black line represents the cumulative number of strikes across time.[6]

Prelimenary anecdotal and descriptive evidence suggests that the FFF movement was successful in raising awareness of climate issues and changing public attitudes (e.g., Forschungsgruppe Wahlen e.V., 2019, Smith and Bognar, 2019). Drawing on Politbarometer (2019) surveys, we can provide additional support for this notion. Amongst others, the survey asks respondents to list the two most pressing political issues in Germany. As illustrated by the grey line in Figure 1, the share of interviewees that mentioned environmental protection as one of the primary issues steadily increased from around 10% to almost 60% over the course of 2019. Foreshadowing our regression results, Figure 1 also suggests that increases in the level of concern are positively related to FFF strike activity. Individuals are more likely to express concern for environmental protection after surges in the number of protests.

Finally, the inset figure highlights that awareness and prioritisation of climate-related issues is a recent phenomenon. Over the period 2000–2018, the fraction of population that viewed environmental protection as a main issue hovered around 4%. Only in 2019—shaded in grey—did this share shoot up dramatically. Surveys suggest that the public expected the climate protests and the associated sudden spike in environmental awareness to lead to political changes (Forschungsgruppe Wahlen e.V., 2019). Starting with the next section, we begin developing the building blocks necessary to empirically test this issue.

2.2 Germany's Political Landscape

Unlike the United States, Germany has a multiparty system. As a consequence, governments are typically formed by coalitions of parties, both a the state and federal level. In our analysis of electoral outcomes, we will focus on those political parties that are currently represented in the German Federal parliament. Four of these parties are positioned on the right of the political spectrum. The first, the FDP (Free Democratic Party), advocates for a liberal market economy and a simple tax system. The second party is the CDU (Christian Democratic Union). Considered a people's party (*Volkspartei*), it represents conservative as well as traditional Christian values and advocates a market economy. Third, the CSU (Christian Social Union) is the so-called "sister party" of the CDU. Together, the CDU and the CSU form the "Union". In elections to the federal parliament, the CSU stands in Bavaria, whereas the CDU competes in the remaining 15 federal states. The CSU's political agenda is very similar to the CDU's, but can be considered as more conservative and more traditional. The final right-of-center party, the AfD (Alternative for Germany), can be classified as right-wing populist. While it initially received attention for its right-

[6]Further details on the spatiotemporal diffusion of the protest movement are provided in Section 3.

wing liberal skepticism regarding the EU and the Eurozone, it has since then significantly radicalized, disapproving for instance of the admission of refugees. Crucially in the context of our analysis, the AfD, however, is critical of climate science. As the only political party it has called for an end to all major climate action efforts (including the abandonment of the Paris Climate Agreement and the European Green Deal).

Among the left-of-center parties, the SPD (Social Democratic Party) is also considered as a people's party. It stands for social justice and has close ties with Germany's worker unions. Next, the Alliance 90/the Greens (henceforth, the Greens) has its origins in several social movements (e.g., the anti-nuclear movement and multiple civil rights movements) and is perceived by voters as the party with the by-far highest level of climate competency (Forschungsgruppe Wahlen, 2019). It had a well-developed and explicit climate strategy in place before the start of the FFF movement. This was not the case for other parties. Finally, the Left Party is the successor party of the SED, the communist ruling party of the former German Democratic Republic, and promotes social justice and peace.

3 Data

For our analysis, 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.[7] Second, we link daily repeated cross-sectional survey data on citizens' political preferences and voting intentions to protest participation in their county of residence. 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. Third, we create a newspaper×day panel dataset that relates reporting on climate change to protest participation in the newspapers' area of circulation.

We compile the 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. The sources are described in more detail below along with the data construction process.

3.1 Cell Phone-Based Mobility Data

We obtain cell phone-based mobility data from Teralytics. This database reports the daily number of journeys between all county-pairs for the year 2019. The data include both information on journeys that take place within each of Germany's 401 counties as well as journeys between counties. Terarlytics identifies daily flows using mobile phone tracking technology applied to the the universe of mobile signals of the Telefonica O_2 mobile network costumers.[8] This mobile network provider had a market share of 31 percent in 2019

[7] German counties ('Landkreise') are the third level of administrative division, thus corresponding to districts in England or counties in the US.

[8] The mobile phone signals are transformed into journeys using machine learning algorithms. Thereby a journey is defined as a movement between an origin-destination pair if the mobile phone user remains at the destination for a minimum of 30 minutes.

(Statista, 2020). To obtain mobility patterns representative of total population, Teralytics extrapolates measured mobility based on O_2's regional market share. For the year 2019, we observe a total of 64.4 billion journeys between county-pairs. The vast majority of journeys (92.7 percent) do not exceed 30 kilometers.[9]

3.2 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 must be notified of public gatherings such as rallies and demonstrations at least two weeks in advance. Depending on the jurisdiction, rallies have to be registered with the police, city council, or other regulatory agencies. We contacted all relevant authorities and requested a full list of climate protests that were registered in their jurisdictions over the course of 2019. 44% of the authorities responded to our request and provided exact information on location and time of a total of 1,938 protests. To fill in existing gaps and ensure that we take into account marches that were not registered with authorities, we complement the protest data obtained from authorities with information on location and date of strikes extracted from social media posts (Twitter, Facebook, and Instagram) as well as protest activity reported on the official website of FFF Germany.[10] These sources provided us with an additional 1,968 strikes. After combining all data sources and dropping duplicates, we manually geocoded the location of the strikes.

Our final strike data encompasses 3,906 protests which took place 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. Similarly, Panel (b) shows that protest activity was continuous throughout the year. Furthermore, regular spikes in the number of protests are discernible on Fridays. Clearly reflected in the protest numbers are also the four global climate events (March, May, September, and November).

3.3 Election Data

Our analysis incorporates results from three types of elections: European Parliament elections, state elections (in Brandenburg, Saxony, and Thuringia), and German federal elections. The most recent round of each type of election took place after the start of the FFF movement, thus allowing us to investigate its effect on the electorate. More specifically, we compare vote shares of the main political parties before and after the climate protests. 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. Our primary outcome variable is the *change* in the vote share of the Greens (*Bündnis 90/Die Grünen*).

The European parliament as well as the state elections take place approximately every five years, with the most recent round held in 2019 and the preceding one in 2014. 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 relevant to our analysis are May 26, 2019 versus May 24, 2014. For the state elections in Brandenburg, Saxony, and Thuringia, we draw on data from the State Returning Officers (*Landeswahlleiter)* and the

[9] The distance is measured as the geodesic distance between the centroids of two geographies.

[10] 1,583 additional strikes were retrieved from the website of FFF Germany, 385 from social media posts.

Statistical Offices of the Länder. The elections were held in September/October of 2019 versus August/September of 2014.[11]

A Federal Returning Officer (*Bundeswahlleiter*) reports the results of federal elections. Unlike European and state elections, the federal elections take place every four years. The latest round of the federal elections were held in 2021. We will thus analyse if the protests of 2019 induces changes in the vote share of Greens between the federal elections of 26 September 2021 and 24 September 2017.

In total, our election dataset encompasses 849 observation at the county×election level. Appendix Table A.2 reports summary statistics of the key election outcomes.

3.4 Voting Intentions Survey Data

The Forsa Bus survey is conducted by forsa Institute for Social Research and Statistical Analysis, a commercial, long-established German market research, opinion polling and election survey company. The Forsa Bus is a voluntary daily repeated cross-sectional telephone survey (CATI) and representative of Germany.[12] Each day (in 2019) exactly 500 (new) German speaking participants aged 14 and older answer about 40 questions mostly regarding social attitudes, (realized/hypothetical) voting behavior and political preferences as well as basic demographic variables such as household size, age, gender, number of children, education etc. Additionally, the survey contains the respondents county of residence which gives us the chance to link the survey to our protest participation data.

3.5 Twitter Data

To create the daily panel data on politicians' Twitter activity, we proceed in four steps. 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 a total of 736 parliament members). Second, we use Twitter's API to collect all tweets (original and retweets) posted by these parliament members between 4 January 2019 and 31 December 2019. This results in a database of 288,490 individual tweets. Third, we apply a keyword search to identify which of the tweets refer to climate change-related topics. Tweets are defined as being climate change-related if they contain at least one of phrases listed in Appendix Table A.1. In the final step, we aggregate the data at the politician×day level, resulting in a dataset with a total of 180,638 observations. We use a dummy variable indicating whether a politician posts a climate change-related tweet on a given day or not as our main outcome variable. Summary statistics of the dataset are presented in Appendix Table A.3.

[11] The specific election dates are: 27 October 2019 and 14 September 2014 (Brandenburg), 1 September 2019 and 31 August 2014 (Saxony), and 27 October 2019 and 14 September 2014 (Thuringia).

[12] Forsa Bus 2019 is available through the GESIS Research Data Center Elections and GESIS Data Archive (forsa, Berlin (2020): Forsa-Bus 2019. ZA6850 Version: 1.0.0. GESIS Data Archive. Dataset. https://doi.org/10.4232/1.13552))

3.6 Newspaper Data

We obtain newspaper content from the GENIOS Online Press Archive.[13] This archive gives access to articles of 281 German print media outlets.[14] Using keyword searches, we identify the number articles for each outlet and publication date featuring climate change-related content. Specifically, we classify an article as climate change-related if it contains one of the keywords listed in Table A.1.

We link the newspapers to protest participation using the outlets' area of circulation. To this end, we first match each newspaper to information on the geographical distribution of its readership. The data on readership is provided for the German Audit Bureau of Circulation (IVW), but available only for a subset of outlets that are in the GENIOS archive. In total, we are able to identify the area of circulation of 130 newspapers and magazines. For each of these news outlets, we construct a variable capturing its area of circulation. For each media outlet, we rank all German counties according to readership numbers and define as area of circulation those counties that together account for 75% of total circulation.[15]

Our final newspaper×day dataset encompasses 130 news outlets and covers the year 2019. We report key summary statistics in Appendix Table A.4.

3.7 Control Variables

We construct a variety of county-level controls for our analysis. These include demographic variables (total population, average age, and share of minors) as well as economic ones (GDP per capita, labor productivity, and unemployment share). In analogy to our outcome variables, we first-difference the controls. That is, we compute the difference between 2019 and 2014.

4 Measuring Local Engagement in Fridays for Future

The aim of our analysis is to investigate how the local strength of engagement in FFF protest activity influences the behavior of the electorate. Measuring the former is, however, challenging. In our hand-collected data on climate protests, information on rally crowd sizes is very sparse (more about this below). However, even if crowd sizes at protests were known to us, it would not inform us about what counties the FFF protesters originate from. Indeed, many types of mass protests take place in some central location such as the main city of a region, with its participants originating both from within outside that location (e.g., neighboring or most distant counties). To overcome this measurement problem, we combine the cell phone-based mobility data with our climate protest database to predict the number of individuals that originate from one specific county and participate in climate protests on a given day.

[13] See https://www.genios.de/presse-archiv/.

[14] In the following, we use the terms 'media outlet', 'outlet', and 'newspaper' interchangeably.

[15] Our results are not sensitive to the exact choice of cut off.

4.1 County×Day-Level Protest Participation Measure

To construct our local protest participation measure, we proceed in two steps. First, we identify excess mobility between county 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 in which protests take place. This procedure is outlined in detail below.

We identify excess mobility by estimating a standard gravity equation. This allows us to compute expected (i.e., average) mobility between any county-pair and day. Excess mobility is then simply given by the difference between observed and expected mobility, i.e., the residuals. We start by running the following regression equation:

$$\text{journeys}_{ijt} = \vartheta_{ij} + \varphi_d + \eta_w + \psi_m + \Phi_t + \varepsilon_{ijt}, \tag{1}$$

where journeys_{ijt} denote the number of journeys between origin i and destination j on day t. The origin-destination fixed effects (ϑ_{ij}) absorb any time-invariant differences in the level of mobility across pairs, including structural differences between within and cross-county movements. To account for temporal variation in the mobility patterns, we include fixed effects for the day-of-the-week (φ_d), the week-of-the-year (η_w), and the month (ψ_m). We further include a dummy variable (Φ_t) that captures whether day t is a public holiday.[16]

The parsimonious regression equation (1) explains a very high proportion of the variance in the mobility flows, as measured by an R-squared of 0.97. As indicated above, the remaining unexplained variation—i.e. the residuals—constitutes the basis for our strike participation measure. The residuals capture how many more (or fewer) journeys are made from county i to county j than expected. Formally, we compute them as:

$$e_{ijt} = (\text{journeys}_{ijt} - \widehat{\text{journeys}}_{ijt}), \tag{2}$$

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. 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 in which a climate protest occurs. Formally, we predict the total number of strike participants that originate from county i on day t, as:

$$\text{P}_{it} = \sum_{j=1}^{J} \text{I}_{j,t}\, e_{ijt}. \tag{3}$$

Total protest participation of county i on day t is symbolised by P_{it}. The indicator variable $\text{I}_{j,t}$ takes the value of one if a strike occurs in county j on day t, and zero otherwise.

Figure 3 visualises our strike participation measure for a climate protest in Berlin that took place on 29 March 2019. This particular protest was attended by Greta Thunberg and drew a large crowd. The figure illustrates that protest participants predominantly originate from within Berlin and the surrounding counties. This pattern of participation also holds more generally. It is therefore important to note that the total protest participation of a county

[16] We account for the following holidays: All Saints' Day, Ascension Day, Assumption Day, Christmas, Corpus Christi, Epiphany, Easter, German Unity Day, Good Friday, Labour Day, New Year's Day, Penance Day, Pentecost, Reformation Day as well as Carnival season and New Year's Eve.

can be decomposed into two parts: participation in protests that take place in the own (i.e. home) county and participation in protests that take place in other counties. This decomposition is represented as:

$$\mathrm{P}_{it} = \sum_{j=1}^{J} \mathrm{I}_{j,t}\, e_{ijt} = \underbrace{\underbrace{\mathrm{I}_{i,t}\, e_{iit}}_{\mathrm{P}^H_{it}}}_{\substack{\text{protest participation} \\ \text{in home county}}} + \underbrace{\underbrace{\sum_{j \neq i}^{J} \mathrm{I}_{j,t}\, e_{ijt}}_{\mathrm{P}^F_{it}}}_{\substack{\text{protest participation} \\ \text{in other counties}}}. \tag{4}$$

The first term of the decomposition, P^H_{it}, represents participation in protests that take place 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 zero on days on which there are no protest in the home county i. The second term (P^F_{it}) reflects journeys to protests that take place in other counties. Fluctuation in total protest participation is overwhelmingly driven by participation in marches that take place in the home county; 96% of the variation in total strike participation P_{it} is due to variation in P^H_{it}.

4.2 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. In this case, we aggregate local protest participation over time. The aggregation process can be written as:

$$\mathrm{P}_{i\tilde{t}} = \sum_{t=1}^{\tilde{t}} \sum_{j=1}^{J} \mathrm{I}_{j,t}\, e_{ijt} = \underbrace{\underbrace{\sum_{t=1}^{\tilde{t}} \mathrm{I}_{i,t}\, e_{iit}}_{\mathrm{P}^H_{i\tilde{t}}}}_{\substack{\text{protest participation} \\ \text{in home county}}} + \underbrace{\underbrace{\sum_{t=1}^{\tilde{t}} \sum_{j \neq i}^{J} \mathrm{I}_{j,t}\, e_{ijt}}_{\mathrm{P}^F_{i\tilde{t}}}}_{\substack{\text{protest participation} \\ \text{in other counties}}}, \tag{5}$$

where $\tilde{t}$ represents the day before the election. Thus, the cumulative protest participation measure is simply computed as the sum of daily protest participation between 1 January 2019 and the day preceding the election.As with the daily data, the overwhelming part of the variation in total cumulative protest participation ($\mathrm{P}_{i\tilde{t}}$) is driven by participation in marches held in the home county ($\mathrm{P}^H_{i\tilde{t}}$).

4.3 Validation

The purpose of our protest participation measure is to predict how many individuals from a given county participate in climate protests. Ideally, we would like to test how well our predictions align with (i) how many individuals from a given county participate in protests, and (ii) the total number of individuals attending protests held in a given county (i.e., crowd sizes). However, information on the origin of protesters is non-existent. Data on the size of protests (i.e. the total number of people attending a given protest) are also sparse. To nevertheless show that our approach to predicting strike participation can successfully capture variation in the total number and origin of protesters, we provide two pieces of evidence.

For a small subset of protests, local authorities we contacted attached information on the number of participants. Based on this sample of 471 strikes that were held in 84 separate counties, we can compute the county-specific cumulative number of people that attended the protests between 1 January 2019 and the time of the European Parliament elections. We then relate these numbers to cumulative attendance predicted by our approach.[17] Panel (a) of Figure 4 depicts the resulting scatterplot. Reassuringly, there is a strong positive correlation between observed and predicted participation. The correlation coefficient is 0.588. The strength of correlation increases considerably—to 70.2%— when we compute the natural logarithm of the predicted and observed cumulative protest participation (panel (b)). The results of Figure 4 suggest that using logarithmic values may be more appropriate. However, with high(er) frequency data (e.g., politician×day-level data), predicted (and observed) protest participation is often zero. Because the logarithm is not defined at zero, we use 'raw' predicted protest participation as our main explanatory variable throughout. In Appendix B we show that we obtain very similar—and even stronger—results if we use logarithmic values in our analysis of election outcomes. Overall, Figure 4 provides evidence that our approach can successfully predict protest crowd sizes.

As a way of illustrating that our measure allows us to infer the origin of protest participants, we draw on football (soccer) match attendance figures. Specifically, we collect data on the number of away fans for each game that took place in 2019 in the first and second Bundesliga.[18] Additionally, we also gather information on the date of the match, the location of the stadium it was held in, and the origin of the away team. Combined, this provides us with an estimate of the number of people that travel from the county where the away team originates from to the county in which the stadium is located. We can then use these origin-to-destination supporter flows to test how well they align with our protest participation measure on match day. Plot 5 depicts the results. There is a strong positive correlation between predicted and observed origin-to-destination flows. This strongly suggests that our approach allows us to predict variation in the number of individuals who leave a given county to attend a large-scale public event.

4.4 Rainfall-Driven Protest Participation Measure

To address concerns about nonrandom protest participation, we will *inter alia* use local rainfall shocks as an exogenous source of variation to predict local protest participation (Madestam *et al.*, 2013). The intuition underlying this approach is that more intense rainfall on the day of a rally discourages individuals from participating, but it is arguably uncorrelated with other factors that determine electoral outcomes.

To construct the rainfall-based protest participation measure, we extract information on precipitation from the ERA5-Land hourly database (Muñoz Sabater *et al.*, 2021).[19]. This

[17] Note that our protest participation measure described in equation (5) predicts the number of protesters that originate from county i. To compute the total number of participants that end up travelling to the protest in destination j, we simply need to sum up the excess flows into county j on strike days. Formally: $\mathrm{P}_{jt} = \sum_{i=1}^{i} e_{ijt}$.

[18] The Bundesliga is the top level of the German football (soccer) league system.

[19] Data can be downloaded from the Copernicus Climate Change Service Climate Data Store cds.climate.copernicus.eu/

database reports hourly amounts of precipitation at a spatial resolution of 0.1°×0.1°. We aggregate this data at the county×day level. For each county and day, we then define rainfall shocks as the difference between the rainfall measured on that day and the average amount of rainfall measured on that specific date in the ten preceding years.[20] Protest participation is then predicted in a simple two-step procedure. First, we regress local strike participation on rainfall shocks:

$$\mathrm{P}_{it} = \beta \left(Rain_{it} - \overline{Rain_i}\right) + \alpha_i + \theta_t + \epsilon_{it}, \tag{6}$$

where P_{it} is the local strike participation of county i on day t, $Rain_{it}$ is rainfall observed on that day, and $\overline{Rain_i}$ is the 10-year average of rainfall for that particular day. County fixed effects, date fixed effects and error term are represented by α_i, θ_t, and ϵ_{it}, respectively.

In the second step, we compute the predicted participation as:

$$\widehat{\mathrm{P}_{it}} = \widehat{\beta} \times \left(Rain_{it} - \overline{Rain_i}\right) + \widehat{\alpha_i} + \widehat{\theta_t}. \tag{7}$$

Figure 6 documents that our rainfall-based participation measure strongly predicts contemporaneous strike participation. A one-standard deviation increase in (excess) rainfall on day t reduces local participation in climate protests on day t by 0.017 standard deviations (Table C.3) . Crucially, we also observe in Figure 6 that rainfall shocks on rally days t are unrelated to protest participation in the 7 preceding and succeeding days. Point estimates for the leads and lags are small and statistically non-significant throughout. This illustrates that we can use local rainfall shocks to predict variation in the number of strike participants on a specific day.

Based on the daily rainfall-predicted protest participation, we compute cumulative rainfall-driven protest participation as:

$$\widehat{\mathrm{P}_{i\tilde{t}}} = \sum_{t=1}^{\tilde{t}} \widehat{\beta} \times \left(Rain_{it} - \overline{Rain_i}\right) + \widehat{\alpha_i} + \widehat{\theta_t}. \tag{8}$$

As before, $\tilde{t}$ reflects the time period between 1 January 2019 and the day preceding the election.

5 Protest Participation and Electoral Outcomes

5.1 Empirical Strategy

We first examine the impact of the FFF movement in Germany on elections outcomes. The following first-difference model serves as the baseline for the subsequent empirical analysis:

$$\Delta(\text{Share Greens}_{i,\tilde{t}}) = \beta\, \mathrm{P}_{i\tilde{t}} + \tau_{s,\tilde{t}} + \mu \mathbf{X}_{i,\tilde{t}} + \xi_{i,\tilde{t}}, \tag{9}$$

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

[20] We use deviations from expected values to account for the fact that rainfall levels structurally differ across regions (and hence may be correlated with unobserved differences in local characteristics). In practice, however, our results are very similar when we use 'raw' rainfall data (rather than demeaned data) in our analysis. Results are available upon request.

participation in county i up the day preceding the election $\tilde{t}$.[21] 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 determine both local protest participation and election outcomes, which would bias our estimates. Our first-differencing approach accounts for time-invariant disparities in county-level characteristics, such as historical voting patterns. Time-varying correlated factors, however, remain a concern. We address this worry using three complementary approaches. First, we control for a battery of time-varying county-level controls. In regression equation (9) these are symbolised by $\mathbf{X}_{i,\tilde{t}}$. Second, we document by means of placebo election tests the absence of pre-trends. Third, we show that we obtain very similar results if we use the rainfall-predicted participation measure instead of our main protest activity measure as explanatory variable. Variation in the former is solely driven by exogenous rainfall shocks.

5.2 Vote Share of the Green Party

In Table 1, we test whether increased local participation in climate protests raises 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). The results—reported in panel A, column (1)—document that there is strong positive relationship between strike participation and the likelihood of voting the Green Party. The point estimate implies that a one-standard deviation increase in protest activity raises the vote share by economically meaningful 0.446 percentage points. Evaluated at the Green's average gain of 6.3 percentage points in the latest round of elections compared to the previous one, this amounts to 7%. In column (2), we control for additional county-level characteristics. The extended set of controls encompasses both demographic and economic county characteristics. Inclusion of these controls leaves the point estimate almost unchanged.

In addition to affecting the Green Party's vote share, we also find that local engagement in support of FFF influences voter turnout. Columns (3)–(4) show that turnout increases with local protest activity. At a first pass, this suggests that protest-induced voter mobilisation could have contributed to the increase in the Greens' vote share. However, the economic magnitude of the FFF effect on turnout is small. Evaluated at the average increase in voter turnout of 7.36 percentage points compared to preceding elections, the point estimate of 0.148 in column (4) only corresponds to a rise of 2%. Furthermore, we find that the coefficients in columns (1) and (2) remain virtually unchanged if we re-run the regressions while additionally controlling for changes in voter turnout (see Appendix Table C.1 in Online Appendix C). These last two sets of results indicate that protest activity increases support for the Greens primarily through vote switching rather than through mobilisation, and we shall return to this issue subsequently.

As outlined previously, the main threat to the validity of our empirical approach is that unobserved time-varying factors bias our results. The stability of point estimates across the regressions with basic and extended sets of country-level controls is a first indication that this is unlikely to be the case (e.g., Oster, 2019, Altonji *et al.*, 2005). As a second

[21] As outlined in Section 3, European Parliament elections, state elections, and federal elections took place on different dates. Hence, the value of $\mathrm{P}_{i\tilde{t}}$ varies with the county *and* the election.

piece of evidence, we document that local protest participation does not predict variation in voter behaviour in preceding election cycles. The point estimate of cumulative protest participation is statistically non-significant and close to zero for both changes in vote shares of the Greens (column 5) and turnout (column 6) in the previous election cycle. This illustrates that our protest participation measure does not capture any pre-trends.

As a final approach in assuaging concerns related to confounding unobserved factors, we re-run the regressions presented in panel A but now replace our main protest participation measure with rainfall-predicted participation. Variation in the latter is only driven by local rainfall shocks. Panel B documents that this produces very similar estimates, indicating that our main OLS approach produces unbiased estimates. Across all columns the coefficient of rainfall-predicted protest participation is statistically indistinguishable from its counterpart in panel A. Together with the absence of pre-trends, this strongly suggests that our protest participation measure is capturing the causal effects of local FFF engagment on election outcomes. Given this result—and to simplify exposition— we subsequently only report estimates obtained using our main climate strike participation measure. Appendix Tables B.1–B.5 show that results are very similar throughout if we use the rainfall-predicted measure instead.

Summing up, we find that increased participation in the 2019 climate protests raises the vote share of the Greens in subsequent elections. Furthermore, the results suggest that this shift is primarily driven by existing voters switching party allegiance rather than a mobilisation of new voters. To gain a first insight into these voter movements, we next look at the change in vote share across all major political parties.

5.3 Vote Shares of Other Major Parties

Unlike the United States, Germany has a multiparty system, with six parties currently represented in the federal and most state-level parliaments. In Table 2, we order these six parties according to their political orientation from left to right. We then successively test how local engagement in FFF has influenced their vote shares. Focusing first on the parties on the left spectrum, we observe that both the socialist Left Party and the center-left Social Democratic Party (SPD) see a decrease in support in counties with high local FFF engagement. This is consistent with FFF activity sensitizing left-leaning voters to climate issues and inducing to them switch to the Greens, the party most committed to tackling the climate crisis.

Next, consider the changes in vote shares among the right-of-center parties. Most interestingly, we find that the far-right Alternative for Germany party (AfD) experiences strong climate-protest related losses. A one-standard deviation increase in local protest activity causes a 0.19 percentage points drop in the vote share of the AfD. This implies that, without the FFF movement, the AfD's average vote gain of 2.05 percentage points compared to preceding elections would have been 10 percent higher. The other interesting result is that, in counties with high protest activity, the center-right Union saw (CDU/CSU) a percentage-wise small but statistically significant increase in their support. As AfD voters are unlikely to switch to the Green Party, this result indicates that the FFF movement caused some voters previously voting AfD to switch to the CDU/CSU. Finally, the remaining right-of-center party, the liberal Free Democrats (FDP), saw a FFF-related drop in their support.

Taken together, columns (1)–(6) of Table 2 produce two main insights. Left-of-center, FFF protest activity results in a sizeable shift towards the Greens. Among the right-of center parties, support for the CDU increases while the AfD experiences substantial losses. We next turn towards investigating potential channels underlying our main results.

6 Mechanisms

In democratic societies, voters reveal their political preferences by voting for the party that best represents these preferences. With this, the question is through which mechanisms did the FFF movement contribute to the increase in political preferences for green policy. We explore the plausibility of three possibilities: reverse intergenerational transmission of pro-environmental attitudes from children to parents, changes in politicians' public stance on climate issues, and increased newspager coverage of climate change.

6.1 Reverse Intergenerational Transmission

Some first evaluations of environmental education school programmes have showcased that children can be important agents in fostering climate change concerns among their parents (see, e.g., Lawson *et al.*, 2019). We hypothesize that this might be an important mechanism in the context of FFF, too. Those who engaged in the climate movement were often not yet eligible to vote. Their participation in climate protests, however, may have forced their parents to engage with environmental issues, thereby ultimately shaping their demand for green politics.

In a first step, we test this mechanism by examining whether the FFF effect plays out differently for voters with and without children. To that end, we draw on our individual-level survey data from the forsa Institute for Social Research and Statistical Analysis. 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 took place the Sunday following the interview. We match to each respondent 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 age of 18 or not.

To get at these, we run the following regression:

$$V_{r,i,t} = \theta_p \, \mathrm{P}_{i,\tilde{t}} \times \mathrm{Kids} + \theta_n \, \mathrm{P}_{i,\tilde{t}} \times (1 - \mathrm{Kids}) + \delta_i + \tau_t + \mu \mathbf{X}_{r,i,t} + \xi_{r,i,t}. \qquad (10)$$

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 effects of local protest participation up to the day of the interview ($\mathrm{P}_{i\tilde{t}}$) 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). This implies that we compare voting intentions of parents as well as non-parents residing in the same county at different times (i.e., having experienced different levels of protest participation up to the interview) while holding time-invariant local characteristics constant.

Table 3 presents the results from estimating model (10). In column (1), the dependent variable is a dummy indicating whether respondents would vote green if the next general election took place in the week of the interview. We observe that stated support for the Green Party significantly increases with the intensity of local protest activity, but only among respondents that share a household with children or youth (i.e., individuals younger than 18). By contrast, individuals residing in households without children are not more likely to vote Greens as a result of higher protest activity.

In column (2), the outcome variable of interest is a dummy for not having voted for the Greens in the last general election but intending to do so at the time of the interview. On average, 13.6 percent of respondents state an intention to switch party allegiance to the Green Party. For respondents with children, a one-standard deviation increase in local protest activity increases the switching intention by 0.6 percentage points or 4.4 percent. There is, however, again no significant effect on the switching intention of respondents without children. In columns (3) to (7), we investigate from which parties the Greens draw new voter support from. We observe that the climate movement has caused parents who previously voted for other left-of-center parties (The Left and the SPD) to switch allegiance to the Greens. This is not the case, however, for respondents without children. Among respondents who previously supported one of the right-of-center parties, we observe no significant FFF-induced changes in switching intentions, neither for parents nor for non-parents. In a non-reported regression, we also explored whether individuals who abstained from voting in previous general election are more likely to state an intention to vote for the Greens if the reside in areas with high FFF engagement. We found no evidence of climate movement-induced mobilization. This result is consistent with the modest effect of FFF protest activity on voter turnout (see Table 1).

A second, more indirect, approach to address the reverse intergenerational transmission hypothesis is to decompose total protest participation along two dimensions: participation in protests that are held in the own (home) county and participation in rallies that happen elsewhere.[22] The idea is the following. Protest activity in the home county is directly observable by all residents of the county, and this may directly raise the general public's awareness of climate change issues. However, this direct effect is not as salient if children and youth leave the home county to participate in FFF protests elsewhere. In this case, an effect on political preferences more likely materializes through protest participants sharing their views and experiences within their social and family network. Thus, evidence consistent with the reverse intergenerational transmission hypothesis would be finding that the FFF effect on election outcomes is not solely explained by within-county protest participation, but also by participation in rallies away from home.

Table C.2 shows this to be indeed the case. On the one hand, we find that a one-standard deviation increase in cumulative within-county protest participation raises the vote share of the Green Party by 0.361 percentage points. However, it is also the case that away-from-home protest participation triggers a rise in support for the Greens in the home county: a one-standard deviation increase in this participation measure causes the vote share of the Green Party to increase by 0.153 percentage. This is a remarkable result considering that the overwhelming part of the variation in counties' total protest activity is due to differences in within-county protest participation. Back-of-the-envelope calculations suggest that for every away-from-home protest participant, 0.018 Green Party votes are gained.

[22] See Section 4 for more details.

6.2 Politicians

The vote decision depends *inter alia* on how the electorate evaluates party candidates on specific issues of public policy, which in turn depends on how politicians publicly position themselves towards them. Substantial vote shifts from one election to the next might therefore be explained by changes in politicians' issue orientation. In the context of our study, the question, thus, 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

$$T_{p,c,t} = \gamma \mathrm{P}_{c,t} + \psi_p + \zeta_{s,t} + \varepsilon_{p,c,t}, \tag{11}$$

where $T_{p,d,t}$ is an indicator capturing whether politician p representing constituency c posts climate change-related content on Twitter on day t. $\mathrm{P}_{c,t}$ is the local protest participation in constituency c on day t as defined in equation (3). 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. The error term is represented by $\varepsilon_{p,c,t}$ and clustered simultaneously by politician and date (see, e.g., Cameron *et al.*, 2011).

Table B.3 presents the results. Column (1) shows that MPs are significantly more likely to tweet about climate change when protest activity in their electoral district is high. A one-standard deviation increase in a constituency's protest activity raises the probability an MP posts a tweet related to climate change by 0.5 percentage points. In terms of economic magnitude this is a modest effect. Given that, on average, 12 percent of all MPs tweet on climate change on a given day, the coefficient size corresponds to a 4 percent increase.

However, this effect likely masks heterogeneities across MPs from different political parties. In particular, for politician's public engagement with climate change to serve as an explanation for the Green Party's FFF-related vote gains, we would expect to see that MPs of the Greens are more responsive to protest activity in their constituency than MPs of other parties. In column(2), we test for this by estimating separate slope coefficients for each political party. Strikingly, this exercise indeed reveals that the social media responsiveness of green MPs is much larger than that of those from other political parties. The climate protest effect for the Greens is three times larger than the average effect reported in column (1). In other words, a one-standard deviation increase in own-constituency protest activity increases the probability a Green Party MP posts climate-related content by more than 11 percent. The results in column (2) further reveal that a higher protest activity also induces members of the Left Party to post more climate change-related content. Relative to Green Party MPs, the size of the effect is considerably smaller. MPs of others parties seem to not react to protest activity in their electoral district. Coefficients are close to zero and statistically non-significant for members of the SPD, FDP, Union, and AfD. This lack of reaction could be due conflicts between the demands of the FFF movement and the (perceived) preferences of core party voters.

Finally, Column (3) illustrates that protest activity in an MP's own constituency does not influence her propensity to post non-climate related content.

6.3 Newspapers

The political effects of media have long been documented. Media sources such as newspapers may influence the electorate through the content of their reports (Gerber *et al.*, 2009). Thus, in our context, increased media coverage of climate change is another possible mechanism through which FFF-induced vote gains of the Green Party might be explained.

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 a first step, we employ the following panel regression approach:

$$A_{n,r,t} = \gamma \mathrm{P}_{r,t-1} + \psi_{n,r} + \zeta_t + \varepsilon_{n,r,t}, \tag{12}$$

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 area of circulation. We lag the explanatory variable since our data captures 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 (Cameron *et al.*, 2011). The main parameter of interest, γ, captures the immediate effect of FFF strike participation on content.

In a second step, we test whether local protest activity also leads to a permanent shift in newspaper coverage of climate topics. We do this using a following first-difference model:

$$\Delta A_{n,r,} = \alpha + \theta \mathrm{P}_{r,\tilde{t}} + \epsilon_{n,r}. \tag{13}$$

The variable $\Delta A_{n,r}$ represents the difference in the total number of articles on climate change between the 5-month period from August to December 2018 and the same 5-month period in 2019. During the first period, no significant climate activity took place in Germany. August-December 2018 thus constitutes our pre-FFF time period. In order to minimize the risk of conflating general shifts towards more coverage of climate change-related topics with reporting on recent strike activity, we compute cumulative protest participation, $\mathrm{P}_{a,\tilde{t}}$, only for the period January through July 2019. That is, we do not take into account protest activity that occurs in the period August–December 2019. The coefficient θ thus captures whether newspapers are more likely to continue to report on climate topics after exposure to strike activity.

Column (1) of Table 5 showcases that local protest participation immediately impacts newspaper content. A one-standard deviation increase in protest activity raises the number of article containing climate change keywords by 0.077. Evaluated at the sample mean of 1.652 articles, this represents an increase of 5%. As discussed above, this effect represents a composite effect, consisting of reporting on protest activity itself and reporting on climate change-related topics.

Since the estimate in Column (1) fails to capture any longer-term impacts of local protest participation, we next turn to our first-difference specification in equation (13). Column (2) presents the results. We observe strong longer-term impacts of local protest activity. Compared to the period August through December 2018, newspapers publish an additional

322 climate-related articles in the same period of 2019, and a one-standard deviation increase in local protest participation raises this number by 58 or 18 percent.

6.4 Strategic Voting

The FFF movement not only affected the electoral fortunes of the Green Party, but it also had heterogenous effects for Germany's right-of-center parties: while support for the far-right AfD dropped substantially, the center-right Union experienced relatively strong gains. This is an intriguing result that warrants further investigation to unpack possible explanations.

To do so, we draw again on the *forsa* survey data to first investigate if voters changing party allegiance from the AfD to the Union might explain the shift in vote shares among these two right-of-center parties. The positive and statistically significant point estimate in column (1) of Table 6 documents that vote switching indeed plays an important role. A high local protest intensity causes interviewees who voted for the AfD in the previous election to now support the Union.

There are two possible explanations for this. The first is that the reverse intergenerational transmission mechanism is at play here as well. AfD voters might be senitized to climate-related topics by youths' local FFF protest activity and therefore want to support a party that supports climate change measures. The AfD, however, is critical of climate science. As the only major German political party, it has called for an end to all major climate action efforts, including the abandonment of the Paris Climate Agreement and the European Green Deal. Thus, local protest activity may have induced AfD supporters to change party allegiance to the Union, a party still positioned right-of-center but perceived by voters to have a stronger climate orientation (Bukow, 2019). If this mechanism is at play, we would expect to see that vote switching from AfD to the Union occurs predominantly among respondents with children. A second explanation for vote switching from the AfD to the Union is strategic voting. Observing high local protest participation could raise concerns among the AFD supporters that the Greens gain sufficient political power to influence the political agenda. To counteract this effect and constrain the Greens in their policy-making ability, AfD voters could have chosen to switch to the Union, a major party with values still relatively close to their political preferences. Note that this explanation does not involve a transmission of pro-environmental values from children to parents. For it to be of relevance, we would expect to find that vote switching intentions are not concentrated among respondents with children.

In column (2) of 6, we estimate separate slope coefficients capturing the effects of local protest participation for parents and non-parents, respectively. Differently from the intention to switch to the Greens (see Table 3), FFF now only induces former AfD supporter without children to switch to the Union. For AfD supporters with children, the FFF effect is small and statistically insignificant. We consider this as consistent with our speculation that the FFF movement has caused AfD supporter to cast a strategic vote.

In addition to vote switching, reduced turnout could offer an explanation for the differential effects of climate strikes on vote shares of the AfD and Union. AfD supporters may abstain from voting when protest activity in their county is high. However, column (3) of Table 6 indicates that this is not a relevant mechanism. Local variation in FFF protest numbers does not result in an increase in abstention rates among former AfD voters.

Summing up, this section has been an attempt to highlight some important mechanisms for understanding the political effects of the FFF movement. Our analysis suggests several mediating pathways: reverse intergenerational transmission of pro-environmental attitudes from children to parents, stronger climate-related social media presence by Green Party politicians, increased coverage of environmental issues in local media, and strategic voting. Of course, these mechanism might work in combination, conceivably reinforcing each other. For example, youths' environmental engagement may directly shape adults' pro-environmental attitudes and influence their vote decision. It may also act as signal to politicians of changing voter preferences, inducing them to change how they position themselves towards climate issues. This, in turn, may feed back into the vote decision. Disentangling these pathways would be an interesting and important area for future work.

7 Concluding Remarks

It is widely accepted that keeping global warming within 2°C would avoid more economic losses globally than the cost of achieving the goal (IPCC, 2022). 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 (Sanderson and O'Neill, 2020). However, continued climate inaction has left many observers pessimistic about heading off 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 (2020), one shock that can deliver a push towards a transformation are demonstrations by citizens that saliently highlight the full scale 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 from high- to low-carbon technologies. And, ultimately, environmentally-friendly values would evolve, putting an end to the climate trap.

Our paper speaks to the first part of this chain. Focusing on the FFF protest movement in Germany, we show that youths' engagement in demand of climate action has a robust effect on political outcomes. We estimate that a one standard-deviation increase in local protest activity increases the vote share of the Green Party by 8 percent, which is the result of voter movements to the Greens from other left-of-center parties with a less climate-oriented political agenda. Intergenerational transmission of pro-environmental attitudes from children to parents appears to be one key driver: the increased support for the Greens feeds itself entirely off voters with children of FFF-relevant ages. There are two other mechanisms we find evidence for. First, Green Party candidates react to strong protest activity in their constituency by increasing their climate-related social media presence, which might affect voters' relative evaluation of candidates and, ultimately, their vote decision. Second, building on the idea that media may influence the electorate 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. As a caveat, beyond the scope of this study to explore, there remains the question of how these mechanisms combine to produce the overall effect on political outcomes.

As a nonindented byproduct of FFF, support of Germany's far-right party, the AfD, dropped substantially in counties where protest activity was high. This is an intriguing result, suggesting that the political impact of the FFF movement goes beyond an increase in the demand for green politics. To the contrary, we provide evidence that the FFF movement has caused some voters, those whose political preferences are orthogonal to political agenda of the Greens, to change their vote decision so as to prevent the Greens from gaining political power and exerting influence on policy.

Our study offers an interesting 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 proxies for thousands of FFF rallies the geographic distribution of its participants. We believe this approach could be a useful tool for mapping out the evolution of social mass movements in future studies.

Our paper leaves open many avenues of further enquiry. The perhaps most important question is whether the FFF effect will persist into the future. If in the model of Besley and Persson (2020) an enhanced influence of climate activists were to push society over a tipping towards a green transformation, we would ultimately expect to see a change in culture towards environmentally-friendly values. As a first step towards addressing this, it would be interesting to explore how youths' engagement in FFF has affected adults' consumption behavior in terms of carbon-consciousness.

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Figures and Tables

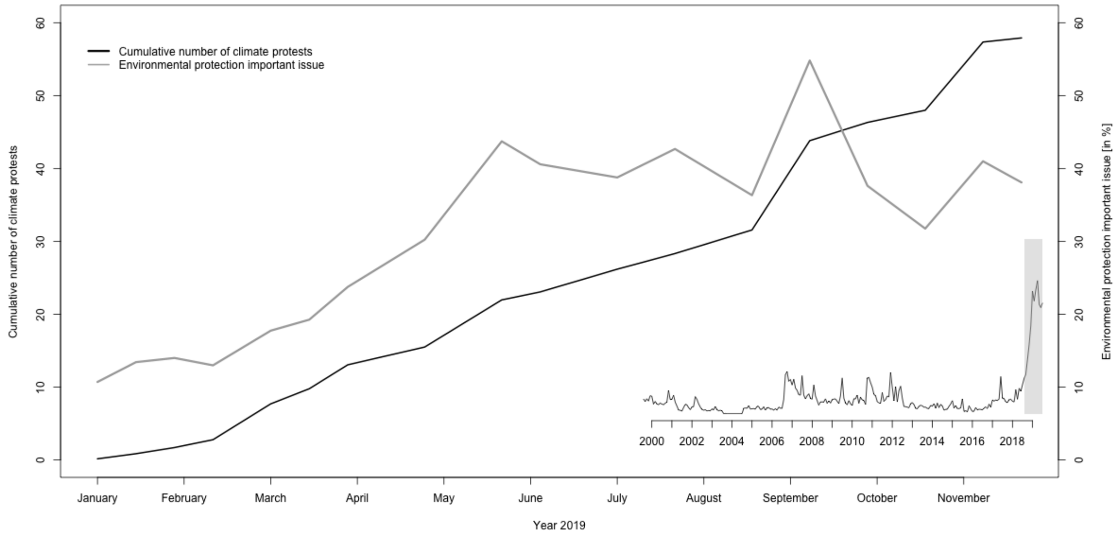

Figure 1. Strike activity and public opinion
Figure depicts the cumulative number of climate protests in Germany in 2019 (black line). Protest data are hand-collected from various sources (see Section 3 for details). The grey line represents the proportion of individuals naming environmental protection as one of the most pressing issues in Germany over the course of 2019. The inset plot depicts the same proportion over the time period 2000-2019. Grey shading represents the year 2019. Survey data are drawn from Politbarometer (2019).

(a) (b)

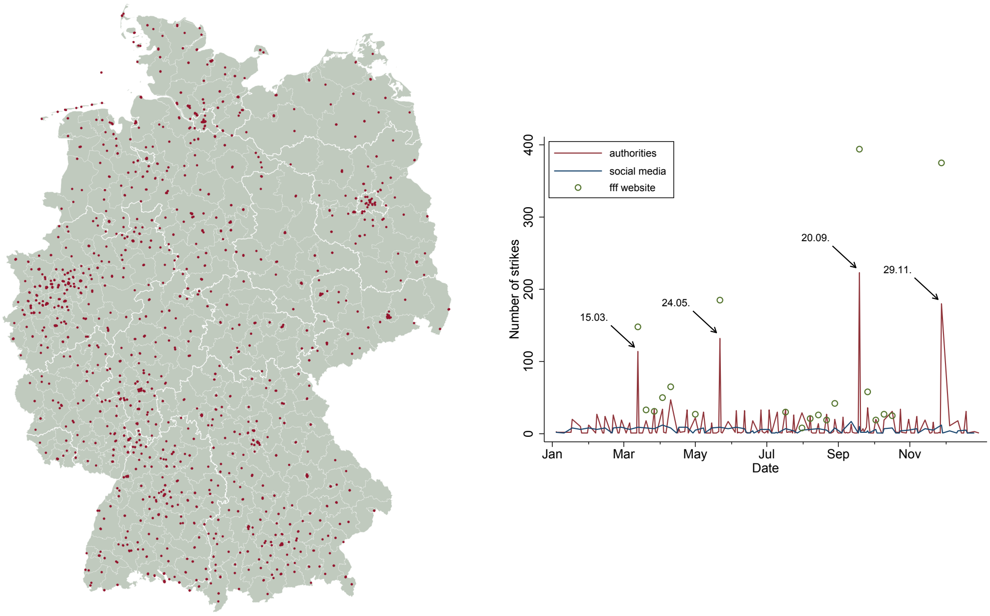

Figure 2. Locations of climate strikes in 2019
Panel (a): Map depicts the location of climate strikes (red dots) for year 2019. The bold white lines represent state boundaries whereas the thin white lines represent county borders. Panel (b): Figure depicts the daily number of strikes by data soruce. The indicated dates above the spikes mark the four global climate strikes.

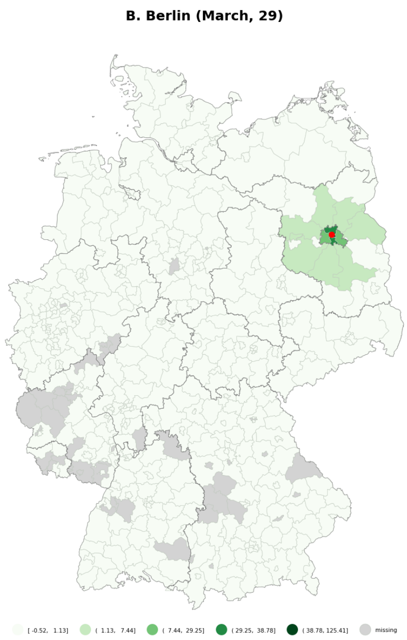

Figure 3. Strike participation for selected strikes
Notes: The maps show the counties' strike participation (as defined by Eq.(3)) in the climate strike held Berlin on 19 March 2019. A darker shade of green indicates greater protest participation. The color scale classification is obtained using the Fisher-Jenks natural breaks algorithm. The red dots mark the strikes' location, grey areas indicate missing data (censored), bold grey lines indicate state boundaries, thin grey lines county borders.

(a) (b)

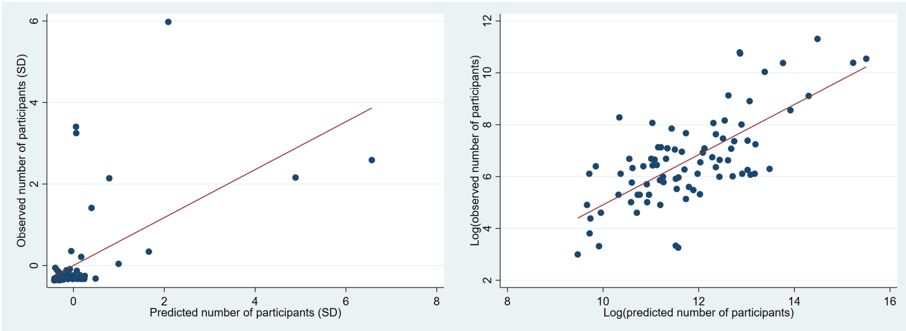

Figure 4. Validation, strike size
Observed number of participants are the cumulative reported number of strike participants at the strike location up to the European elections as reported by local authorities. Predicted number of strike participants are the cumulative excess journeys to a given strike location (for days with reported participants only) up to the European election. Panel (a) depicts the correlation in levels. Panel (b) depicts the correlation in log values.

(a) (b)

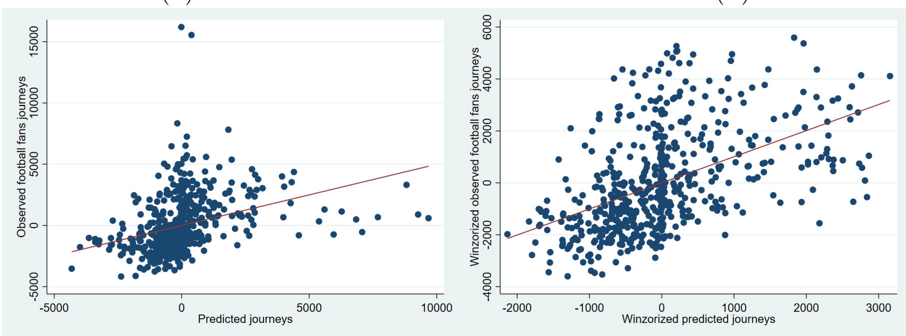

Figure 5. Validation, soccer fans journeys
Observed football fans journeys are the observed number of supporters of the away team that attend the match (fuballmafia.de). Predicted journeys are the mobile phone based predicted excess journeys from the county of the away team to the county of the home team on the day of the match. For both variables we partial out date fixed effects. Panel (a) depicts the correlation between observed and predicted journeys of away team supporters. Panel (b) depicts the correlation between the winsorized (5 percent cut off) of observed soccer fans journeys and the winsorized (5 percent cut off) predicted journeys.

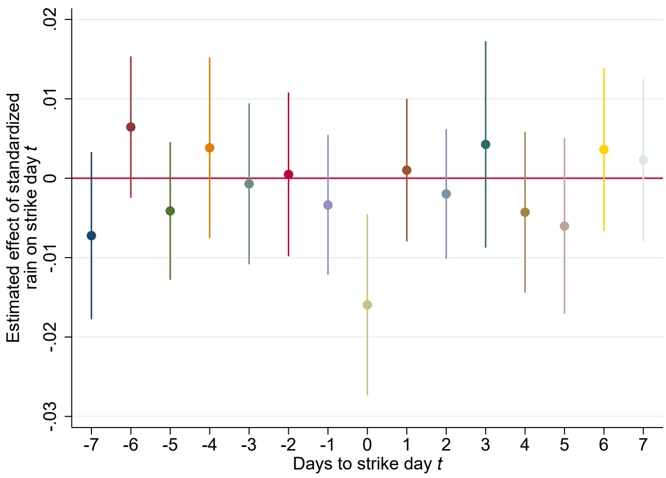

Figure 6. Strike participation for selected strikes
Notes: Figure depicts the point estimates and 95% confidence intervals of the effect of rainfall shocks on 7-day leads and lags of protest participation.

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

	Δ Vote share Green Party		Δ Voter turnout		Δ Vote share Green Party Placebo	Δ Voter turnout Placebo
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Cumulative protest participation index						
Participation index (SD)	0.446***	0.430***	0.126***	0.148***	-0.015	-0.065
	(0.087)	(0.088)	(0.049)	(0.050)	(0.024)	(0.978)
Panel B: Rainfall-predicted cumulative protest participation index						
Predicted participation index (SD)	0.462***	0.447***	0.083*	0.104**	-0.011	0.275
	(0.091)	(0.091)	(0.043)	(0.044)	(0.024)	(0.909)
State×election FE	✓	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓	✓
Economic controls	-	✓	-	✓	✓	✓
Mean dependent variable	6.316	6.316	7.356	7.356	0.604	-0.512
Observations	849	849	849	849	843	843

Notes: 'Participation index (SD)' is the standardized cumulative participation index, as defined by equation (5), 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. 'Rainfall-predicted participation index (SD)' is the standardized rainfall-predicted cumulative participation index, as defined by equation (8), 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. 'Δ Vote share Green Party placebo' is the change in Greens' vote share between previous election cycles. 'Δ Voter turnout placebo' is the change in the share of eligible citizens that vote between previous 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.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. White-Huber standard errors are reported in parentheses.

Table 2. Strike participation and vote shares of all major political parties

	Left-of-Center			Right-of-Center		
	Δ The Left	Δ Greens	Δ SPD	Δ FDP	Δ Union	Δ AfD
	(1)	(2)	(3)	(4)	(5)	(6)
Participation index (SD)	-0.068***	0.430***	-0.123**	-0.071**	0.160***	-0.193***
	(0.025)	(0.088)	(0.057)	(0.033)	(0.057)	(0.052)
State×Election FE	✓	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓	✓
Economic controls	✓	✓	✓	✓	✓	✓
Mean dependent variable	-3.0970	6.3158	-2.7138	1.4788	-7.6379	2.0450
Observations	849	849	849	849	849	849

Notes: 'Participation index (SD)' is the standardized cumulative participation index, as defined by equation (5), 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. The dependent variable represents the change in vote share between election cycles for the Left, the Greens, the SPD, the FDP, the Union, and the AfD, respectively.'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.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. White-Huber standard errors are reported in parentheses.

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

	Vote Greens	Switch to Greens	Switch The Left to Greens	Switch SPD to Greens	Switch FDP to Greens	Switch Union to Greens	Switch AfD to Greens
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HH with children × participation index (SD)	0.431***	0.568***	0.131***	0.239***	0.174	0.321	-0.010
	(0.035)	(0.029)	(0.047)	(0.139)	(0.093)	(0.239)	(0.030)
HH without children × participation index (SD)	-0.235	-0.171	-0.125	-0.036	-0.210**	-0.224	0.035
	(0.237)	(0.240)	(0.079)	(0.100)	(0.067)	(0.201)	(0.021)
County FE	✓	✓	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓	✓	✓
Previous party FE	✓	✓	✓	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓	✓	✓	✓
Mean dependent variable	23.239	13.650	14.440	5.663	1.284	5.625	0.203
Observations	88,071	80,784	80,784	80,784	80,784	80,784	80,784

Notes: 'Participation index (SD)' is the standardized cumulative participation index, as defined by equation (5), computed up to the day before the interview. 'HH with children' is a dummy equal to one if a children are present in a household. 'HH without children' is a dummy equal to one if no children are present in a household. 'Vote Greens' is a dummy indicating whether a respondent intends to vote for the Greens in the next federal election. 'Switch to Greens' is a dummy indicating whether a respondent intends to vote for the Greens in the next federal election having previously not voted for this party. The dependent variable in columns (3)–(7) is an indicator that is equal to one if a respondent states that (s)he intends to vote for the Greens having previously voted for the respective party. 'Previous party FE' are dummies capturing which party the respondent voted for in the previous federal election. 'Individual controls' include a dummy capturing whether children are present in a household.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Two-way clustered standard errors at the county and date dimension are reported in parentheses.

Table 4. Protest participation and politicians' social media presence

	Climate tweet		Non-climate tweet
	(1)	(2)	(3)
Participation index (SD)	0.480**		
	(0.219)		
Left × participation index (SD)		0.889***	0.257
		(0.304)	(0.307)
Green × participation index (SD)		1.480***	0.369
		(0.367)	(0.390)
SPD × participation index (SD)		0.217	0.188
		(0.268)	(0.311)
FDP × participation index (SD)		0.557	0.192
		(0.426)	(0.394)
Union × participation index (SD)		-0.116	0.175
		(0.238)	(0.274)
AfD × participation index (SD)		-0.052	-0.449
		(0.347)	(0.346)
Politician FE	✓	✓	✓
State×Time FE	✓	✓	✓
Mean dependent variable	12.197	12.197	38.271
Observations	180,638	180,638	180,638

Notes: 'Participation index (SD)' is the standardized daily participation index, as defined by equation (3). Climate tweet is an indicator variable that takes the value of one if a politician posts climate-related tweets, and zero otherwise. Non-climate tweet is an indicator variable that takes the value of one if a politician posts non-climate-related tweets, and zero otherwise.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors two-way clustered at the politician and day dimension are reported in parentheses.

Table 5. Protest participation and newspaper content

	# articles with climate keywords	
	Daily Panel	Long difference
	(1)	(2)
Participation index (SD)	0.094**	60.021***
	(0.045)	(17.507)
Newspaper FE	✓	✓
Time FE	✓	✓
Mean dependent variable	1.652	321.753
Observations	47,320	130

Notes: **Column (1)** reports estimates of equation (12) using newspaper×day panel data for 2019. 'Participation index (SD)' is the lagged standardized daily participation index, as defined by equation (3). The dependent variable '# articles with climate keywords' is the number of articles in a given newspaper and day that are related to climate change (based on the keyword search described in Table A.1). Standard errors two-way clustered at the newspaper day level are reported in parentheses.
Column (2) reports estimates of equation (13) using long-difference data. 'Participation index (SD)' is the standardized cumulative participation index, as defined by equation (5), computed for the period January 2019–July 2019. The dependent variable '# articles with climate keywords' is the change in the total number articles that are related to climate change between the 5-month period August-December 2018 and the same 5-month period in 2019 (based on the keyword search described in Table A.1.). White-Huber standard errors are reported in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Protest participation and voting intentions for right-of-center parties

	Switch AfD to Union		Abstain from voting
	(1)	(2)	(3)
Participation index (SD)	0.135***		0.055
	(0.045)		(0.041)
HH with children × participation index (SD)		0.037	
		(0.052)	
HH without children × participation index (SD)		0.158***	
		(0.049)	
County FE	✓	✓	✓
Week FE	✓	✓	✓
Previous party FE	✓	✓	✓
Individual controls	✓	✓	✓
Mean dependent variable	0.714	0.714	12.521
Observations	80,784	80,784	82,922

Notes: 'Participation index (SD)' is the standardized cumulative participation index, as defined by equation (5), computed up to the day before the interview. 'HH with children' is a dummy equal to one if a children are present in a household. 'HH without children' is a dummy equal to one if no children are present in a household. 'Switch AfD to Union' is a dummy indicating whether a respondent intends to vote for the Union in the next federal election having previously voted for the AfD. 'Abstain from voting' is an indicator taking the value of one if a respondent intends to abstain from voting in the next federal election, and zero otherwise. 'Previous party FE' are dummies capturing which party the respondent voted for in the previous federal election. 'Individual Controls' include a dummy capturing whether children are present in a household.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Two-way clustered standard errors at the county and date dimension are reported in parentheses.

Online Appendix

A Data and summary statistics

Table A.1. Cimate keywords

fridaysforfuture	gretathunberg	change	energiewende
klimakrise	verkehrswende	allefuersklima	voteclimate
klimaschutz	klimawandel	klimanotstand	fridays4future
demo	allefürsklima	notmyklimapaket	sciforfuture
fridayforfuture	kohle	schoolstrike4climate	systemchangenotclimatechange
klimastreik	demonstrieren	parentsforfuture	globalclimatestrike
climate	keingradweiter	fridaysforfurture	demonstriert
klima	klimapolitik	demos	climatechange
klimagerechtigkeit	streik	netzstreikfürsklima	streiks
fff	leavenoonebehind	klimaziele	umwelt
co2	actnow	klimawahl	ffffordert
climatestrike	parents4future	strike	klimacamp
neustartklima	climatejustice	scientists4future	climateemergency
streiken	protest	demonstration	abwrackprämie
kohleausstieg	bewegung	klimapaket	

Table A.2. Descriptive statistics of key variables: Elections data

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Obs.**
Δ vote share Greens	6.316	4.032	-7.431	19.655	849
Δ vote share Left	-3.097	2.934	-14.351	7.466	849
Δ vote share SPD	-2.714	8.414	-21.331	16.040	849
Δ vote share FDP	1.479	1.371	-3.846	5.319	849
Δ vote share Union	-7.638	3.820	-17.634	4.832	849
Δ vote share AfD	2.045	5.979	-5.995	22.677	849
Δ turnout	7.356	7.334	-5.321	23.835	849
Cumulative protest participation (SD)	0	1	-0.617	11.698	849
Rainfall-predicted cumulative protest participation (SD)	0	1	-0.624	11.821	849

Table A.3. Descriptive statistics of key variables: Twitter data

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Obs.**
Any climate tweet	12.197	32.726	0	100	180,638
Any non-climate tweet	38.271	48.605	0	100	180,638
Cumulative protest participation (SD)	0	1	-0.156	18.436	180,638
Greens×Cumulative protest participation (SD)	0.006	0.401	-0.156	18.436	180,638
Left×Cumulative protest participation (SD)	0.007	0.437	-0.156	18.436	180,638
SPD×Cumulative protest participation (SD)	-0.002	0.480	-0.156	18.436	180,638
FDP×Cumulative protest participation (SD)	-0.002	0.338	-0.156	18.436	180,638
Union×Cumulative protest participation (SD)	-0.008	0.455	-0.156	18.436	180,638
AfD×Cumulative protest participation (SD)	-0.001	0.310	-0.156	18.436	180,638

Table A.4. Descriptive statistics of key variables: Newspaper data

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
	Newspaper×day-level sample				
Number of articles with climate keywords	1.652	2.994	0	95	47,320
Cumulative protest participation (SD)	0	1	-0.242	18.366	47,320
	First-difference sample				
Δ Number of articles with climate keywords	321.754	206.964	-15	1,325	130
Cumulative protest participation (SD)	0	1	-0.392	9.233	130

B Robustness

B.1 Rainfall-predicted participation measure

Table B.1. Rainfall-predicted protest participation and vote shares of all major political parties

	Left-of-Center			Right-of-Center		
	Δ The Left	Δ Greens	Δ SPD	Δ FDP	Δ Union	Δ AfD
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall-predicted participation index (SD)	-0.073***	0.447***	-0.121**	-0.074**	0.153***	-0.188***
	(0.025)	(0.091)	(0.058)	(0.034)	(0.057)	(0.052)
State ×Election FE	✓	✓	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓	✓	✓
Economic Controls	✓	✓	✓	✓	✓	✓
Mean dependent variable	-3.0970	6.3158	-2.7138	1.4788	-7.6379	2.0450
Observations	849	849	849	849	849	849

Notes: 'Rainfall-predicted participation index (SD)' is the standardized cumulative participation index, as defined by equation (8), 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. The dependent variable represents the change in vote share between election cycles for the Left, the Greens, the SPD, the FDP, the Union, and the AfD, respectively.'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.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. White-Huber standard errors are reported in parentheses.

Table B.2. Rainfall-predicted protest participation and voting intentions: parents versus non-parents

	Vote Greens	Switch to Greens	Switch The Left to Greens	Switch SPD to Greens	Switch FDP to Greens	Switch Union to Greens	Switch AfD to Greens
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HH with children ×	0.414***	0.498***	0.167***	0.257***	0.174*	0.301	-0.010
rainfall-predicted participation index (SD)	(0.089)	(0.074)	(0.040)	(0.070)	(0.102)	(0.189)	(0.029)
HH without children	-0.183	-0.129	-0.078	-0.005	-0.181**	-0.188	0.031
rainfall-predicted participation index (SD)	(0.203)	(0.209)	(0.060)	(0.054)	(0.088)	(0.176)	(0.022)
County FE	✓	✓	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓	✓	✓
Previous party FE	✓	✓	✓	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓	✓	✓	✓
Mean dependent variable	23.239	13.650	14.440	5.663	1.284	5.625	0.203
Observations	88,071	80,784	80,784	80,784	80,784	80,784	80,784

Notes: 'Rainfall-predicted participation index (SD)' is the standardized cumulative participation index, as defined by equation (8), computed up to the day before the interview. 'HH with children' is a dummy equal to one if a children are present in a household. 'HH without children' is a dummy equal to one if no children are present in a household. 'Vote Greens' is a dummy indicating whether a respondent intends to vote for the Greens in the next federal election. 'Switch to Greens' is a dummy indicating whether a respondent intends to vote for the Greens in the next federal election having previously not voted for this party. The dependent variable in columns (3)–(7) is an indicator that is equal to one if a respondent states that (s)he intends to vote for the Greens having previously voted for the respective party. 'Previous party FE' are dummies capturing which party the respondent voted for in the previous federal election. 'Individual controls' include a dummy capturing whether children are present in a household.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Two-way clustered standard errors at the county and date dimension are reported in parentheses.

Table B.3. Protest participation and politicians' social media presence

	Climate tweet		Non-climate tweet
	(1)	(2)	(3)
Rainfall-predicted participation index (SD)	0.237		
	(0.316)		
Left × rainfall-predicted participation index (SD)		0.874	0.091
		(0.564)	(0.486)
Green × rainfall-predicted participation index (SD)		2.167***	0.680
		(0.534)	(0.461)
SPD × rainfall-predicted participation index (SD)		-0.181	0.860**
		(0.355)	(0.404)
FDP × rainfall-predicted participation index (SD)		0.046	0.311
		(0.719)	(0.513)
Union × rainfall-predicted participation index (SD)		-0.850**	0.030
		(0.389)	(0.420)
AfD × rainfall-predicted participation index (SD)		-0.541	-0.851
		(0.568)	(0.534)
Politician FE	✓	✓	✓
State×Time FE	✓	✓	✓
Mean dependent variable	12.197	12.197	38.271
Observations	180,638	180,638	180,638

Notes: 'Rainfall-Predicted Participation index (SD)' is the standardized daily participation index, as defined by equation (7). Climate tweet is an indicator variable that takes the value of one if a politician posts climate-related tweets, and zero otherwise. Non-climate tweet is an indicator variable that takes the value of one if a politician posts non-climate-related tweets, and zero otherwise.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the politician level are reported in parentheses.

Table B.4. Rainfall-predicted protest participation and newspaper content

	# articles with climate keywords	
	Daily Panel	Long difference
	(1)	(2)
Rainfall-predicted participation index (SD)	0.166*	59.101***
	(0.088)	(17.531)
Newspaper FE	✓	✓
Time FE	✓	✓
Mean dependent variable	1.652	321.753
Observations	47,320	130

Notes: **Column (1)** reports estimates of equation (12) using newspaper×day panel data for 2019. 'Rainfall-predicted participation index (SD)' is the lagged standardized daily participation index, as defined by equation (7). The dependent variable '# articles with climate keywords' is the number of articles in a given newspaper and day that are related to climate change (based on the keyword search described in Table A.1). Standard errors two-way clustered at the newspaper day level are reported in parentheses.
Column (2) reports estimates of equation (13) using long-difference data. 'Rainfall-predicted participation index (SD)' is the standardized cumulative participation index, as defined by equation (8), computed for the period January 2019–July 2019. The dependent variable '# articles with climate keywords' is the change in the total number articles that are related to climate change between the 5-month period August-December 2018 and the same 5-month period in 2019 (based on the keyword search described in Table A.1.). White-Huber standard errors are reported in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.5. Rainfall-predicted strike participation and voting intentions for right-of-center parties

	Switch AfD to Union		Abstain from voting
	(1)	(2)	(3)
Rainfall-Predicted Participation index (SD)	0.125***		0.058*
	(0.041)		(0.033)
HH with children × participation Index (SD)		0.017	
		(0.051)	
HH without children × participation Index (SD)		0.151***	
		(0.045)	
County FE	✓	✓	✓
Week FE	✓	✓	✓
Previous party FE	✓	✓	✓
Individual controls	✓	✓	✓
Mean dependent variable	0.714	0.714	12.521
Observations	80,784	80,784	82,922

Notes: 'Rainfall-predicted participation index (SD)' is the standardized cumulative participation index, as defined by equation (8), computed up to the day before the interview. 'HH with children' is a dummy equal to one if a children are present in a household. 'HH without children' is a dummy equal to one if no children are present in a household. 'Switch AfD to Union' is a dummy indicating whether a respondent intends to vote for the Union in the next federal election having previously voted for the AfD. 'Abstain from voting' is an indicator taking the value of one if a respondent intends to abstain from voting in the next federal election, and zero otherwise. 'Previous party FE' are dummies capturing which party the respondent voted for in the previous federal election. 'Individual Controls' include a dummy capturing whether children are present in a household.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Two-way clustered standard errors at the county and date dimension are reported in parentheses.

B.2 Further robustness

Table B.6. Log protest participation, vote share of the Green Party, and voter turnout

	Δ Vote share Green Party		Δ Voter turnout		Δ Vote share Green Party Placebo	Δ Voter turnout Placebo
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Log cumulative protest participation index						
Log participation index	0.3627***	0.3567***	0.2627***	0.2711***	-0.0431*	0.0039
	(0.0750)	(0.0736)	(0.0760)	(0.0756)	(0.0245)	(0.0148)
Panel B: Log rainfall-predicted cumulative protest participation index						
Log predicted participation index	0.5159***	0.5078***	0.1632**	0.1761**	-0.0385	0.0078
	(0.0950)	(0.0929)	(0.0831)	(0.0830)	(0.0291)	(0.0161)
State×election FE	✓	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓	✓
Economic controls	-	✓	-	✓	✓	✓
Mean dependent variable	6.316	6.316	7.356	7.356	0.604	-0.512
Observations	849	849	849	849	842	842

Notes: 'Log participation index' is the logged cumulative participation index, as defined by equation (5), 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. 'Log rainfall-predicted participation index' is the logged rainfall-predicted cumulative participation index, as defined by equation (8), 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. 'Δ Vote share Green Party placebo' is the change in Greens' vote share between previous election cycles. 'Δ Voter turnout placebo' is the change in the share of eligible citizens that vote between previous 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. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. White-Huber standard errors are reported in parentheses.

Table B.7. Log protest participation and vote shares of all major political parties

	Left-of-Center			Right-of-Center		
	Δ The Left	Δ Greens	Δ SPD	Δ FDP	Δ Union	Δ AfD
	(1)	(2)	(3)	(4)	(5)	(6)
Log participation Index	-0.000	0.357***	-0.206***	-0.027	0.173**	-0.275***
	(0.038)	(0.074)	(0.070)	(0.027)	(0.083)	(0.071)
Mean dependent variable	-3.0970	6.3158	-2.7138	1.4788	-7.6379	2.0450
Observations	849	849	849	849	849	849
State ×Election FE	✓	✓	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓	✓	✓
Economic Controls	✓	✓	✓	✓	✓	✓

Notes: 'Participation index (SD)' is the standardized cumulative participation index, as defined by equation (5), 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. The dependent variable represents the change in vote share between election cycles for the Left, the Greens, the SPD, the FDP, the Union, and the AfD, respectively.'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. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. White-Huber standard errors are reported in parentheses.

C Supporting information

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

Dependent	Vote share Green Party	
	(1)	(2)
Panel A: Cumulative protest participation index		
Participation index (SD)	0.430***	0.431***
	(0.088)	(0.088)
Δ voter turnout		-0.004
		(0.032)
Observations	849	849
Panel B: Rainfall-predicted cumulative protest participation index		
Predicted participation index (SD)	0.445***	0.446***
	(0.089)	(0.090)
Δ voter turnout		-0.002
		(0.032)
Observations	849	849
State $\times$Election FE	✓	✓
Demographic controls	✓	✓
Economic controls	✓	✓

Notes: 'Participation index (SD)' is the standardized cumulative participation index, as defined by equation (5), 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. 'Rainfall-predicted participation index (SD)' is the standardized rainfall-predicted cumulative participation index, as defined by equation (8), 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. '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.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. White-Huber standard errors are reported in parentheses.

Table C.2. Protest participation at home and away

	Δ Vote share Green Party	Δ Voter turnout
	(1)	(2)
Participation index	0.361***	0.166***
in home county (SD)	(0.085)	(0.051)
Participation index	0.153**	-0.049
in away counties (SD)	(0.069)	(0.052)
State ×Election FE	✓	✓
Demographic Controls	✓	✓
Economic Controls	✓	✓
Mean dependent variable	6.316	7.356
Observations	849	849

Notes:
Notes: 'Participation index (SD) in home county (SD)' is the standardized cumulative participation index in the home county, as defined by equation (5), 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 (5), 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.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. White-Huber standard errors are reported in parentheses.

Table C.3. Rainfall-driven protest participation

	Participation index (SD)
	(1)
Rainfall deviation (SD)	-0.017***
	(0.005)
Observations	56,233
County FE	✓
Time FE	✓

Notes: 'Rainfall deviation (SD)' is the standardized rainfall deviation from the 10 year mean, defined by equation (6), computed at the county-day level. 'Participation index (SD)' is the standardized participation index, as defined by equation (5), computed is the at the county-day level.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$