The Power of Youth: Political Impacts of the "Fridays for Future" Movement*

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Abstract

We study the impact of the "Fridays for Future" climate protest movement in Germany on citizen political behavior and explore possible mechanisms. Throughout 2019, large crowds of young protesters, the majority of whom were under voting age, skipped school to demand immediate and far-reaching climate change mitigation measures. We first construct a spatially and temporally highly disaggregated measure of protest participation based on cell phone-based mobility data and hand-collected information on nearly 4,000 climate protests. Then, using various empirical strategies to address the issue of non-random 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 after. 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 provide some of the impetus that is needed to push society toward overcoming the climate trap.

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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 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": although 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 they exacerbate 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 toward prioritizing a green transformation. The FFF movement has been particularly strong in Germany, where it has gained significant traction in 2019, staging thousands of local climate protests across the country.

Despite the growing prevalence of youth spearheading mass climate protests, it is still an open question whether their activism can bring about political change. This

[1] The last nineteen years have been among the 20 hottest on record since temperature measurements 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."

study sheds light on this issue. We examine the impact of the FFF protest movement in Germany on citizen political behavior. In particular, we ask whether adults are influenced to vote for "green" political parties if local youth are more active in the FFF movement. We find strong evidence for this to be the case and explore three possible mechanisms. First, we test whether the FFF effect can be explained by reverse intergenerational transmission whereby youth raise their parents' environmental awareness and increase their demand for green politics. Second, we explore whether politicians publicly position themselves differently towards climate change if protest activity in their constituency is high. And third, we examine whether higher rates of climate protest participation shape the content of local media.

A main challenge our analysis faces is to measure the degree of local engagement in the FFF protest movement. This is a difficult task due to the geography of mass protests: while rallies are often organized in some central location (e.g., the main city of a region), its participants typically come from both within and outside that location (e.g., neighboring or more distant counties). Commonly used measures of protest activity, such as the presence or size of a rally in a given location, only coarsely capture where the supporters of a protest movement originate.

We overcome this obstacle by creating a spatially and temporally highly disaggregated measure of engagement in the FFF protest movement. We first hand-compile information on the location and dates of almost 4,000 climate protests using information from police forces, city councils, municipal authorities, and official FFF announcements. Additionally, we draw upon data on daily population flows within and between German counties. These are derived from cell phone tracking records that capture the number of journeys made between 260,000 origin-destination county pairs on a daily basis. Using this data in a standard gravity model, we identify daily excess population flows between each county pair. We then match these flows to the location and date of climate protests and compute protest participation for a given county and day as the sum of all excess flows from that county to all counties (including their own) where protests occur. For any given day, our measure of local protest participation therefore predicts how many individuals from a given county participate in FFF protests held either in the county or outside it. Several sensitivity tests corroborate the validity our approach.

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 after. The difficulty in establishing a causal relationship between the two is purging unobservable factors that may influence 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 using placebo tests the absence of differential pre-trends. Third, we use an instrumental variables-like 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 significantly altered the political landscape. The *Alliance 90/The Greens* is the party in Germany's multiparty system that prioritizes climate and consistently ranks first in nationwide climate competency surveys. Our first major finding is that a one-standard-deviation increase in local protest activity increases the vote share of the Greens by roughly 0.64 percentage points. Quantitatively this is a large effect. In the elections we study, the Greens' vote share increased by, on average, 5.9 percentage points when compared to previous elections (from a mean of 9.6%). This means that local FFF engagement can explain roughly 11% of the Greens' average vote gain over 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 appears to shifted voters away from other major political parties and toward the Greens.

Turning to factors that may explain these results, we argue that several complementary mechanisms are plausibly at play. The first is what we call the "reverse intergenerational transmission" channel, which states that youth involvement in the FFF movement may increase their parents' concerns about climate change and thus their proclivity 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 exists only 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 toward climate change, and this has influenced voters' evaluation of candidates and, ultimately, their vote decision. Based on a politician×day panel that links Twitter activity of German federal parliament members to climate protest activity in their constituency, we show that the latter induces primarily the Greens' members to post more climate change-related content. In quantitative terms, a one-standard-deviation increase in own-constituency protest activity increases the likelihood of a Green party member of parliament posting climate-related content by 15%.

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 mechanism through which the FFF-induced vote gains of the Greens might be explained. Drawing upon the content of 281 German print media outlets, we find that if protest activity is high in their area of circulation, local newspapers indeed report more on climate change, both in the short- and long-term. The effects are sizeable, with a one-standard-deviation increase in local protest participation raising climate-related newspaper content by up to 21%.

Our final result shows that the political impact of the FFF movement goes beyond vote swings toward the Greens. In particular, we find that in counties with high protest activity, there are remarkable voter movements among Germany's right-of-center parties: the extreme-right Alternative for Germany (AfD) suffers significant losses, whereas support for the center-right Christian Democratic Union (CDU) increases. We present evidence indicating that the voter swing among the right-leaning electorate cannot be explained by the reverse intergenerational transmission channel, but rather by strategic voting in which former AfD supporters switch to the CDU to prevent the Greens from gaining sufficient political power to influence policy making.

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" toward a new dynamic path where a green transformation materializes. Our empirical findings provide a new take on this. Environmental activism by those who are too young to vote provides some of the impetus needed to overcome the frictions that cause the climate trap, in theory. In particular, youth participation in FFF appears to have influenced their parents' political preferences, as well as influencing how politicians publicly position themselves toward climate change, and impacting the intensity of media reports on environmental issues. Finally, as an unintended consequence of the climate movement, there has been a significant drop in far-right party support, most likely as a result of strategic voting.

Our paper touches upon several strands of literature. First, it has antecedents in small but insightful literature examining the impact of social and political movements. Studying the Tea Party protests in the United States, Madestam *et al.* (2013) established that the movement has caused a shift to the right in policymaking. Meanwhile, focusing on the 2020 presidential election in the United States, Klein Teeselink and Melios (2021) documented a strong shift in support for the Democratic candidate in counties that experienced more Black Lives Matter protesting activity after George Floyd's death. Using daily variation in the number of protesters during Egypt's Arab Spring, Acemoglu *et al.* (2018) showed that more intense protests are associated with lower stock market valuations of firms connected to politicians in power relative to unconnected firms. Additionally, several papers have studied the determinants of protest participation (Finkel and Opp, 1991, Finkel and Muller, 1998, Cantoni *et al.*, 2019, Bursztyn *et al.*, 2021).

Second, our study contributes to a body of work examining the influence of certain interventions for environmental awareness and behavior. According to Hungerman and Moorthy (2022), the original 1970 Earth Day had long-term effects on support for environmental spending and local air quality. Deryugina and Shurchkov (2016) provided experimental evidence that information provision on scientific consensus on climate change affects the public's beliefs about climate change in the short-run but does not increase the public's belief that policy action is warranted.[4]

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

[4] A large body of 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).

how older generations pass these down to younger generations (Bisin and Verdier, 2001, Fernández *et al.*, 2004, Fernández and Fogli, 2009, Figlio *et al.*, 2019), only a few studies, mostly outside economics, have looked into the reverse intergenerational transmission. This body of work has established, *inter alia*, that younger generations influence their parents' attitudes toward various controversial topics, including unhealthy consumption behavior (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 Seychelles, Damerell *et al.* (2013) showed that adults exhibit a more comprehensive knowledge of wetlands and improved water management behavior when their child has received wetland-based environmental education. Similarly, Lawson *et al.* (2019) presented an experimental evaluation of an educational intervention program designed to build climate change concern among parents through their middle school-aged children in the United States. They found that parents of children in the treatment group expressed higher levels of climate change concern than parents in the control group.

Finally, our research relates to studies that use cell phone data to examine economically and socially important phenomena. A significant portion of this literature focuses on the study 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.*, 2021).

The remainder of the paper proceeds as follows. Section 2 provides background information on the FFF movement. Section 3 contains a description of the data we use. Section 4 outlines our methodology for tracking climate protest participation over time and space. Section 5 investigates the role of youth environmental activism in adult voting behavior, by first discussing our empirical strategy and presenting the findings. Section 6 explores mechanisms that could explain our findings. Finally, Section 7 concludes the paper.

2 Background

2.1 Fridays for Future

FFF is an international youth-led climate movement that calls on politicians to take immediate, science-based action to address climate change. The key demand is that governments adhere to the 2015 Paris Agreement, which targets reducing global greenhouse gas emissions to a level that limits global warming to 1.5 degrees Celsius compared to pre-industrial levels. To raise awareness and publicly express their demands, local FFF chapters organize regular protest marches. These typically occur on Fridays, where participating students skip classes to attend the protest (Smith and Bognar, 2019). As a result, the FFF movement is also frequently referred to as a "School Strike for Climate," which is reflected in the demographics of the activists. Protesters are mostly high school or college 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 more decisive 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, mobilizing around 7.6 million people (De Moor *et al.*, 2020). With large-scale public gatherings being prohibited in many countries, implying a temporary end of the protest marches, the FFF movement lost momentum with the emergence of COVID-19 in 2020.

Germany reflects the global temporal dynamics of the FFF movement. Although the first climate protests occurred 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 approximately 50,000 protesters. Engagement in FFF protest activity experienced further boost in March when Greta Thunberg attended marches in Berlin and Hamburg. March also saw the first global climate strike, staged on the 15th. On that day, an estimated 300,000 people took to the streets of Germany to demand climate action. Climate rallies continued throughout the year (mostly on Fridays), with dramatic increases in participation seen during the three global strike days that followed. The second—held on May 24, 2019—was strategically chosen to precede the European parliament elections, which FFF declared as "climate election." For Germany, over 300 strikes with a total of 320,000 participants were recorded (Die Zeit, 2019). During the third climate strike, the largest protest crowds were observed (September 20, 2019). Although more than 7.6 million people worldwide participated in climate strikes, Germany alone saw 1.4 million protesters in more than 500 locations (De Moor *et al.*, 2020). The fourth and last global climate protest of 2019 occurred 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 visualizes the temporal dynamics of the FFF protests in Germany for 2019. The solid black line represents the cumulative number of strikes across time.[6] In the two years after 2019, the spread of COVID-19 made street rallies impossible over extended periods and FFF street protests in Germany largely ground to a halt (Hockenos, 2020, Haßler *et al.*, 2021). Our analysis will therefore explore the political impacts of the 2019 climate protest movement.

Anecdotal and descriptive evidence suggests that the 2019 FFF climate protests were successful in raising public awareness of climate issues and changing public

[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).

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

attitudes (Forschungsgruppe Wahlen, 2019b, Smith and Bognar, 2019). Drawing on Politbarometer (2019) surveys, we can provide additional support for this notion. The survey, among other things, asks respondents to list the two most pressing political issues in Germany. As shown by the grey line in Figure 1, the proportion of interviewees who mentioned environmental protection as one of the most important 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 concern are positively related to FFF strike activity. Individuals are more likely to express concern for environmental protection after surging in the number of protests.

Finally, the inset figure highlights that awareness and prioritization of climate-related issues is a recent phenomenon. Over 2000–2018, the fraction of the 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 climate protests and the resulting surge in environmental awareness to lead to political changes (Forschungsgruppe Wahlen, 2019b). Starting with the next section, we begin developing the building blocks necessary to test this issue empirically.

2.2 Germany's Political Landscape

Unlike the United States, Germany has a multiparty system. Consequently, governments are typically formed by coalitions of parties, both at the state and federal levels. We will focus our analysis of electoral outcomes on the political parties currently represented in the German Federal parliament. The two major parties are (a) the Union and (b) the SPD (Social Democratic Party). The Union is made up of two parties: the CDU (Christian Democratic Union) and the CSU (Christian Social Union). They are considered a people's party, represent conservative and traditional Christian values, and advocate a market economy. In elections to the federal parliament, the CSU stands in Bavaria, whereas the CDU competes in the remaining 15 federal states. The second major party, the left-of-centre SPD, is also considered a people's party. It stands for social justice and has close ties with Germany's worker unions.

In addition to the Union and the SPD, there are four (relatively) smaller parties. (c) 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 by-far the highest level of climate competency (Forschungsgruppe Wahlen, 2019a). Before the FFF movement, it had a well-developed and explicit climate strategy in place. This was not the case for other parties, namely (d) The FDP (Free Democratic Party), which advocates for a liberal market economy and a simple tax system, and (e) The Left Party, which is the successor party of the SED, the communist ruling party of the former German Democratic Republic, and promotes social justice and peace. Finally, (f) the AfD (Alternative for Germany) can be classified as right-wing populist. The AfD is critical of climate science, which is vital in the context of our analysis. As the sole political party, it has demanded that all major climate action efforts be halted (including the abandonment of the Paris Climate Agreement and the European Green Deal).

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 connect daily repeated cross-sectional survey data on citizens' political preferences and voting intentions to protest participation in their home county. Third, we construct a politician×day panel that combines Twitter activity of the members of the German federal parliament ('Bundestag') with protest participation in their electoral district. Fourth, we create a newspaper×day panel dataset that relates reporting on climate change to protest participation in the newspapers' area of circulation.

We compile 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 in the following 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 region-pairs for the year 2019. The regions—i.e., the origins and destination—are congruent with German counties except for large metropolitan areas that are split into subunits.[8] The mobility data include information on journeys that occur within each of the 513 regions and journeys between the regions. Terarlytics identifies daily flows using mobile phone tracking technology applied to the universe of mobile signals of the Telefonica O_2 mobile network costumers.[9] In 2019, this mobile network provider had a market share of 31%(Statista, 2020). To obtain mobility patterns representative of total population, Teralytics extrapolates measured mobility based on O_2's regional market share. For

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

[8]Of the 401 German counties, 355 are congruent with the Teralytics regions. The remaining 46 counties are split into subunits, with a maximum of five subunits per county for the largest metropolitan counties.

[9]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.

2019, we observe 64.4 billion journeys between county pairs. The vast majority of journeys (92.7%) do not exceed 30 kilometers.[10]

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 must be registered with the police, city council, or other regulatory agencies. We contacted all relevant authorities and requested a complete list of climate protests registered in their jurisdictions during 2019. A total of 44% of the authorities responded to our request, providing precise information on the location and time of 1,938 protests. To fill in existing gaps and ensure that we consider marches that were not registered with authorities, we supplement the protest data obtained from authorities with information on location and date extracted from social media posts (Twitter, Facebook, and Instagram), and protest activity reported on the official website of FFF Germany. These sources provided us with an additional 1,968 strikes.[11] 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 occurred in 373 separate counties on 186 dates. Panel (a) of Figure 2 showcases the widespread nature of the protests, with 93% of all counties witnessing at least one protest during 2019. Similarly, Panel (b) shows that the protest activity was continuous throughout the year. Furthermore, regular spikes in the number of protests are discernible on Fridays. The four global climate events are clearly reflected in the protest (March, May, September, and November).

3.3 Election Data

Our analysis incorporates results from three types of elections: European parliament elections, state elections (in Baden-Württemberg, Berlin, Bremen, Brandenburg, Hamburg, Mecklenburg–Western Pomerania, Rhineland-Palatinate, Saxony, Saxony-Anhalt, and Thuringia), and German federal elections. The most recent round of each type of election occurred 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 previous one. Our primary outcome variable is the *change* in the vote share of the Greens (*Bündnis 90/Die Grünen*).

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

[11] 1,583 additional strikes were retrieved from the website of FFF Germany, 385 from social media posts.

The European parliament and the state elections take place approximately every five years. Results of the European Parliament (EP) elections are taken from the Federal Statistical Office and the Statistical Offices of the Länder. The EP election dates for our analysis are May 26, 2019 versus May 24, 2014. We use data from the State Returning Officers (*Landeswahlleiter)* and the Statistical Offices of the Länder for state elections. Elections were held in September/October of 2019 in Brandenburg, Bremen, Saxony and Thuringia, as opposed to August/September of 2014.[12] The elections in Hamburg were held on 23 February 2020, rather than 15 February 2015. Meanwhile, elections were held in March/September 2021 in Baden-Württemberg, Berlin, Mecklenburg–Western Pomerania, Rhineland-Palatinate and Saxony-Anhalt, as opposed to March/Septembe r2016.[13]

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

In total, our election dataset encompasses 958 observation at the county$\times$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 daily repeated cross-sectional telephone survey (CATI) that is voluntary and representative of Germany.[14] Each day (in 2019), precisely 500 (new) German speaking participants answer about 40 questions mostly regarding social attitudes, (realized/hypothetical) voting behavior, political preferences, and basic demographic variables such as household size, age, gender, number of children, and education. Additionally, the survey contains the respondent county of residence that gives us the chance to link the survey to our protest participation data.

[12]The specific election dates are: 27 October 2019 and 14 September 2014 (Brandenburg), 26 May 2019 and 10 May 2015 (Bremen), 1 September 2019 and 31 August 2014 (Saxony), and 27 October 2019 and 14 September 2014 (Thuringia).

[13]The specific election dates are: 14 March 2021 and 13 March 2016 (Baden-Württemberg as well as Rhineland-Palatinate), 26 September 2021 and 4 September 2016 (Mecklenburg–Western Pomerania), 26 September 2021 and 18 September 2016 (Berlin), and 6 June 2021 and 13 March 2016 (Saxony-Anhalt).

[14]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))

3.5 Twitter Data

We proceed in four steps to create the daily panel data on politicians' Twitter activity. First, we identify the members of the German parliament ('Bundestag') that have an official Twitter account and are affiliated with a political party. This is the case for 499 politicians (out of 736 parliament members). Second, we use Twitter's API to collect all tweets (original and retweets) posted by these parliament members between January 4, 2019, and December 31, 2019. This results in a database of 288,490 individual tweets. Third, we apply a keyword search to identify which tweets refer to climate change-related topics. Tweets are climate change-related if they contain at least one of the phrases listed in Appendix Table A.1. Finally, we aggregate the data at the politician×day level, yielding a dataset with a total of 180,638 observations. We use the share of climate tweets in total tweets posted by a politician on a given day as our main outcome variable. Appendix Table A.4 contains summary statistics for the dataset.

3.6 Newspaper Data

We obtain newspaper content from the GENIOS Online Press Archive.[15] This archive gives access to articles from 281 German print media outlets.[16] 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 protest participation to media content using the area of circulation of the newspapers. To this end, we first match each newspaper with information on its readership's geographical distribution. The readership data is provided by the German Audit Bureau of Circulation (IVW), but is only available for a subset of outlets in the GENIOS archive. In total, we can identify the area of circulation of 130 newspapers and magazines. For each news outlet, we construct a variable capturing its area of circulation. Meanwhile, for each news outlet, we rank all German counties according to readership numbers and define area of circulation as counties that account for 75% of total circulation.[17]

Our final newspaper×day dataset encompasses 130 news outlets and covers the year 2019. We report key summary statistics in Appendix Table A.5.

3.7 Control Variables

We construct various county-level controls for our analysis. These include demographic variables (total population, average age, and share of minors) and economic ones (GDP per capita, labor productivity, and unemployment share). In analogy

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

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

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

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

Our analysis aims to investigate how the local strength of engagement in FFF protest activity influences the electorate's behavior. However, measuring the former is difficult. The information on rally crowd sizes in our hand-collected data on climate protests is extremely limited (more about this below). Even if we knew the size of crowds at protests, we would not know which counties the FFF protesters come from. Indeed, many types of mass protests occur in some central locations, such as the main city of a region, with its participants originating both from within the outside that location (e.g., neighboring or most distant counties). To address this measurement issue, we combine cell phone-based mobility data with our climate protest database to predict the number of people who originate in a specific county and participate in climate protests on a given day.

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 region pairs. Second, we match these flows to the location and date of climate protests and compute the protest participation measure for a given county and day as the sum of all excess flows from that county to all counties where protests occur. This procedure is outlined in detail below.

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

$$\text{journeys}_{r(i)r(j)t} = \vartheta_{r(i)r(j)} + \varphi_{r(i)t} + \eta_{r(j)t} + \varepsilon_{r(i)r(j)t}. \tag{1}$$

We denote the number of journeys between origin $r(i)$ and destination $r(j)$ on day t as $\text{journeys}_{r(i)r(j)t}$. As outlined in Section 3 the Teralytics regions are equivalent to counties or subdivisions thereof. The mapping of regions to counties is captured by $r(\cdot)$. That is, $r(i)$ represents the region of origin equivalent to (or part of) county i and $r(j)$ is the destination region congruent with (or lying in) county j. The origin-destination fixed effects ($\vartheta_{r(i)r(j)}$) absorb any time-invariant differences in the level of mobility across pairs, including structural differences between within and cross-region movements. To account for temporal variation in the mobility patterns, we follow the standard gravity literature on panel data and include origin×day ($\varphi_{r(i)t}$) and destination×day ($\eta_{r(j)t}$) fixed effects.

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 earlier, the remaining unexplained variation (i.e. the residuals) constitutes the basis for our strike participation measure. The residuals capture how many more journeys are made from origin $r(i)$ to destination $r(j)$ than expected. For the subsequent analysis, we aggregate these excess flows at the county-pair level. Formally, this can be represented as follows:

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

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 where a climate protest occurs. Formally, we predict:

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

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

Figure 3 visualizes our strike participation measure for a climate protest in Berlin that occurred on March 29, 2019. Greta Thunberg attended this protest, which drew a large crowd. The figure illustrates that protest participants predominantly originate from within Berlin and the surrounding counties. This pattern of participation holds true in general. It is thus important to note that a county's total protest participation can be decomposed into two parts: participation in protests that occur in the own (i.e., home) county and participation in protests that occur in other counties. This decomposition is represented as:

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

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

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. Here, we aggregate local protest participation over time. The aggregation process can be written as:

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

where $\tilde{t}$ represents the day before the election. For elections that occurred in 2019, the cumulative protest participation measure is the sum of daily protest participation between January 1, 2019, and the day preceding the election. For the elections in our sample that took place after 2019, the total daily protest participation for the entire year 2019 is defined as the cumulative protest participation measure. This assignment is based on the fact that the COVID-19 pandemic and related mobility restrictions prohibited large-scale gatherings, including FFF protests, for much of 2020 and 2021. As a result, the movement ground largely to a halt (see Section 2).[18] As with the daily data, the overwhelming part of the total cumulative protest participation ($\mathrm{P}_{i\tilde{t}}$) variation is driven by participation in marches held in the home county ($\mathrm{P}_{i\tilde{t}}^{H}$).

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 like to see how well our predictions match with (i) how many people from a given county participate in protests, and (ii) the total number of people attending protests in a given county (i.e., crowd sizes). However, information on the origin of protesters is non-existent. Data on protest size (the total number of people attending a given protest) are also scarce. We provide two pieces of evidence to demonstrate that our approach to predicting strike participation can successfully capture variation in the total number and origin of protesters.

[18]Robustness checks will distinguish between the FFF effect in the short run (i.e., on 2019 election outcomes) and the longer run (i.e., on post-2019 election outcomes), and the potential concern that different counties' exposure to the COVID-19 pandemic may bias our results.

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 who attended the protests between January 1, 2019, and the time of the European Parliament elections. We then relate these numbers to cumulative attendance using our approach.[19] 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. Overall, Figure 4 shows that our method can successfully predict protest crowd sizes.

To illustrate that our measure allows us to infer the origin of participants of mass events, we draw on football (soccer) match attendance figures. Specifically, we collect data on the number of away fans for each game that occurred in 2019 in the first and second Bundesliga.[20] We also collect information on the date of the match, the location of the stadium, and the origin of the away team. Combined, this provides us with an estimate of the number of people who travel from the county where the away team originates from to where the stadium is located. We can then use these origin-to-destination supporters flows to test how well they align with our protest participation measure on game days. Figure 5 depicts the results. There is a strong positive correlation between predicted and observed origin-to-destination flows. This strongly suggests that our method can forecast the number of people who leave a given county to attend a large-scale public event in another county.

4.4 Rainfall-Driven Protest Participation Measure

To address concerns about nonrandom protest participation, we will predict local protest participation using local rainfall shocks as an exogenous source of variation (Madestam *et al.*, 2013). The intuition behind this approach is that heavier rain on the day of a rally discourages people from attending, but it is arguably unrelated to other factors that influence 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).[21]. This database reports hourly amounts of precipitation at a spatial resolution of $0.1° \times 0.1°$. We aggregate this data at the county×day level. For each county and day, we then define rainfall shocks as the percent difference between the rainfall measured on that day and the average amount of rainfall measured on that specific

[19] 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: $\mathrm{P}_{jt} = \sum_{i=1}^{i} e_{ijt}$.

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

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

date in the ten preceding years.[22] Protest participation is then predicted in a simple two-step procedure. First, we regress local protest participation on rainfall shocks:

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

where P_{it} is the local protest 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 the following:

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

Figure 6 documents that our rainfall-based participation measure strongly predicts contemporaneous protest 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 throughout and statistically non-significant except for the $t+7$ lead estimate. This illustrates that we can use local rainfall shocks to predict the variation in the number of protest participants on a specific day.

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

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

As before, $\tilde{t}$ reflects the time period between January 1, 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 election outcomes. The following first-difference model serves as the baseline for the subsequent empirical analysis:

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

[22] We use deviations from the 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.

where $\Delta(\text{Share Greens}_{i,\tilde{t}})$ is the change in the vote share of the Greens in county i over the last election cycle. Our main independent variable is $\mathrm{P}_{i\tilde{t}}$, the cumulative protest participation in county i up the day preceding the election $\tilde{t}$.[23] The state×election fixed effects, $\tau_{s,\tilde{t}}$, which are equivalent to trends in our first-difference model, absorb any state-and election-specific shifts in voter behaviour.

The main threat to the validity of our empirical strategy is that there may be unobserved factors that influence both local protest participation and election outcomes, biasing our estimates. Our first-difference method accounts for time-invariant disparities in county-level characteristics, such as historical voting patterns. However, time-varying correlated factors continue to be a source of concern. We address this concern in three complementary approaches. First, we account for a set of time-varying county-level controls. In regression equation (9) these are symbolized by $\mathbf{X}_{i,\tilde{t}}$. Second, we document the absence of pre-trends by using placebo election tests. 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 an explanatory variable. The 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 findings in Column (1) of panel A show that there is a strong positive relationship between strike participation and voting for the Green Party. According to the point estimate, a one-standard-deviation increase in protest activity raises the vote share by an economically significant 0.64 percentage points. Indeed, in the elections we study, the Greens' vote share increased by 5.9 percentage points on average (from a mean of 9.6%), implying that a one-standard-deviation increase in local protest activity can explain roughly 11% of that increase. We control for additional county-level characteristics in Column (2). The comprehensive set of controls includes demographic and economic county characteristics. The inclusion of these controls leaves the point estimate almost unchanged.

In addition to affecting the Green Party's vote share, we find that local engagement in support of FFF influences voter turnout. Columns (3) and (4) show that turnout increases with local protest activity. At a first pass, this suggests that protest-induced voter mobilization could have contributed to the increase in the Greens' vote share. However, the magnitude of the FFF effect on turnout is small. Evaluated at the average increase in voter turnout of 6.228 percentage points compared to preceding elections, the point estimate of 0.184 in column (4) only corresponds to a rise of 3%. Furthermore, we find that the coefficients in columns (1) and (2) remain

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

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 mobilization, and we shall return to this issue subsequently.

The main threat to the validity of our empirical approach, as previously stated, 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 indicates that this is unlikely to be the case (e.g., Oster, 2019, Altonji *et al.*, 2005). As a second piece of evidence, we document that local protest participation does not predict variation in voter behavior in preceding election cycles. Demonstrating that our protest participation metric does not capture any pre-trends, for both changes in Green vote shares (Column 5) and turnout (Column 6) in the previous election cycle, the point estimate of cumulative protest participation is statistically non-significant and close to 0.

As a final step toward alleviating concerns about confounding unobserved factors, we re-run the regressions presented in panel A, but this time we replace our main protest participation measure with rainfall-predicted participation. The 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. With the absence of pre-trends, this strongly suggests that our protest participation measure is capturing the causal effects of local FFF engagement 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.2 and B.6 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. Moreover, these shifts appear to be driven by existing voters switching party allegiance rather than a mobilization of new voters. To gain an initial understanding of these voter movements, we examine 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. Apart from the Greens, five parties are currently represented in federal and most state legislatures: the two people's parties, the center-right Union and center-left Social Democratic Party (SPD), as well as the liberal FDP, the socialist Left Party (The Left), and the far-right Alternative for Germany (AfD). In Table 2, we examine how local involvement in FFF has influenced vote shares for these parties. For the SPD, the FDP, and the Left, we observe that a one-standard-deviation increase in local protest activity causes decreases in vote shares by 0.9 to 1.6 percentage points. This is consistent with FFF activity sensitizing voters of these parties to climate issues and inducing to them switch to the Greens, the party most committed to tackling the climate crisis.

Consider how the vote shares of the two remaining parties have changed. Surprisingly, the far-right AfD suffers the greatest climate-protest-related losses of any party. A one-standard-deviation increase in local protest activity causes 0.27 percentage points drop in the vote share of the AfD. This implies that, without the FFF movement, the AfD's average vote gain of 1.32 percentage points compared to preceding elections would have been 20% higher. Simultaneously, the center-right Union saw a percentage-wise small but statistically significant increase in their support in counties with high protest activity. As AfD voters are unlikely to switch to the Green Party, this result suggests that the FFF movement caused some voters previously voting AfD to switch to the Union.

Section 6 delves deeper into these findings by examining individual-level survey data on voting intentions. First, however, we will talk about the robustness of our main findings.

5.4 Robustness

We run an array of robustness tests to document that specific assumptions or data construction choices do not drive our findings. The results in Table B.1 show that using the natural logarithm of our protest participation measure (rather than the untransformed values) as a measure of local FFF engagement yields qualitatively equivalent results (Column (1)). This is also true when we use the total number of protests in a county as an alternative measure of protest intensity (Column (2)). Similarly, using a Poisson pseudo-maximum-likelihood regression approach rather than an OLS regression approach when estimating our gravity model (1) changes the result very little (Column (3)). Weighting observations based on population numbers produces very similar results (Column (4)).

To illustrate that counties at either end of the population distribution do not drive our results, we drop the 5% counties with the smallest and largest population, respectively. Column (5) demonstrates that this has little effect on our estimate. To alleviate concerns that exposure to the COVID-19 pandemic could be correlated with our participation measure and thus bias our results, we use two complementary approaches. First, we take into account the (average) local COVID-19 incidence. This effectively leaves the point estimate unchanged (column (6)). Second, we separately estimate regression equation (9) for elections that occurred before COVID (i.e. in 2019) and after the disease's arrival. The two resulting estimates are very similar in size compared to our main setup and statistically indistinguishable from each (columns (7)-(8)). This also indicates that the effect of protest participation is not only immediate, but persists over at least two years.

We show that our results, in addition to being robust, are unlikely to be the result of chance. To that end, we permute protest participation across counties at random and then re-run the regression equation (9). We repeat this exercise 1,000 times and present the results in Figure B.1. Point estimates are centered around 0 and orders of magnitude smaller than the coefficients reported in Table 1 (Column (2)).

6 Mechanisms

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

6.1 Reverse Intergenerational Transmission

Some first evaluations of environmental education school programs 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 also be an important mechanism in the context of FFF. Those who engaged in the climate movement were often not yet eligible to vote. However, their participation in climate protests may have forced their parents to engage with environmental issues, ultimately shaping their demand for green 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 occurred 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:

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

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 and non-parents living in the same county at different times (i.e., having experienced varying levels of protest participation prior to the interview) while controlling for time-invariant local characteristics.

Table 3 displays the results from estimating model (10). The dependent variable in Column (1) is a dummy for not having voted for the Greens in the previous general election but intending to do so at the time of the interview. On average, 13% of respondents state an intention to switch party allegiance to the Green Party. A one-standard-deviation increase in local protest activity increases switching intention by 0.6 percentage points among respondents with children. However, there is no significant effect on respondents without children's switching intentions. In columns 3–7, we look at which parties are bringing in new voters for the Greens. We observe that the climate movement has caused parents who previously voted for the two main people's parties (The Union and SPD) to switch allegiance to the Greens. This is not the case, however, for respondents without children. We observe a similar pattern among respondents who previously supported the FDP, but the point estimate for respondents with children is not statistically significant. The local climate protest activity also increases intentions to switch to the Greens among previous supporters of the Left, but the effect comes from respondents without children. Finally, there are no significant FFF-induced changes in switching intentions among AfD supporters, whether parents or non-parents. In non-reported regression, we also explored whether individuals who abstained from voting in the previous general election are more likely to state an intention to vote for the Greens if the residence was in areas with high FFF engagement. We found no evidence of climate-related mobilization. This result is consistent with the FFF's modest effect on voter turnout (see Table 1).

A second, more indirect approach to dealing with the reverse intergenerational transmission hypothesis is dividing total protest participation into two dimensions: participation in protests held in one's own (home) county and in rallies held elsewhere.[24] The idea is the following. Protest activity in the home county is directly observable by all county residents, and this may raise the public's awareness of climate change issues. However, this direct effect is not as salient if children and youth leave the home county to participate in FFF protests elsewhere. Here, an effect on political preferences more likely materializes through protest participants sharing their views and experiences within their social and family network. Thus, evidence supporting the reverse intergenerational transmission hypothesis would be finding that the FFF effect on election outcomes is explained not only by within-county protest participation, but also by participation in rallies away from home.

Table C.2 demonstrates that this is indeed the case. On the one hand, we find that increasing cumulative within-county protest participation by one-standard-deviation increases the Green Party's vote share by 0.43 percentage points. However, away-from-home protest participation also causes an increase in the Green support in the home county: a one-standard-deviation increase in this measure causes the Green Party's vote share to increase by 0.29 percentage points. This is a remarkable result,

[24]See Section 4 for more details.

given that differences in within-county protest participation account for the vast majority of the variation in counties' total protest activity. Back-of-the-envelope calculations suggest that 0.018 Green Party votes are gained for every away-from-home protest participant.

6.2 Politicians

The vote decision depends on *inter alia* how the electorate evaluates party candidates on specific public policy issues, which in turn depends on how politicians publicly position themselves toward them. Substantial 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

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

where $S_{p,c,t}$ is the share of climate tweets in total tweets posted by politician p representing constituency c on day t. $\mathrm{P}_{c,t}$ is the local protest participation in constituency c on day t as defined in equation (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 4 presents the results. shows that MPs are significantly more likely to tweet about climate change when the protest activity in their electoral district is high. A one-standard-deviation increase in a constituency's protest activity raises the share of climate tweets an MP posts by 0.4 percentage points or 7% of the mean.

However, this effect likely masks heterogeneities across MPs from different political parties. In particular, for politicians' public engagement with climate change to explain 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. We test for this in Column (2) by estimating separate slope coefficients for each political party. This exercise reveals that green MPs are indeed far more responsive on social media than those from other political parties. The climate protest effect for Green politicians is nearly three times greater than the average effect reported in Column (1). Column (2) results show that increased protest activity encourages members of the Left Party and the FDP to post more climate change-related content. Relative to Green Party MPs, the size of the effect is considerably smaller. MPs of other parties seem to not react to protest activity in their electoral district. Coefficients are small and statistically non-significant for members of the SPD, Union, and AfD. This lack of reaction could be due to conflicts between the demands of the FFF movement and core party voters' (perceived) preferences.

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 circulation area. We lag the explanatory variable since our data capture print media content. In all regressions, we control for newspaper fixed effects, $\psi_{n,r}$, and date dummies, ζ_t. The error term is represented by $\varepsilon_{n,r,t}$ and clustered simultaneously by newspaper and date (Cameron *et al.*, 2011). The main parameter of interest, γ, captures the immediate effect of FFF strike participation on content.

In a subsequent step, we examine whether local protest activity results in a permanent shift in newspaper coverage of climate issues. We accomplish this by employing the first-difference model described below:

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

The variable $\Delta A_{n,r}$ represents the difference in the total number of climate change articles published between August and December of 2018 and the same period in 2019. During the first period, no significant climate activity occurred in Germany. August-December 2018 thus constitutes our pre-FFF period. To minimize the risk of conflating general shifts toward 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 consider protest activity that occurs in August–December 2019. Thus, the coefficient θ captures whether newspapers are more likely to continue reporting on climate issues after being exposed to strike activity.

Column (1) of Table 5 demonstrates how local protest participation immediately impacts newspaper content. A one-standard-deviation increase in protest activity raises the number of articles containing climate change keywords by 0.15. Compared to the sample mean of 1.65 articles, this represents a 9% increase. As previously discussed, this effect is a composite of reporting on protest activity and reporting on climate change-related topics.

Because the estimate in Column (1) does not account for any long-term effects of local protest participation, we proceed to our first-difference specification in equation (13). Column (2) displays the outcomes. We see significant long-term effects of local protest activity. In the same period of 2019, newspapers publish 321 more climate-related articles than in the same period of 2018, and a one-standard-deviation increase in local protest participation raises this number by 68, or 21%.

6.4 Strategic Voting

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

To do so, we revisit the forsa survey data to see if voters switching from the AfD to the Union can explain the shift in vote shares between these two right-of-center parties. The positive and statistically significant point estimate in Column (1) of Table 6 indicates that vote switching 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 also at play here. AfD voters might be sensitized 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 abandoning the Paris Climate Agreement and the European Green Deal. Thus, local protest activity may have induced AfD supporters to switch party allegiance to the Union, a party that is still right of center but is perceived by voters to have a stronger climate orientation (Bukow, 2019). If this mechanism is at work, we should expect to see a shift in voting preferences from AfD to Union among respondents with children. Strategic voting is a second explanation for vote switching from the AfD to the Union. High local protest participation may cause AfD supporters to worry that the Greens will gain enough 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 Table 6, we estimate separate slope coefficients for parents and non-parents to capture the effects of local protest participation. In contrast to the intention to switch to the Greens (see Table 3), the FFF now only encourages former AfD supporters without children to join the Union. The FFF effect is close to 0 and statistically insignificant for AfD supporters with children. We consider this consistent with our speculation that the FFF movement has caused AfD supporters to cast a strategic vote.

In addition to vote switching, reduced turnout could explain 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 increase abstention rates among former AfD voters.

Summing up, this section has attempted 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, increased 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 tandem, possibly 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). 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 provide a push towards a transformation are demonstrations by citizens that prominently highlight the full scope of the climate crisis. In seeking to garner votes, politicians would react by implementing climate-aligned measures aimed at fostering green investments and consumption. This, in turn, would reorient technological change away from high-carbon and toward low-carbon technologies. Ultimately, environmentally-friendly values would emerge, putting an end to the climate trap.

Our paper addresses the first link in this chain. We demonstrate, using the FFF protest movement in Germany, that youth engagement in demand of climate action significantly impacts political outcomes. We estimate that a one-standard-deviation increase in local protest activity increases the Green Party's vote share by 11%, owing to voter movements to the Greens from other major political parties with a less climate-focused political agenda. One key driver appears to be intergenerational transmission of pro-environmental attitudes from children to parents: increased support for the Greens is entirely dependent on voters with children of FFF-relevant ages. We also find evidence for two other mechanisms. First, Green Party candidates increase their climate-related social media presence in response to strong protest activity in their constituency, which may influence voters' relative evaluation of candidates and, ultimately, their vote decision. Second, building on the idea that media may influence voters through the content they cover, we demonstrate that local newspapers report more on climate change when FFF engagement in their area of circulation is high. As a caveat, beyond the scope of this study to explore, there remains the question of how these mechanisms interact to produce the overall effect on political outcomes.

As a result 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 extends beyond an increase in the demand for green politics. On the contrary, we here provide evidence that the FFF movement has caused some voters, those whose political preferences are orthogonal to the political agenda of the Greens, to change their vote decision 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 approximates the geographic distribution of participants at thousands of FFF rallies. We believe this approach could be a useful tool for mapping out the evolution of social mass movements in future studies.

Our paper leaves open many avenues of further enquiry. The perhaps most important question is whether the FFF effect will persist. If in the model of Besley and Persson (2020) an enhanced influence of climate activists were to push society over a tipping toward a green transformation, we would ultimately expect to see a change in culture toward 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

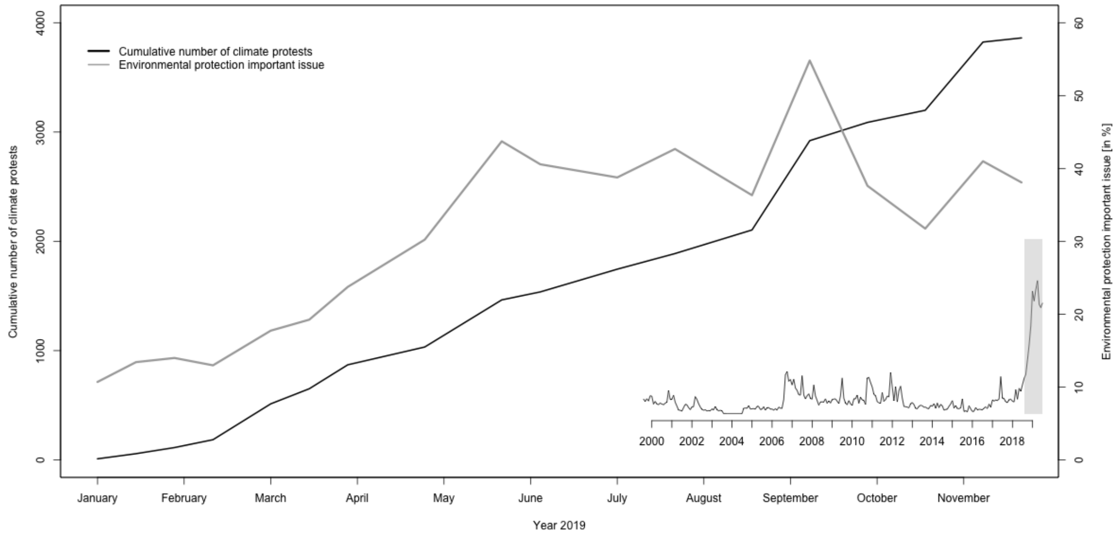

Figure 1. Protest activity and public opinion
Figure depicts the cumulative number of climate protests in Germany in 2019 (black line). Protest data are hand-collected from various sources (see Section 3 for details). The grey line represents the proportion of individuals naming environmental protection 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)

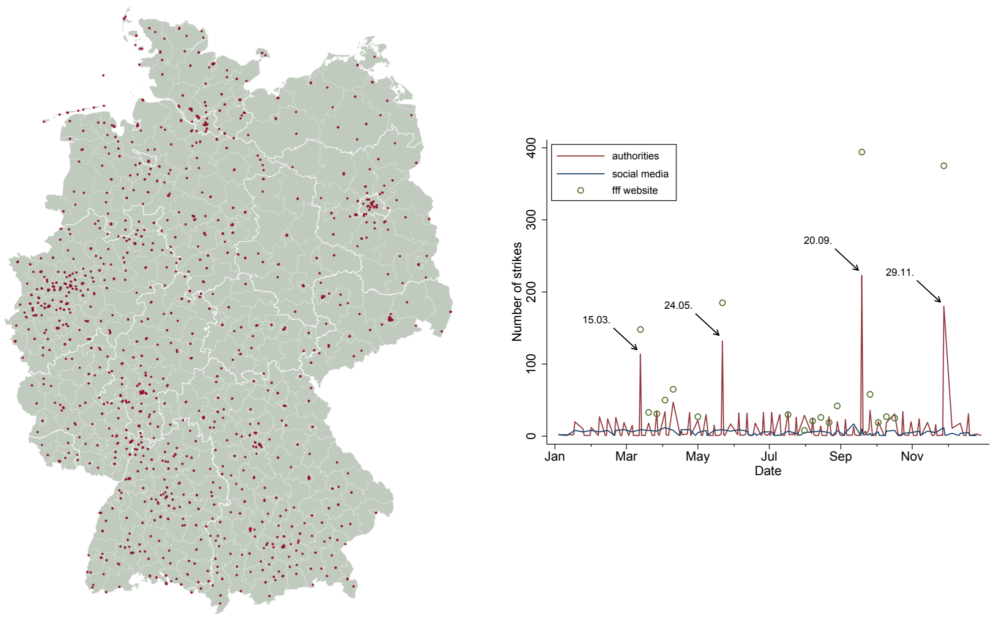

Figure 2. Locations of climate strikes in 2019
Panel (a): Map depicts the location of climate strikes (red dots) for year 2019. The bold white lines represent state boundaries whereas the thin white lines represent county borders. Panel (b): Figure depicts the daily number of strikes by data soruce.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

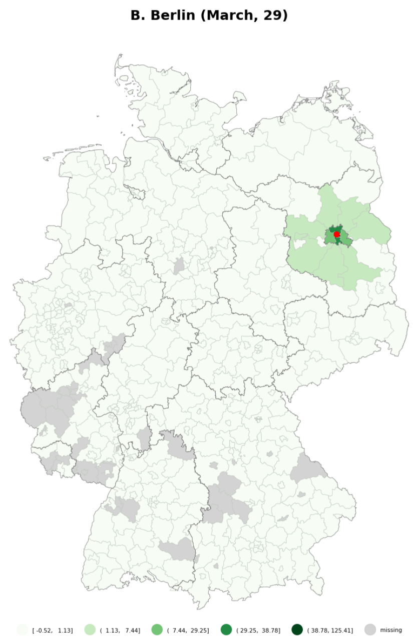

Figure 3. Strike participation for selected strikes
Notes: Map shows counties' protest participation (as defined by Eq.(3)) in the climate protest that occurred in Berlin on 19 March 2019. A darker shade of green indicates higher protest participation. The color scale classification is obtained using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

(a) (b)

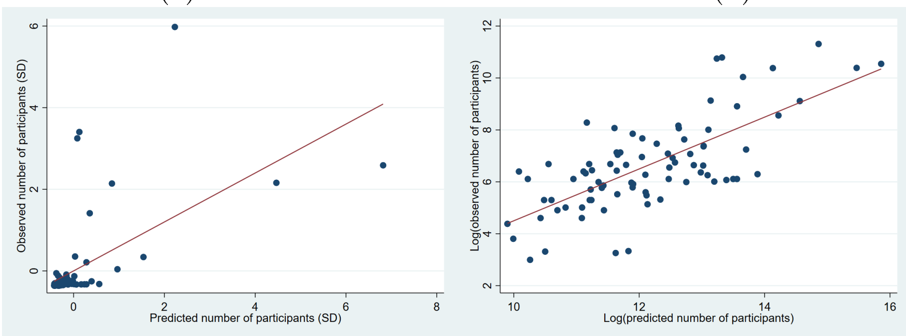

Figure 4. Validation, strike size
Observed number of participants is the reported number of protest participants at the protest location up to the European elections as reported by local authorities. Predicted number of protest participants are the cumulative excess journeys to a given protest location (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)

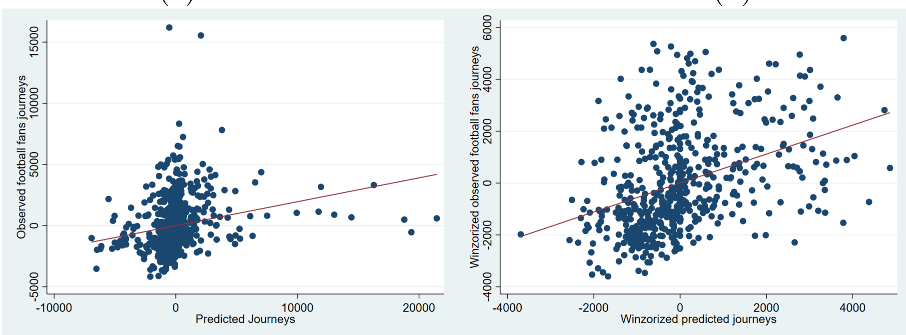

Figure 5. Validation, soccer fans journeys
Observed football fans journeys are the observed number of supporters of the away team that attend the match (`fuballmafia.de`). Predicted journeys are the mobile phone based predicted excess journeys from the county of the away team to the county of the home 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.

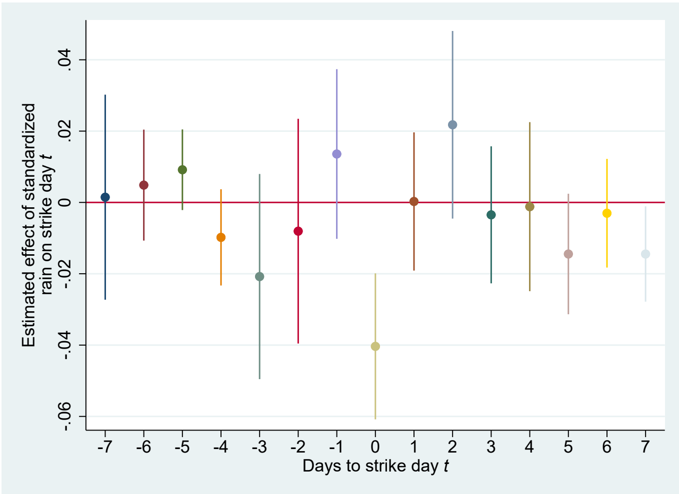

Figure 6. Strike participation for selected strikes

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)	0.640***	0.622***	0.153**	0.184**	-0.097	-0.020
	(0.119)	(0.119)	(0.070)	(0.071)	(0.086)	(0.099)
Panel B: Rainfall-predicted cumulative protest participation index						
Predicted participation index (SD)	0.663***	0.644***	0.117*	0.147**	-0.110	0.013
	(0.121)	(0.121)	(0.066)	(0.068)	(0.089)	(0.100)
State×election FE	✓	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓	✓
Economic controls	-	✓	-	✓	✓	✓
Mean dependent variable	5.934	5.934	6.228	6.228	-0.264	3.894
Observations	958	958	958	958	958	958

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 the standardized rainfall-predicted cumulative participation index 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

	Δ Union	Δ SPD	Δ FDP	Δ The Left	Δ AfD
	(1)	(2)	(3)	(4)	(5)
Participation Index (SD)	0.209**	-0.157**	-0.138**	-0.093**	-0.241***
	(0.085)	(0.075)	(0.057)	(0.040)	(0.071)
State×Election FE	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Economic controls	✓	✓	✓	✓	✓
Mean dependent variable	-7.008	-2.493	1.441	-2.849	1.317
Observations	958	958	958	958	958

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 Union, the SPD, the FDP, the Left 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

	Switch to Greens	Switch Union to Greens	Switch SPD to Greens	Switch FDP to Greens	Switch The Left to Greens	Switch AfD to Greens
	(1)	(2)	(3)	(4)	(5)	(6)
HH with children × participation index (SD)	0.545***	0.727***	0.824**	1.050	-0.363	-0.219
	(0.194)	(0.264)	(0.335)	(1.007)	(0.776)	(0.257)
HH without children × participation index (SD)	-0.114	0.036	-0.475	-1.481**	0.966***	0.269
	(0.125)	(0.268)	(0.294)	(0.600)	(0.294)	(0.169)
County FE	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
Previous party	fixed effects	Union	SPD	FDP	The Left	AfD
Individual controls	✓	✓	✓	✓	✓	✓
Mean dependent variable	13.006	10.441	22.719	9.535	13.230	1.279
Observations	82,786	32,545	20,098	6,953	6,780	5,475

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 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 fixed effects' are dummies capturing which party the respondent voted for in the previous federal election. 'Individual controls' include age-, education-, number of children in household-, type of employment-, income bracket- as well as gender fixed effects. We further control for type of interview.
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

	Share climate tweet	
	(1)	(2)
Participation index (SD)	0.366***	
	(0.127)	
Union ×		-0.058
participation index (SD)		(0.149)
SPD ×		0.201
participation index (SD)		(0.196)
Greens ×		0.908***
participation index (SD)		(0.239)
FDP ×		0.461*
participation index (SD)		(0.257)
Left ×		0.517***
participation index (SD)		(0.154)
AfD ×		0.259
participation index (SD)		(0.211)
Politician FE	✓	✓
State×date FE	✓	✓
Mean dependent variable	5.912	5.912
Observations	180,638	180,638

Notes: 'Participation index (SD)' is the standardized daily participation index, as defined by equation (3). Share climate tweet is the share of climate tweets in total tweets in percentage points posted by a politician on a given day.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors two-way clustered at the politician and week 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)	0.153**	68.075***
	(0.076)	(17.252)
Newspaper FE	✓	✓
Time FE	✓	✓
Mean dependent variable	1.647	321.00
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)	(4)
Participation index (SD)	0.657**		-0.549**	
	(0.304)		(0.247)	
HH with children × participation index (SD)		0.034		-0.572
		(0.491)		(0.388)
HH without children × participation index (SD)		0.756**		-0.546**
		(0.324)		(0.255)
County FE	✓	✓	✓	✓
Week FE	✓	✓	✓	✓
Previous party	AfD	AfD	AfD	AfD
Individual controls	✓	✓	✓	✓
Mean dependent variable	4.880	4.880	3.362	3.362
Observations	5,475	5,475	5,475	5,475

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, having voted for the AfD before. Individual controls' include age-, education-, number of children in household-, type of employment-, income bracket- as well as gender fixed effects. We further control for type of interview.
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 Union	-7.008	4.293	-17.633	11.434	958
Δ vote share SPD	-2.493	8.043	-21.331	16.040	958
Δ vote share Greens	5.933	4.041	-7.430	19.655	958
Δ vote share FDP	1.440	1.434	-3.845	7.746	958
Δ vote share Left	-2.848	2.945	-14.351	7.466	958
Δ vote share AfD	1.317	6.012	-8.810	22.677	958
Δ turnout	6.227	7.888	-10.594	23.834	958
Cumulative protest participation (SD)	0	1	-0.498	13.087	958
Rainfall-predicted cumulative protest participation (SD)	0	1	-0.518	13.165	958

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

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Cumulative protest participation (SD)	0	0.981	-0.465	7.065	82,786
HH with children×Cumulative protest participation (SD)	0.006	0.401	-0.465	7.065	82,786
HH without children×Cumulative protest participation (SD)	0.007	0.886	-.465	7.065	82,786
Switch to Greens	13.017	33.650	0	100	82,786
Switch from Union to Greens	10.440	30.578	0	100	32,547
Switch from SPD to Greens	22.715	41.900	0	100	20,101
Switch from FDP to Greens	9.536	29.373	0	100	6,963
Switch from the Left to Greens	13.226	33.880	0	100	6,797
Switch from AfD to Greens	1.294	11.305	0	100	5,484
Switch from AfD to Union	4.886	21.561	0	100	5,484
Switch from AfD to non voter	3.391	18.103	0	100	5,484

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

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Obs.**
Share climate tweets	5.912	19.395	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.5. Descriptive statistics of key variables: Newspaper data

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Obs.**
	Newspaper×day-level sample				
Number of articles with climate keywords	1.647	2.991	0	95	47,450
Cumulative protest participation (SD)	0	1	-.117	88.260	47,450
	First-difference sample				
Δ Number of articles with climate keywords	321.007	206.718	-15	1,324	130
Cumulative protest participation (SD)	0	1	-.436	9.233	130

B Robustness

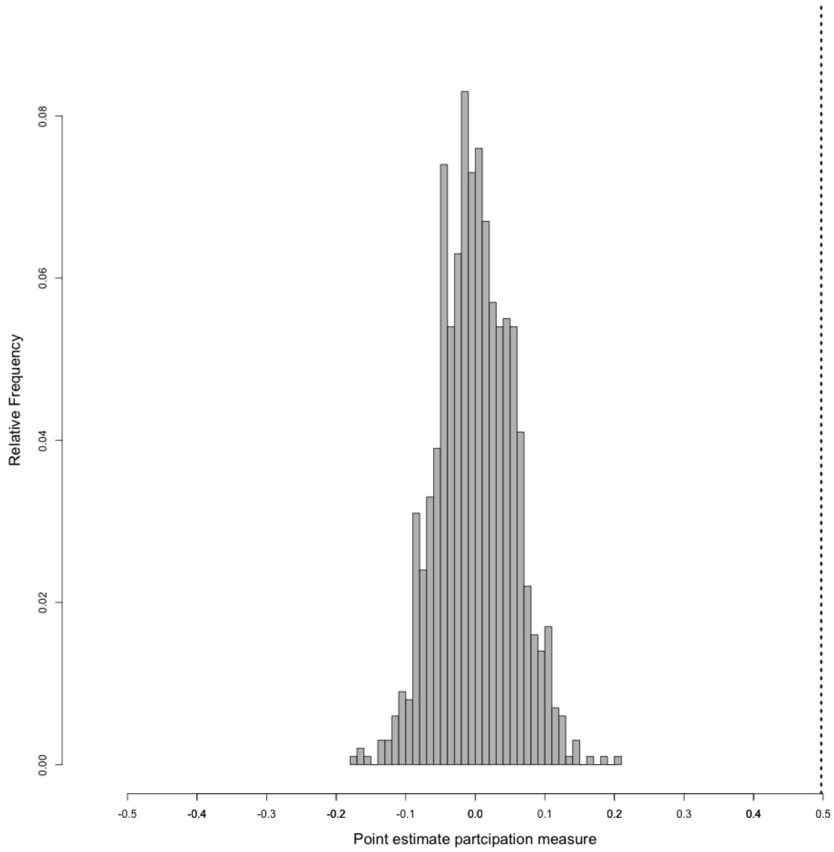

Figure B.1. *Randomisation*
Note. Figure depicts the distribution of point estimates obtained from 1,000 random permutation of protest participation across counties. The dashed black vertical line at 0.497 represents point estimate obtained using the actual protest participation data (see Table 1, column (2)).

Table B.1. Robustness: Protest participation and vote share of the Green Party

	Δ Vote share Green Party							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Participation Index (SD)	0.315***		0.637***	0.588***	0.515**	0.567***	0.455*	0.561***
	(0.070)		(0.103)	(0.137)	(0.256)	(0.118)	(0.271)	(0.128)
Cumulative Number of Protests (SD)		0.416***						
		(0.087)						
State×election FE	✓	✓	✓	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓	✓	✓	✓
Economic controls	✓	✓	✓	✓	✓	✓	✓	✓
Mean dependent variable	5.935	5.935	5.935	5.935	5.935	5.935	7.780	4.257
Observations	958	958	958	958	765	958	456	502
Robustness	Log	Number protests	PPML	Weights	95 percentile	COVID incidence	pre-COVID	post-COVID

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. '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.

B.1 Rainfall-predicted participation measure

Table B.2. Rainfall-predicted protest participation and vote shares of all major political parties

	Δ Union	Δ SPD	Δ FDP	Δ The Left	Δ AfD
	(1)	(2)	(3)	(4)	(5)
Rainfall-predicted Participation Index (SD)	0.203** (0.085)	-0.162** (0.077)	-0.137** (0.057)	-0.093** (0.040)	-0.265*** (0.072)
State×Election FE	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Economic controls	✓	✓	✓	✓	✓
Mean dependent variable	-7.008	-2.493	1.441	-2.849	1.317
Observations	958	958	958	958	958

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 rainfall-predicted cumulative participation of 2019. The dependent variable represents the change in vote share between election cycles for the Union, the SPD, the FDP, the Left 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.3. Rainfall-predicted protest participation and voting intentions: parents versus non-parents

	Switch to Greens	Switch Union to Greens	Switch SPD to Greens	Switch FDP to Greens	Switch The Left to Greens	Switch AfD to Greens
	(1)	(2)	(3)	(4)	(5)	(6)
HH with children × rainfall-predicted participation index (SD)	0.596***	0.835***	0.843**	0.635	-0.158	-0.302
	(0.203)	(0.305)	(0.417)	(0.954)	(0.760)	(0.276)
HH without children × rainfall-predicted participation index (SD)	-0.139	0.115	-0.675**	-1.881***	1.081***	0.244
	(0.122)	(0.296)	(0.340)	(0.627)	(0.338)	(0.186)
County FE	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
Previous party	fixed effects	Union	SPD	FDP	The Left	AfD
Individual controls	✓	✓	✓	✓	✓	✓
Mean dependent variable	13.006	10.441	22.719	9.535	13.230	1.279
Observations	82,786	32,545	20,098	6,953	6,780	5,475

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 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 fixed effects' are dummies capturing which party the respondent voted for in the previous federal election. 'Individual controls' include age-, education-, number of children in household-, type of employment-, income bracket- as well as gender fixed effects. We further control for type of interview.
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.4. Rainfall-predicted protest participation and politicians' social media presence

	Share climate tweet	
	(1)	(2)
Rainfall-predicted participation index (SD)	0.3924**	
	(0.1833)	
Union × rainfall-predicted participation index (SD)		-0.2091
		(0.2883)
SPD × rainfall-predicted participation index (SD)		-0.1634
		(0.2096)
Greens × rainfall-predicted participation index (SD)		1.5196***
		(0.3831)
FDP × rainfall-predicted participation index (SD)		0.2840
		(0.3892)
Left × rainfall-predicted participation index (SD)		0.7581**
		(0.3094)
AfD × rainfall-predicted participation index (SD)		-0.0183
		(0.3717)
Politician FE	✓	✓
State×date FE	✓	✓
Mean dependent variable	5.912	5.912
Observations	180,638	180,638

Notes: Rainfall-predicted participation index (SD)' is the standardized rainfall-predicted cumulative participation index, as defined by equation (8). Share climate tweet is the share of climate tweets in total tweets in percentage points posted by a politician on a given day.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors two-way clustered at the politician and week dimension are reported in parentheses.

Table B.5. Rainfall-predicted protest participation and newspaper content

	# articles with climate keywords	
	Daily Panel	Long difference
	(1)	(2)
Rainfall-predicted participation index (SD)	0.206***	64.982***
	(0.072)	(17.345)
Newspaper FE	✓	✓
Time FE	✓	✓
Mean dependent variable	1.647	321.00
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 rainfall-predicted cumulative participation index, as defined by equation (8). 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 rainfall-predicted 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.6. Rainfall-predicted strike participation and voting intentions for right-of-center parties

	Switch AfD to Union		Abstain from voting	
	(1)	(2)	(3)	(4)
Rainfall-Predicted participation index (SD)	0.772**		-0.532**	
	(0.361)		(0.256)	
HH with children × rainfall-predicted participation index (SD)		-0.062		-0.470
		(0.497)		(0.400)
HH without children × rainfall-predicted participation index (SD)		0.890**		-0.541**
		(0.377)		(0.266)
County FE	✓	✓	✓	✓
Week FE	✓	✓	✓	✓
Previous party	AfD	AfD	AfD	AfD
Individual controls	✓	✓	✓	✓
Mean dependent variable	4.880	4.880	3.362	3.362
Observations	5,475	5,475	5,475	5,475

Notes: 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 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, having voted for the AfD before. Individual controls' include age-, education-, number of children in household-, type of employment-, income bracket- as well as gender fixed effects. We further control for type of interview.
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

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)	0.622***	0.622***
	(0.119)	(0.119)
Δ voter turnout		-0.003
		(0.028)
Observations	958	958
Panel B: Rainfall-predicted cumulative protest participation index		
Predicted participation index (SD)	0.644***	0.644***
	(0.121)	(0.121)
Δ voter turnout		-0.001
		(0.032)
Observations	958	958
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. '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 in home county (SD)	0.428*** (0.115)	0.190** (0.051)
Participation index in away counties (SD)	0.290*** (0.088)	-0.010 (0.059)
State ×Election FE	✓	✓
Demographic Controls	✓	✓
Economic Controls	✓	✓
Mean dependent variable	6.316	7.356
Observations	958	958

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)	-0.011*** (0.003)
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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.4. Protest participation, vote share of the Green Party in 2019 and 2021

	Δ Vote share	
	2019 elections	2021 elections
	(1)	(2)
Participation index (SD)	0.569*	0.601***
	(0.292)	(0.126)
State ×Election FE	✓	✓
Demographic Controls	✓	✓
Economic Controls	✓	✓
Mean dependent variable	7.78	4.25
Observations	456	502

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. '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.