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The Power of Youth: Did the "Fridays for Future" Climate Movement Trickle-Up to Influence Voters, Politicians, and the Media?

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 exploit cell phone-based mobility data and hand-collected information on nearly 4,000 climate protests to construct a spatially and temporally highly disaggregated measure of protest participation. Then, using various empirical strategies to address the issue of nonrandom protest participation, we show that the local strength of the climate movement led to more Green Party votes in state-level and national-level elections during 2019 and after. We provide evidence suggesting that reverse intergenerational transmission of pro-environmental attitudes from children to parents was a key mechanism underlying this effect. In addition, stronger climate-related social media presence by Green Party politicians and increased coverage of environmental issues in local media also appear to have played a role.

JEL-Codes: D720.

Keywords: climate protest movement, citizen political behavior.

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1 Introduction

Children and youth will bear the brunt of climate change over the coming decades. They also constitute the generation with the highest stakes in climate action, as today's responses to climate change will directly affect the rest of their lives (IPCC, 2022). And yet, being too young to vote and hold office, children and youth face limited options to translate their climate change concerns into sustained influence on political decision-making.

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

We examine the impact of the FFF protest movement in Germany on citizen political behavior, politicians, and the media.[1] While it is known that mass protests can change political attitudes and behaviors (see, e.g., Enos *et al.*, 2019, Wasow, 2020, Reny and Newman, 2021), FFF differs from other social movements in the scale of its demands and the intergenerational trade-offs involved in them. The young FFF activists belong to a politically marginalized group whose future well-being is at imminent threat from further delay in climate action (Stern, 2007). However, whereas a large portion of the benefits of mitigation efforts would accrue to their future selves, the costs would have to be incurred now, impacting prices and consumption beyond what adult voters and economic actors appear willing to bear. This is evidenced, for example, by not-in-my-backyard reactions and opposition from organized groups that surface when climate change policies are about to be implemented (Stokes, 2016).[2] Understanding whether FFF managed to shift this resistance offers broader lessons about the political economy of climate change (Besley and Persson, 2020) and the modeling of time preferences in cost-benefit assessments of climate policies (Nordhaus, 2007).

The main question we address is 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

[1] As will be described in more detail later, the FFF movement has been particularly strong in Germany, evidenced by thousands of local climate protests staged across the country throughout 2019.

[2] In France, for example, attempts to increase carbon taxes on consumers led to significant street protests and demonstrations in the form of the "Gilet Jaunes" mass movement (Royall, 2020). Similar examples abound across the globe.

constituency is high. And third, we examine whether higher rates of climate protest participation shape the content of local media.

A key 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 manually 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. To measure local participation in these protests, we then 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. Finally, we draw on the related literature (e.g., Collins and Margo, 2007) and exploit local rainfall as an instrumental variable (IV) for 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 0.76 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 13% 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 have shifted voters away from other major political parties and toward the Greens.

A unique feature of the FFF movement compared to others social movements has been that the young set out to convince older generations to act on climate change. We therefore explore whether FFF's effect on voting behaviour may partly be explained by "reverse intergenerational transmission": Youth involvement in the FFF movement may increase their parents' concerns about climate change and thus their proclivity to vote the Greens. Although a direct test of this mechanism is impossible due to data limitations,[3] we find strong indirect, suggestive evidence in support of it. In particular, 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.

Turning to other factors that might explain our results, we argue that two complementary mechanisms might also be at play. The first builds on the idea that the FFF movement might affect how political candidates publicly position themselves toward climate change, and this has influenced voters' evaluation of candidates and, ultimately, their vote decision. Based on a politician×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 politician posting climate-related content by 18%.

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 22%.

Where do these results leave us? Besley and Persson (2020) have recently coined the notion of a "climate trap". In their model, a transition to a low-pollution economy is technologically feasible, but it does not materialize because it is not jointly optimal for consumers, policymakers, and economic actors to push for change. Compara-

[3] At a minimu, such a direct test would require information on children's environmental activism linked with data on their parents' political attitudes and behaviors, which, to the best of our knowledge, is not available at present from any German data source.

tive statics show that an enhanced influence of environmentalists can propel society 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 climate trap. In particular, youth participation in FFF appears to have influenced their parents' political behavior, as well as influencing how politicians publicly position themselves toward climate change, and impacting the intensity of media reports on environmental issues.

Our findings also offer a lesson for the modeling of time preferences in cost-benefit analyses of climate policies. The question in these assessments is whether it is worthwhile to sacrifice costs of, say, 1% of GDP now to remove climate damages of 5% of GDP a few decades from now. This calculation is typically performed assuming that there exists a time-invariant pure discount rate, capturing an inborn impatience that makes individuals prefer consumption today over consumption tomorrow (Nordhaus, 2007). Our results question this assumption, suggesting instead an approach that allows preferences to evolve as facts from climate science become more salient. Indeed, since the vote decision can be thought of as a measure of revealed preferences (Samuelson, 1987), the fact that FFF caused people to vote green suggests that these are not time-invariant.

Our paper touches upon several strands of literature. Political scientists have recently made significant inroads in empirically analyzing climate change and environmental issues. This has involved work on, *inter alia*, electoral backlash against climate policy (Stokes, 2016), corporate opposition to climate action (Cory *et al.*, 2021), preferences over different forms of climate-related compensation for vulnerable communities (Gaikwad *et al.*, 2022), or the nexus between economic development and gender-specific concerns about climate change (Bush and Clayton, 2023). While this literature has largely focused on politico-economic barriers to moving forward with climate change mitigation, we study whether one of history's largest youth climate movement affected the electorate's demand for green politics, as well as the mechanisms involved in it. Perhaps the closest antecedent of our work is the paper by Hungerman and Moorthy (2022), who demonstrate that activism during the original 1970 Earth Day had long-lasting effects on individuals' environmental attitudes.

Our study also speaks to empirical work on the intergenerational transmission of political attitudes and behaviors. While a substantial part of the literature has highlighted how older generations pass these down to younger generations (Jennings and Niemi, 1968, Tedin, 1974, Sears and Funk, 1999, Plutzer, 2002, Jennings *et al.*, 2009), only few studies have looked into reverse intergenerational transmission whereby children affect the attitudes and behaviors of their parents through trickle-up effects. There exists evidence that educational programs aimed at fostering the political awareness of students lead to higher voter turnout and civic engagement among their parents (Simon and Merrill, 1998, Linimon and Joslyn, 2002, McDevitt and Kiousis, 2006). More recently, it has been causally established that parents' political participation increases when their children enter the electorate (Dahlgaard,

2018). A particularly relevant subset of studies has explored whether children can foster climate change concerns among their parents (Damerell *et al.*, 2013, Lawson *et al.*, 2019).

On the data front, a study closely related to ours is that of **?**, who use cell phone location data to estimate protest size variation during the 2017 United States Women's Marches. On the empirical front, we follow in parts ideas from Collins and Margo (2007) who studied the economic impacts of the 1960s riots in American cities by using local rainfall as an instrumental variable to isolate plausibly exogenous variation in riot severity. Subsequently, this approach has been adapted by Madestam *et al.* (2013) and Klein Teeselink and Melios (2021) to investigate the political consequences of the Tea Party and Black Lives Matter movements, respectively.

2 Background

2.1 Fridays for Future

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 protests in March, May, September, and November. Each event drew huge crowds. For the September protest, the largest of the four, FFF organized 6,000 protests in 185 countries, mobilizing around 7.6 million people (De Moor *et al.*, 2020).

In Germany, the first climate protests occurred in late 2018, but these were restricted to a handful of cities and few activists (Sommer *et al.*, 2019). Starting in early 2019, the German FFF 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 a further boost in March when Greta Thunberg attended rallies in Berlin and Hamburg. March 15 saw the first global climate protest, with an estimated 300,000 people taking to the streets of Germany. Climate rallies continued throughout the year. Organized by local FFF chapters, these typically took place on Fridays (Smith and Bognar, 2019). The protesters were mostly high school or college students who skipped classes to attend rallies, with many of them positioning themselves on the left of the political spectrum (Sommer *et al.*, 2019, De Moor *et al.*, 2020).[4] In the two years after 2019, the spread of COVID-19 made street rallies impossible over extended periods and FFF protests in Germany largely ground to a halt (Hockenos, 2020). Our analysis will therefore explore the political impacts of the 2019 climate protests.

[4]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).

Figure 1 visualizes the temporal dynamics of the FFF protests in Germany 2019. The solid black line represents the cumulative number of protests across time.[5] Drawing on Politbarometer (2019) surveys, we now provide some first empirical evidence that the 2019 FFF movement was successful in raising public awareness of climate issues and changing public attitudes (Forschungsgruppe Wahlen, 2019b, Smith and Bognar, 2019). The survey asks respondents, *inter alia*, 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 steeply increased from around 10% to almost 60% over the course of 2019. Foreshadowing our regression results, a positive correlation between FFF protest activity and climate concern is clearly visible. Finally, the inset figure highlights that awareness and prioritization of climate-related issues is a phenomenon that only gained prominence in 2019. 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 increase dramatically.

2.2 Germany's Political Landscape

Unlike the United States, Germany has a multiparty system. 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 right-of-centre party Union is made up of two parties: the CDU (Christian Democratic Union) and the CSU (Christian Social Union). In elections to the federal parliament, the CSU stands in Bavaria, whereas the CDU competes in the remaining 15 federal states. The left-of-centre party SPD is the second major party and has close ties with Germany's worker unions.

In addition to the Union and the SPD, there are four 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 can be considered as left-wing populist. Finally, (f) the AfD (Alternative for Germany) can be classified as right-wing populist and critical of climate science.

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

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.[6] 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. We now describe these data sources in details, with summary statistics for each of them provided in the supplementary materials.

3.1 Cell Phone-Based Mobility Data

We obtain proprietary 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.[7] 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.[8] In 2019, this mobile network provider had a market share of 31%. To obtain mobility patterns representative of the total population, Teralytics extrapolates measured mobility based on O_2's regional market share. For 2019, we observe 64.4 billion journeys between county pairs.

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

[7] 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.

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

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 (e.g., city councils, the police) must be notified of public gatherings, such as rallies and demonstrations at least two weeks in advance. We contacted all relevant authorities and requested a complete list of climate protests registered in their jurisdictions during 2019. A total of 44% of the authorities responded to our request, providing precise information on the location and time of 1,938 protests. To fill in existing gaps and ensure that we consider marches that were not registered with authorities, we supplement the protest data with information on protest location and date extracted from social media posts (Twitter, Facebook, and Instagram), and protest activity reported on the official website of FFF Germany. These sources provided us with an additional 1,968 strikes.[9] 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. Panel (b) shows that the protest activity was continuous throughout the year. Furthermore, regular spikes in the number of protests are discernible on Fridays as well as on the four global climate events in March, May, September and November.

3.3 Election Data

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

The European parliament and the state elections take place approximately every five years. Results of the European Parliament (EP) elections are taken from the Federal Statistical Office and the Statistical Offices of the Länder. The EP election dates for our analysis are May 26, 2019 versus May 24, 2014. For state elections, we use data from the State Returning Officers (*Landeswahlleiter)* and the Statistical Offices of the Länder. The state elections in our sample and their dates are: Bremen (26 May 2019 versus 10 May 2015), Saxony (1 September 2019 versus 31 August 2014), Brandenburg and Thuringia (27 October 2019 versus 14 September 2014), Hamburg (23 February 2020 versus 15 February 2015), Baden-Württemberg and Rhineland-Palatinate (14 March 2021 versus 13 March 2016), Saxony-Anhalt (6 June 2021 versus 13 March 2016), Mecklenburg-Western Pomerania (26 September 2021 versus 4 September 2016), and Berlin (26 September 2021 versus 18 September 2016). A Federal Returning Officer (*Bundeswahlleiter*) reports the results of federal

[9] 1,583 additional strikes were retrieved from the website of FFF Germany, 385 from social media posts.

elections. Unlike European and state elections, the federal elections occur every four years, and we will analyse if the protests of 2019 induced changes in the Greens' vote share between the federal elections in September 26, 2021, and September 24, 2017. In total, our election dataset encompasses 960 observation at the county×election level.

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.[10] 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 respondents' county of residence which enables us to link the survey to our protest participation data.

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.3. 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 dependent variable.

3.6 Newspaper Data

We obtain newspaper content from the GENIOS Online Press Archive.[11] This archive gives access to articles from 281 German print media outlets.[12] Using key-

[10] 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))

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

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

word searches, we identify the number articles for each outlet and publication date featuring climate change-related content using the keywords listed in Table A.3.

We link protest participation to media content using the area of circulation of the newspapers. To this end, we first match each newspaper with information on its readership's geographical distribution. The readership data is provided by the German Audit Bureau of Circulation (IVW), 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.[13] Our final newspaper×day dataset encompasses 130 news outlets and covers the year 2019.

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 to our dependent 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

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

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.

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

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. These fixed effects estimates represent the mean values of journeys between region pairs, i.e., the average number of journeys between regions. The indicator variables $NS_{r(i)r(j)t}$ is equal to one if there is no FFF event in neither $r(i)$ or $r(j)$. The inclusion of this indicator implies that we are only including non-strike days in the estimation of the average—i.e., typical—bilateral mobility pattern.[14] To account for temporal variation in the mobility patterns, we include date fixed effects (φ_t).[15]

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:

$$e_{ijt} = \sum_{r(j)\in j} \sum_{r(i)\in i} (\text{journeys}_{r(i)r(j)t} - \widehat{\vartheta_{r(i)r(j)}} - \widehat{\varphi}_t), \tag{2}$$

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 (Section 3.2). This enables us to identify which excess flows reflect journeys to climate protest. For each county and day, we then compute its

[14] Including strike days in the estimation of $\vartheta_{r(i)r(j)}$ typically 'mechanically' increases average flows, making detection of smaller protests more difficult.

[15] A more conservative specification would include county×day fixed effects. Our estimates below are robust to this extention. Results can be obtained by the authors.

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^{F}_{it}) 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^{H}_{it}.

4.2 Cumulative County-Level Protest Participation Measure

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

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

where $\tilde{t}$ represents the day before the election. 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).[16] As with the daily data, the overwhelming part of the total cumulative protest participation ($\mathrm{P}_{i\tilde{t}}$) variation is driven by participation in marches held in the home county ($\mathrm{P}^{H}_{i\tilde{t}}$).

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

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:

$$\Delta(\text{Share Greens}_{i,\tilde{t}}) = \beta\, \mathrm{P}_{i\tilde{t}} + \tau_{s,\tilde{t}} + \mu \mathbf{X}_{i,\tilde{t}} + \xi_{i,\tilde{t}}, \tag{6}$$

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 $\tilde{t}$.[17] 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,

[16] 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.

[17] 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.

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 (6) 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 we obtain the same pattern of results if we employ rainfall as an instrumental variable for protest participation.

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 a statistically significant 0.76 percentage points. To aid in interpretation, 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 13% 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 6.223 percentage points compared to preceding elections, the point estimate of 0.124 in column 4 only corresponds to a rise of 2%. Furthermore, we find that the coefficients in columns 1 and 2 remain virtually unchanged if we re-run the regressions while additionally controlling for changes in voter turnout (see Table A.7 in the supplementary material). These 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.[18] 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.

In Panel B of Table 1 we reproduce the results using an alternative measure of local protest activity: the cumulative number of FFF protests a county experienced up to the date of an election, standardized with mean 0 and standard deviation of 1. We continue to find a strong association between FFF protest activity and the Greens' electoral fortunes: a one-standard deviation increase in the number of FFF protests in a county increases the Greens' vote share by 0.57 to 0.58 percentage points. The fact that the point estimates in Panel B are smaller compared to Panel A suggests that our main measure based on cell phone mobility data contains more information than the measure based only on the location and number of protests.

5.3 Robustness

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

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

Finally, we demonstrate that our results are unlikely to be the result of chance. To that end, we permute protest participation across counties at random and then re-

[18] That is, we look at vote share changes between 2014 and 2019 (European Parliament elections) and between 2017 and 2021 (federal elections). For state elections the two elections two election fall within the period 2009–2016.

run model (6). We repeat this exercise 1,000 times and present the results in Figure A.1. Point estimates are centered around 0 and orders of magnitude smaller than the coefficients reported in Table 1 (column 2).

5.4 Instrumental Variable Approaches

As a final approach to support the validity of our results, we implement an instrumental variable approach. We use county-level rainfall levels (in mm) on the first Global Strike Day (15 March 2019) as an exogenous shifter for protest participation. Similar to Collins and Margo (2007), the intuition is that increases in precipitation levels deters participation on this first crucial day of coordinated strike action. This, in turn, should also affect future involvement in the FFF movement, resulting in fewer people participating in subsequent climate protests and lowering cumulative strike participation. We extract information on rainfall from the German weather service (DWD).[19] Figure A.2 in the supplementary material presents descriptive, reduced-form evidence on the role that rainfall on the first Global Strike Day played for changes in the Greens' vote share between the 2015 and 2019 EU elections. Panel (a) presents the geographical variation of the change in the Greens' vote share between the 2015 and 2019 EU elections. In Panel (b), we display the spatial variation in the amount of rainfall on March 15, 2019. Regions in the South-East and West witnessed the strongest rainfall on that day, and many of these regions also saw some of the lowest increases in the Greens' vote share in the 2019 EU election. The binscatter plot in Panel (c) confirms that there is indeed a strong negative correlation between rainfall on the day of the first global climate protest and the Green Party's electoral fortunes in the EU election.

Due to the fact that both rainfall—our instrument—and changes in the vote share of the Green party—our dependent variable–are spatially correlated, simple two-stage least squares (2SLS) estimates are likely upwards biased due to spatial feedback effects. To account for this, we follow Klein Teeselink and Melios (2021) and estimate a Spatial Auto Regressive with additional Auto Regressive error structure model (SARAR) using a two-step Generalised Method of Moments (GMM) estimator, initially described by Drukker *et al.* (2013).

To be precise we estimate the following model:

$$\Delta(\text{Share Greens}_{i,\tilde{t}}) = \beta\, \hat{\text{P}}_{i\tilde{t}} + \lambda \sum_{j \neq i}^{N} W_{i,j}\, \Delta(\text{Share Greens}_{j,\tilde{t}}) + \tau_{s,\tilde{t}} + \mu \mathbf{X}_{i,\tilde{t}} + u_{i,\tilde{t}}, \tag{7}$$

$$u_{i,\tilde{t}} = \rho \sum_{j \neq i}^{N} W_{i,j}\, u_{j,\tilde{t}} + \epsilon_i \tag{8}$$

with λ and ρ the parameter that reflect the intensity of the spatial interdependence in the outcome variable and the error term and that need to be estimated. $W_{i,j}$ is

[19] https://opendata.dwd.de/climate_environment/CDC/grids_germany/hourly/radolan/historical/asc/, accessed on 10.11.2022.

the exogenous weight matrix that governs the structure of the spatial relationship in outcome and error term. In our case, the weight matrix consists of the bilateral inverse distances between counties in our sample. ϵ_i is an idiosyncratic error term. $\hat{\mathrm{P}}_{i\tilde{t}}$ represents protest participation instrumented with rainfall level on the first Global Strike Day (15 March 2019). The additional covariates in equation (7) are described in our main specification in equation (6).

Table 2 reports the results of our IV estimates. Due to the fact that we estimate the non-linear model (7) with a GMM estimator, an explicit first-stage regression does not exist. Columns 1 and 2 therefore show 'relevance' tests, indicating that rainfall on the day of the first global climate strike indeed strongly predicts (i) protest participation on this day and (ii) cumulative protest participation. Column 3 depicts the results of the reduced-form effect of rainfall on the vote share of the Greens. Consistent with our prior, higher precipitation levels on the day of the first Global Climate Strike reduces support for the Greens significantly. In column 4, we quantify the effects of our strike participation measure using the two-step GMM-IV approach. The statistically significant point estimate implies that a one standard deviation increase in protest participation leads to a 0.55 percentage point gain for the Greens. Compared to the the OLS results in Table 1, the GMM-IV results are somewhat smaller but statistically indistinguishable. This lends further support to the plausibility of our OLS estimates in Table 1. In the final column of Table 2, we re-run the placebo test using our GMM-IV approach. Reassuringly, we continue to obtain a small and statistically insignificant estimate. For completness, Table A.6 in the supplementary material shows the corresponding standard 2SLS estimates, which are qualitatively similar but—as expected—with larger point estimates.

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 electoral shift towards the Green Party. We investigate the viability of three mechanisms: reverse intergenerational transmission of pro-environmental attitudes from children to parents, shifts in politicians' public stance on climate issues, and increased newspaper coverage of climate change.

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:

$$V_{r,i,t} = \theta_p \, \mathrm{P}_{i,\tilde{t}} \times \mathrm{Kids} + \theta_n \, \mathrm{P}_{i,\tilde{t}} \times (1 - \mathrm{Kids}) + \delta_i + \tau_t + \mu \mathbf{X}_{r,i,t} + \xi_{r,i,t}. \tag{9}$$

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 our estimation results. The dependent variable in column 1 is a dummy for not having voted for the Greens in the previous general election but intending to do so at the time of the interview. On average, 15% of respondents state an intention to switch party allegiance to the Green Party. A one-standard-deviation increase in local protest activity increases switching intention by 0.4 percentage points among respondents with children. However, there is no significant effect on respondents without children's switching intentions. In columns 2 to 6, we look at which parties are bringing in new voters for the Greens. We observe that the climate movement has caused parents who previously voted for Germany's two major political parties (The Union and SPD) to switch allegiance to the Greens. This is not the case, however, for respondents without children. The pattern of results for the three smaller parties is more varied. Respondents who previously supported the FDP are less likely to switch to the Greens, but only if they have no children (column 4).[20] There are no significant FFF-induced changes in switching intentions among supporters of the Left or the AfD, neither for 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

[20]The views of the Greens and the FDP on how to tackle climate change are vastly different, with the former advocating tougher environmental laws and regulations and the latter calling for market-based solutions. This, together with the fact that FFF has made climate change issues more salient, may have prevented FDP voters from switching to the Greesn.

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 to divide total protest participation into two dimensions: participation in protests held in one's own (home) county and in rallies held elsewhere.[21] 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 4 demonstrates that this is indeed the case. Column 1 shows that a one-standard-deviation higher within-county protest participation increases the Green Party's vote share by 0.36 percentage points. However, as can be seen in column 2, away-from-home protest participation causes an even stronger increase in the Green support in the home county: a one-standard-deviation increase in this measure causes the Green Party's vote share to increase by 0.5 percentage points. This is a remarkable result, 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 0.025 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

$$S_{p,c,t} = \gamma \mathrm{P}_{c,t} + \psi_p + \zeta_{s,t} + \varepsilon_{p,c,t}, \tag{10}$$

[21] See Section 4 for more details.

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 State×date (see, e.g., Cameron *et al.*, 2011).

Table 5 presents the results. Column 1 shows that MPs are significantly more likely to tweet about climate change when the protest activity in their electoral district is high. A one-standard-deviation increase in a constituency's protest activity raises the share of climate tweets its 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 politicians of each 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 more than two times larger than the average effect reported in column 1. Column 2 also shows that increased protest activity encourages members of the Left Party and—somewhat surprisingly—the AfD to post more climate change-related content. Relative to Green Party MPs, the size of the effect is considerably smaller. The increased posting activity of AfD members likely represents their stance against climate change mitigating policies. In fact, by far the majority of tweets from AfD politicians in our sample contain negative statements about FFF activity. Coefficients are small and statistically non-significant for members of the SPD, Union, and FDP. This lack of reaction could be due to conflicts between the demands of the FFF movement and core party voters' (perceived) preferences.

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:

$$A_{n,r,t} = \gamma \mathrm{P}_{r,t-1} + \psi_{n,r} + \zeta_t + \varepsilon_{n,r,t}, \tag{11}$$

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:

$$\Delta A_{n,r,} = \alpha + \theta \mathrm{P}_{r,\tilde{t}} + \epsilon_{n,r}. \tag{12}$$

The dependent variable $\Delta A_{n,r}$ represents the difference in the total number of climate change articles published between August and December of 2019 (i.e., after FFF started) and the same period in 2018 (i.e., before FFF took off). 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 6 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 (12). Column 2 displays the results. We see significant long-term effects of local protest activity. In the period August through December 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 count by almost 70, or 22%.

7 Concluding Remarks

It is widely accepted that keeping global warming within 2°C would avoid more economic losses globally than the cost of achieving the goal (IPCC, 2022). There is also scientific agreement that climate action is needed now, as each additional year of delay in implementing mitigation measures is estimated to cost an additional 0.3–0.9 trillion dollars in total (discounted) future mitigation costs, if the 2°C target is to be ultimately met (Sanderson and O'Neill, 2020). However, continued climate inaction has left many observers pessimistic about avoiding the worst damage from climate change.

Perhaps such pessimism is not entirely warranted. When society is close to a tipping point, where either continued climate inaction or a green transformation are possible future outcomes, even small exogenous shocks can determine the dynamic path it takes. In the model of Besley and Persson (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 13%, 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.

Our study also offers a contribution to measuring how engagement in large social movements evolves spatially and temporally. Many such movements center around large protests or demonstrations in central locations. However, information on protest location and size alone is not sufficient to inform us where support for a movement comes from. Using cell-phone based mobility data, we have developed and cross-validated a measure of protest participation that approximates the geographic distribution of participants at thousands of FFF rallies. We believe

this approach could be a useful tool for mapping out the evolution of social mass movements in future studies. It could also be applied to other contexts in which movements and gatherings of large number of people matter, such as in political uprisings or revolutions.

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Figures and Tables

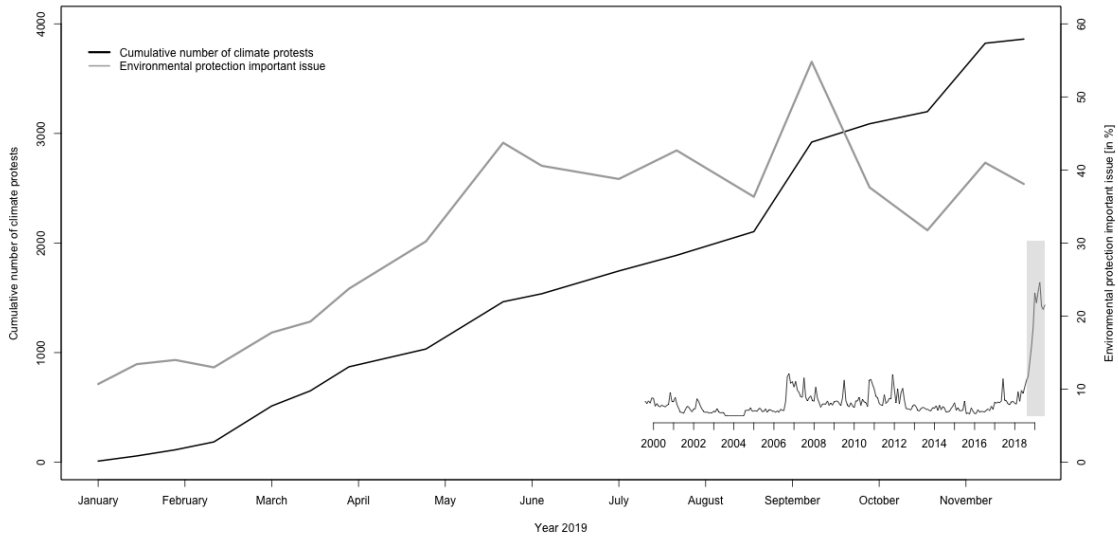


Figure 1. Protest activity and public opinion
The black line depicts the cumulative number of climate protests in Germany in 2019 (black line). Protest data are hand-collected from various sources (see Section 3 for details). The grey line represents the proportion of individuals naming environmental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

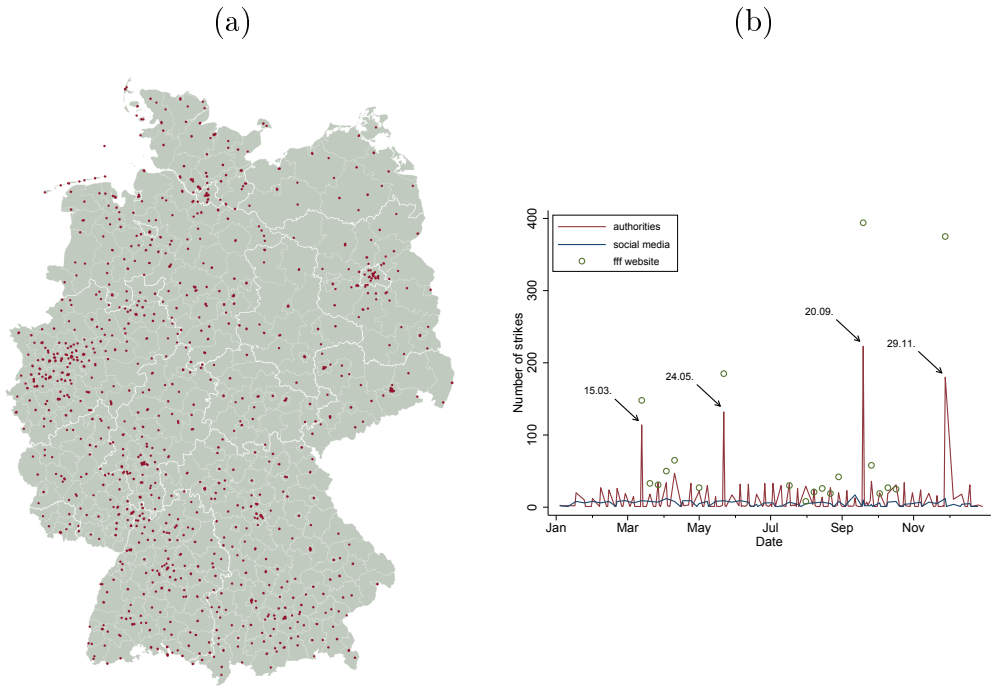


Figure 2. Locations of climate strikes in 2019
Panel (a): Map depicts the location of climate strikes (red dots) for year 2019. The bold white lines represent state boundaries whereas the thin white lines represent county borders. Panel (b): Figure depicts the daily number of strikes by data soruce.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

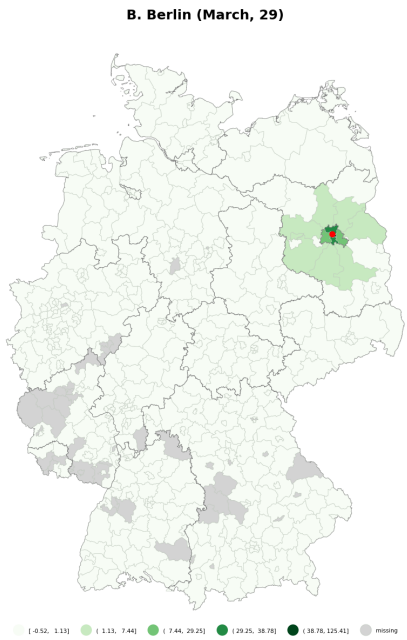


Figure 3. Strike participation for selected strikes
Notes: Map shows counties' protest participation (as defined by Eq.(3)) in the climate protest that occurred in Berlin on 19 March 2019. A darker shade of green indicates higher protest participation. The color scale classification is obtained using 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.

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

Dependent variable:	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:						
Participation index (SD)	0.759***	0.745***	0.110*	0.138**	-0.094	0.056
	(0.105)	(0.105)	(0.065)	(0.066)	(0.085)	(0.094)
Δ Log total population	31.778***	33.642***	16.727***	11.992***	-3.847	10.406
	(3.204)	(3.643)	(3.934)	(4.631)	(2.667)	(6.411)
Δ Share minors	-82.653***	-81.209***	-47.094	-58.558*	-85.298***	30.309
	(26.730)	(27.327)	(33.764)	(32.748)	(19.076)	(35.630)
Δ Average age	-1.573***	-1.461***	0.108	-0.218	-0.662***	0.809*
	(0.314)	(0.343)	(0.383)	(0.415)	(0.242)	(0.451)
Δ Log GDP per capita		-0.315		0.257	1.342	5.250*
		(1.997)		(2.408)	(1.360)	(2.891)
Δ Unemployment share		-0.107		0.321**	0.111	0.112
		(0.109)		(0.137)	(0.071)	(0.167)
Δ Log labour productivity		0.042		0.033	-0.028	-0.085
		(0.039)		(0.049)	(0.027)	(0.056)
Panel B:						
Number of days with protests (SD)	0.584***	0.575***	0.101*	0.123**	-0.101	0.106
	(0.076)	(0.076)	(0.054)	(0.054)	(0.080)	(0.082)
Δ Log total population	31.988***	34.078***	16.680***	11.951**	-3.697	9.985
	(3.210)	(3.657)	(3.945)	(4.642)	(2.653)	(6.380)
Δ Share minors	-81.284***	-79.623***	-47.081	-58.524*	-85.060***	29.461
	(27.334)	(27.870)	(33.761)	(32.756)	(19.067)	(35.514)
Δ Average age	-1.547***	-1.421***	0.117	-0.209	-0.670***	0.819*
	(0.324)	(0.352)	(0.383)	(0.415)	(0.243)	(0.452)
Δ Log GDP per capita		-0.307		0.267	1.325	5.286*
		(1.988)		(2.408)	(1.355)	(2.892)
Δ Unemployment share		-0.121		0.321**	0.108	0.122
		(0.111)		(0.137)	(0.070)	(0.165)
Δ Log labour productivity		0.046		0.034	-0.028	-0.086
		(0.040)		(0.049)	(0.027)	(0.056)
State×election FE	✓	✓	✓	✓	✓	✓
Mean dependent variable	5.943	5.943	6.223	6.223	-0.268	3.900
Observations	960	960	960	960	960	960

Notes: The results are from ordinary least squared regressions, with White-Huber standard errors reported in parentheses. In Panel A (respectively, Panel B), the protest participation index (respectively, the number of days with protests) is standardized so that the mean is 0 and the standard deviation is 1. All control variables are entered as first differences, symbolized by 'Δ'. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2. Instrumental variables results

Dependent variable:	Participation index 15.03.19 (SD)	Participation index (SD)	Δ Vote share Green Party		Δ Vote share Green Party Placebo
	'Relevance'		Reduced form	IV	IV
	(1)	(2)	(3)	(4)	(5)
Participation index (SD)				0.549**	-0.134
				(0.239)	(0.196)
Rainfall 15.03.19 (SD)	-0.090***	-0.095***	-0.163**		
	(0.027)	(0.023)	(0.076)		
Δ Log total population	1.993	2.954**	36.097***	33.918***	-4.774*
	(1.660)	(1.217)	(3.604)	(3.862)	(2.854)
Δ Share minors	14.713	2.046	-111.168***	-112.709***	-72.888***
	(11.425)	(8.923)	(26.719)	(25.685)	(18.499)
Δ Average age	-0.220	-0.307***	-1.908***	-1.794***	-0.606***
	(0.139)	(0.099)	(0.314)	(0.303)	(0.232)
Δ Log GDP per capita	2.216*	2.687***	4.536*	2.609	0.468
	(1.252)	(1.003)	(2.340)	(2.232)	(1.670)
Δ Unemployment share	-0.135***	-0.106***	-0.226**	-0.161	0.123*
	(0.052)	(0.040)	(0.109)	(0.116)	(0.073)
Δ Log labour productivity	-3.364***	-3.019***	-3.203	-1.105	-0.724
	(1.277)	(1.051)	(2.553)	(2.448)	(1.811)
λ	2.863***	2.247***	0.446***	0.422***	0.938***
	(0.402)	(0.385)	(0.100)	(0.103)	(0.250)
ρ	-2.834	-4.076***	1.326***	1.279***	0.653
	(2.207)	(1.030)	(0.348)	(0.350)	(0.495)
State×election FE	✓	✓	✓	✓	✓
Mean dependent variable	0	0	5.942	5.942	-0.268
Observations	960	960	960	960	960

Notes: Results are from two-step GMM regressions of a Spatial Auto Regressive with additional Auto Regressive error structure model (SARAR). Heteroskedasticity robust standard errors are reported in parentheses. λ and ρ show the spatial autocorrelation parameters for the outcome and the error term as well as the respective t-test statistics in parentheses. The protest participation index is standardized so that the mean is 0 and the standard deviation is 1. All control variables are entered as first differences, symbolized by 'Δ'. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

Dependent Variable:	Switch to Greens	Switch Union to Greens	Switch SPD to Greens	Switch FDP to Greens	Switch The Left to Greens	Switch AfD to Greens
	(1)	(2)	(3)	(4)	(5)	(6)
HH with children ×	0.442***	0.724**	1.214**	1.109	-1.060	-0.281
Participation index (SD)	(0.151)	(0.324)	(0.515)	(1.287)	(0.924)	(0.247)
HH without children ×	-0.171	0.320	-0.198	-2.003**	0.336	0.321
Participation index (SD)	(0.161)	(0.358)	(0.368)	(0.809)	(0.321)	(0.200)
County FE	✓	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓	✓
Previous party	fixed effects	Union	SPD	FDP	The Left	AfD
Individual FE	✓	✓	✓	✓	✓	✓
Mean dependent variable	14.754	11.976	25.388	10.805	14.992	1.389
Observations	76,563	30,245	18,440	6,514	6,439	5,171

Notes: Results from ordinary least squared regressions, with two-way clustered standard errors at the county and week dimension reported in parentheses. The protest participation index is standardized so that the mean is 0 and the standard deviation is 1. 'Previous party fixed effects' are dummies capturing which party the respondent voted for in the previous federal election. 'Individual FE' include fixed effects for age, education, number of children in household, employment, income bracket, and gender. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Protest participation in home county and in away counties

Dependent Variable:	Δ Vote share Green Party	Δ Voter turnout
	(1)	(2)
Participation index in home county (SD)	0.363***	0.088
	(0.112)	(0.068)
Participation index in away counties (SD)	0.499***	0.071
	(0.105)	(0.076)
Δ Log total population	32.511***	11.783**
	(3.631)	(4.642)
Δ Share minors	-91.197***	-57.956*
	(26.926)	(33.509)
Δ Average age	-1.682***	-0.287
	(0.349)	(0.428)
Δ Log GDP per capita	2.227	1.868
	(2.399)	(3.242)
Δ Unemployment share	-0.074	0.344**
	(0.108)	(0.139)
Δ Log labour productivity	-1.075	-0.222
	(2.664)	(3.905)
State ×Election FE	✓	✓
Mean dependent variable	5.943	6.223
Observations	960	960

Notes: The results are from ordinary least squared regressions, with White-Huber standard errors reported in parentheses. The protest participation indices in home county and away counties are standardized so that the mean is 0 and the standard deviation is 1. All control variables are entered as first differences, symbolized by 'Δ'. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Protest participation and politicians' social media presence

Dependent variable:	Share climate tweet	
	(1)	(2)
Participation index (SD)	0.409***	
	(0.117)	
Union ×		0.041
Participation index (SD)		(0.128)
SPD ×		0.169
Participation index (SD)		(0.153)
Greens ×		1.052***
Participation index (SD)		(0.193)
FDP ×		0.232
Participation index (SD)		(0.201)
Left ×		0.651***
Participation index (SD)		(0.189)
AfD ×		0.379*
Participation index (SD)		(0.211)
Politician FE	✓	✓
State×date FE	✓	✓
Mean dependent variable	5.889	5.889
Observations	197,830	197,830

Notes: Results are from ordinary least squared regressions, with two-way clustered standard errors at the politician and state×date dimension reported in parentheses. The protest participation index is standardized so that the mean is 0 and the standard deviation is 1* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Protest participation and newspaper content

Dependent variable:	# articles with climate keywords	
	Daily Panel	Long difference
	(1)	(2)
Participation index (SD)	0.148***	69.601***
	(0.044)	(17.204)
Newspaper FE	✓	✓
Time FE	✓	✓
Mean dependent variable	1.660	321.00
Observations	47,060	130

Notes: Results in column 1 are from ordinary least squared regression, with two-way clustered standard errors at the newspaper and day dimension reported in parentheses. Results in column 2 are from ordinary least squared regression, with White-Huber standard errors reported in parentheses. The protest participation index is standardized so that the mean is 0 and the standard deviation is 1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Supplementary Materials

A Additional Figures and Tables

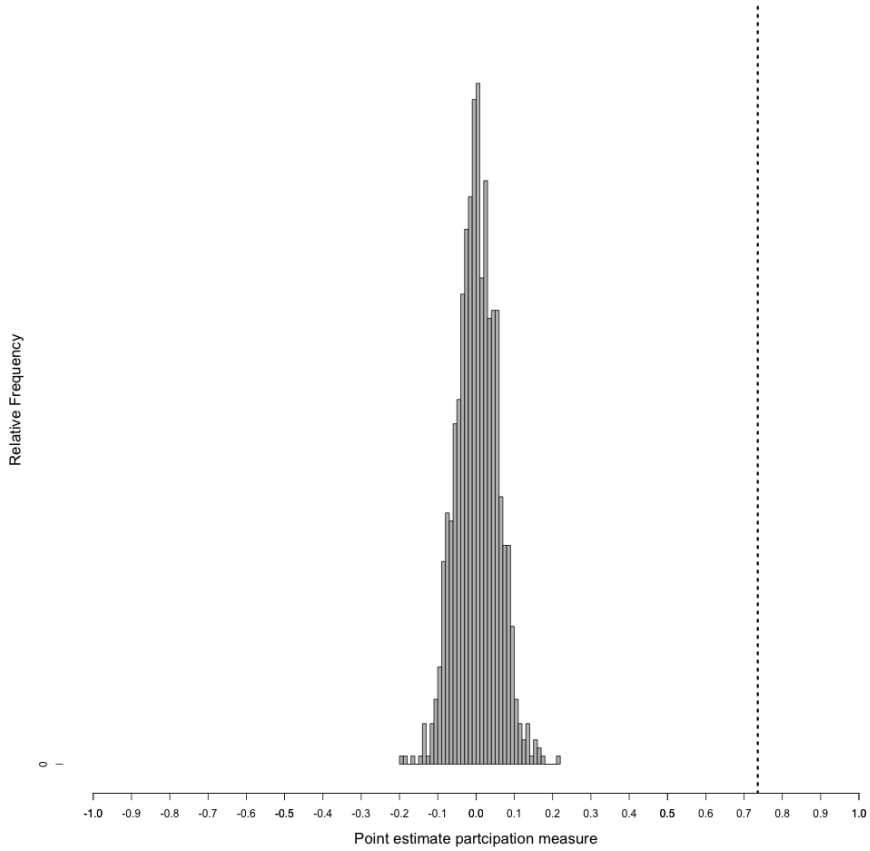
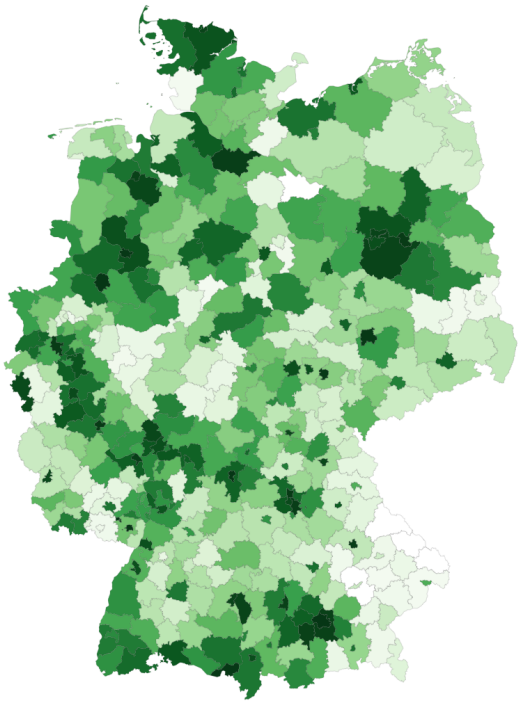
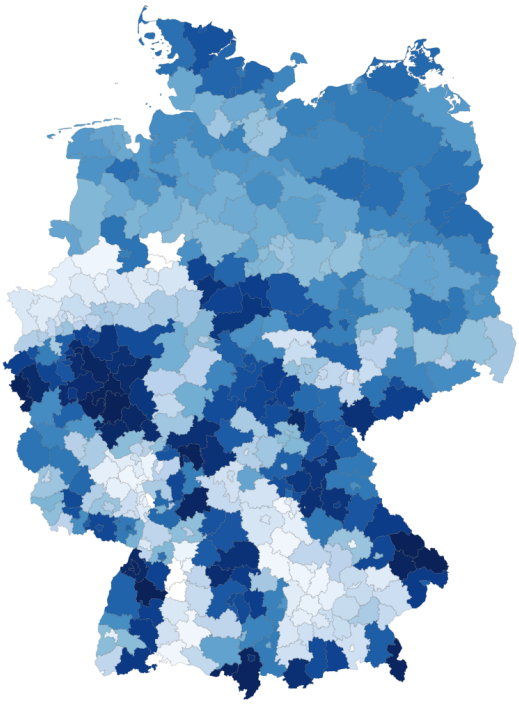


Figure A.1. *Randomisation*
Note. Figure depicts the distribution of point estimates obtained from 1,000 random permutation of cumulative protest participation across counties as defined by equation (5). The dashed black vertical line at 0.497 represents point estimate obtained using the actual protest participation data (see Table 1, column (2)).

(a) Δ Vote share Greens in 2019 EU election



(b) Rainfall on March 15, 2019 (first global climate protest)



(c) Correlation Δ vote share Greens and rainfall on March 15, 2019

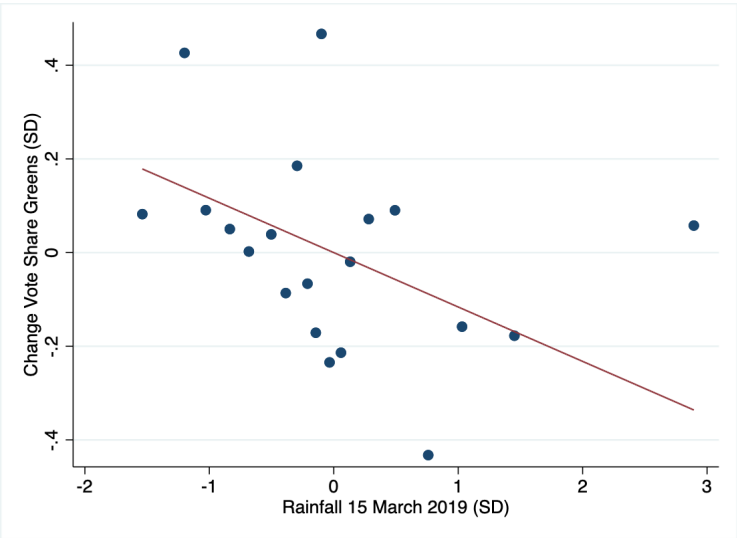


Figure A.2. Spatial variation across counties
Panel (a) depicts the change in the vote share of the Greens for elections to the European Parliament on 26.05.2019. Panel (b) depicts the amount of rainfall (mm) on 15 March 2019. Panel (c) depicts the binned scatter plot (20 bins) of the standardized change in vote share of the Greens (EU election) and the standardized amount of rainfall (mm) on March 15, 2019. Federal state fixed effects partialled out throughout. Darker shadings in (a) and (b) indicate higher values.

Table A.1. Descriptive statistics of key variables: Elections data

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Δ vote share Greens	5.943	4.043	-7.431	19.655	960
Δ turnout	6.223	7.887	-10.595	23.835	960
Cumulative protest participation index (SD)	0	1	-0.542	12.261	960
Rainfall 15.03.19 (SD)	0	1	-1.292	5.327	960

Notes: '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. 'Cumulative protest 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 15.03.19 (SD)' is the county-specific rainfall level on the first Global Strike Day (15 March 2019).

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

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
HH with children×Cumulative protest participation (SD)	-0.006	0.429	-.500	7.131	76,563
HH without children×Cumulative protest participation (SD)	0.006	0.903	-.501	7.131	76,563
Switch to Greens	14.753	35.464	0	100	76,563
Switch from Union to Greens	11.975	32.468	0	100	30,245
Switch from SPD to Greens	25.388	43.524	0	100	18,440
Switch from FDP to Greens	10.805	31.047	0	100	6,514
Switch from the Left to Greens	13.226	33.880	0	100	6,439
Switch from AfD to Greens	1.294	11.305	0	100	5,171

Notes: 'Cumulative protest participation (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. 'Switch from Union to Greens' is a dummy indicating whether a respondent intends to vote for the Greens in the next federal election having previously voted for the Union. 'Switch from FDP to Greens' is a dummy indicating whether a respondent intends to vote for the Greens in the next federal election having previously voted for the FDP. 'Switch from the Left to Greens' is a dummy indicating whether a respondent intends to vote for the Greens in the next federal election having previously voted for the Left. 'Switch from AfD to Greens' is a dummy indicating whether a respondent intends to vote for the Greens in the next federal election having previously voted for the AfD.

Table A.3. 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.4. Descriptive statistics of key variables: Twitter data

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Obs.**
Share climate tweets	5.888	19.324	0	100	197,830
Cumulative protest participation (SD)	0	1	-0.153	28.912	197,830
Union×Cumulative protest participation (SD)	-0.008	0.455	-0.156	18.436	197,830
SPD×Cumulative protest participation (SD)	-0.002	0.480	-0.156	18.436	197,830
Greens×Cumulative protest participation (SD)	0.006	0.401	-0.156	18.436	197,830
FDP×Cumulative protest participation (SD)	-0.002	0.338	-0.156	18.436	197,830
Left×Cumulative protest participation (SD)	0.007	0.437	-0.156	18.436	197,830
AfD×Cumulative protest participation (SD)	-0.001	0.310	-0.156	18.436	197,830

Notes: Share climate tweet is the share of climate tweets in total tweets in percentage points posted by a politician on a given day. 'Cumulative protest participation (SD)' is the standardized daily participation index, as defined by equation (3). 'Union' is a dummy equal to one if the political is member of the Union. 'Union' is a dummy equal to one if the political is member of the Union. 'SPD' is a dummy equal to one if the political is member of the SPD. 'Greens' is a dummy equal to one if the political is member of the Greens. 'FDP' is a dummy equal to one if the political is member of the FDP. 'Left' is a dummy equal to one if the political is member of the Left . 'AfD' is a dummy equal to one if the political is member of the AfD.

Table A.5. Descriptive statistics of key variables: Newspaper data

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Obs.**
	PanelA: Newspaper×day-level sample				
# of articles with climate keywords	1.660	2.991	0	95	47,060
Cumulative protest participation (SD)	0	1	-.117	88.260	47,060
	Panel B: First-difference sample				
Δ Number of articles with climate keywords	321.000	206.718	-15	1,324	130
Cumulative protest participation (SD)	0	1	-.436	9.233	130

Notes: Panel A: '# 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.3). 'Cumulative protest participation (SD)' is the lagged standardized daily participation index, as defined by equation (3).
Panel B: '# 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.3.) 'Participation index (SD)' is the standardized cumulative participation index, as defined by equation (5).

Table A.6. IV Results

	Δ Vote share Green Party		Δ Vote share Green Party Placebo
	(1)	(2)	(3)
Participation index (SD)		1.513*	0.053
		(0.827)	(0.584)
Rainfall 15.03.19 (SD)	-0.150*		
	(0.077)		
Δ Log total population	36.372***	28.938***	-4.901
	(3.748)	(5.796)	(4.236)
Δ Share minors	-74.642***	-90.053***	-89.706***
	(24.250)	(26.512)	(19.378)
Δ Average age	-1.749***	-1.483***	-0.593**
	(0.316)	(0.332)	(0.243)
Δ Log GDP per capita	5.806**	1.291	-0.436
	(2.415)	(3.222)	(2.355)
Δ Unemployment share	-0.158	0.029	0.118
	(0.104)	(0.145)	(0.106)
Δ Log labour productivity	-5.026*	-0.008	0.608
	(2.672)	(3.608)	(2.637)
	First-stage: Participation index (SD)		
Rainfall 15.03.19 (SD)		-0.099***	-0.099***
		(0.026)	(0.026)
State×election FE	✓	✓	✓
Mean dependent variable	5.943	5.943	-0.268
Kleibergen-Paap F statistic		14.989	14.989
Observations	960	960	960

Notes: Results are from two-step least square regressions. Heteroskedasticity robust standard errors are reported in parentheses. The protest participation index is standardized so that the mean is 0 and the standard deviation is 1. All control variables are entered as first differences, symbolized by 'Δ'. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7. Protest participation, vote share for the Green Party, and voter turnout

Dependent	Vote share Green Party	
	(1)	(2)
Participation index (SD)	0.740***	0.741***
	(0.065)	(0.106)
Δ voter turnout		-0.004
		(0.028)
Δ Log total population	33.338***	33.389***
	(3.674)	(3.666)
Δ Share minors	-79.267***	-79.512***
	(27.042)	(26.991)
Δ Average age	-1.585***	-1.586***
	(0.349)	(0.349)
Δ Log GDP per capita	3.395	3.404
	(2.414)	(2.408)
Δ Unemployment share	-0.069	-0.068
	(0.108)	(0.109)
Δ Log labour productivity	-2.395	-2.396
	(2.676)	(2.676)
State ×Election FE	✓	✓
Mean dependent variable	5.943	5.943
Observations	960	960

Notes: The results are from ordinary least squared regressions, with White-Huber standard errors reported in parentheses. Protest participation index is standardized so that the mean is 0 and the standard deviation is 1. All control variables are entered as first differences, symbolized by 'Δ'.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. White-Huber standard errors are reported in parentheses.

Table A.8. 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)			0.573***	0.926***	0.825***	0.839***	0.593***	0.791***
			(0.086)	(0.140)	(0.145)	(0.116)	(0.206)	(0.123)
Log Participation Index	0.864***							
	(0.114)							
Participation Index per Capita (SD)		0.309***						
		(0.089)						
Δ Log total population	31.473***	38.548***	33.943***	33.672***	31.930***	29.720***	30.866***	36.671***
	(3.662)	(3.874)	(3.772)	(4.336)	(3.927)	(3.624)	(4.798)	(5.594)
Δ Share minors -80.097***	-60.384**	-73.946***	-46.132	-74.171**	-77.089***	-95.763***	-66.229	
	(26.919)	(28.302)	(27.394)	(31.239)	(29.590)	(26.606)	(35.050)	(40.452)
Δ Average age	-1.580***	-1.410***	-1.664***	-1.390***	-1.525***	-1.704***	-1.507***	-1.665***
	(0.346)	(0.372)	(0.351)	(0.380)	(0.382)	(0.339)	(0.477)	(0.502)
Δ Log GDP per capita	3.794	6.113**	4.295*	6.702**	3.520	3.728	7.416**	0.036
	(2.451)	(2.572)	(2.483)	(3.185)	(2.573)	(2.404)	(3.743)	(3.120)
Δ Unemployment share	-0.090	-0.134	-0.095	-0.106	-0.182	-0.100	-0.022	-0.111
	(0.108)	(0.112)	(0.110)	(0.124)	(0.113)	(0.108)	(0.150)	(0.155)
Δ Log labour productivity	-2.731	-5.500*	-3.283	-4.941	-3.454	-2.850	-6.375	0.978
	(2.698)	(2.835)	(2.755)	(3.345)	(2.823)	(2.648)	(4.083)	(3.519)
Δ COVID incidence						-0.000***		
						(0.000)		
State×election FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean dependent variable	5.943	5.943	5.943	7.020	5.884	5.943	7.789	4.264
Observations	960	960	960	960	935	960	457	503
Robustness	Log	Per Capita	PPML	Weights	95 percentile	COVID incidence	pre-COVID	post-COVID

Notes: The results are from ordinary least squared regressions, with White-Huber standard errors reported in parentheses. All control variables are entered as first differences, symbolized by 'Δ'. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Validation of the Protest Participation Measure

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.

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.[22] Panel (a) of Figure B.1 depicts the resulting scatterplot. Reassuringly, there is a strong positive correlation between observed and predicted participation. The correlation coefficient is 0.588. Overall, Figure B.1 shows that our method can successfully predict protest crowd sizes.

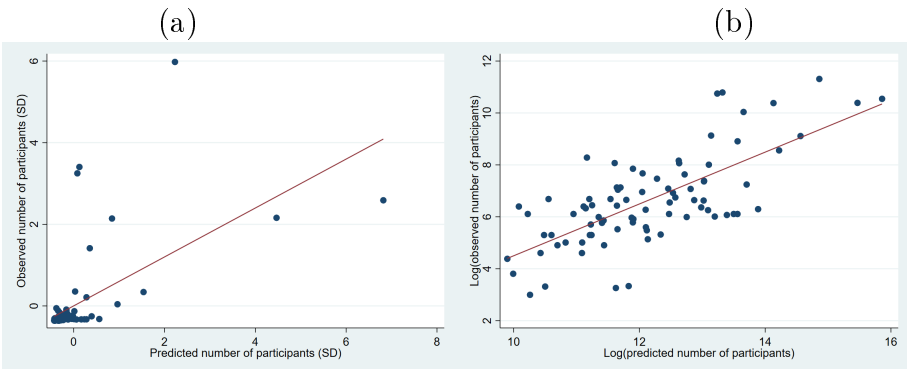


Figure B.1. Validation, strike size
Observed number of participants is the reported cumulative number of protest participants at the protest location up to the European elections as reported by local authorities. Predicted number of protest participants are the cumulative excess journeys to a given protest location (for days with reported participants only) up to the European election as defined by equation (5).
Panel (a) depicts the correlation in levels. Panel (b) depicts the correlation in log values.

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

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

the first and second Bundesliga.[23] 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 B.2 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.

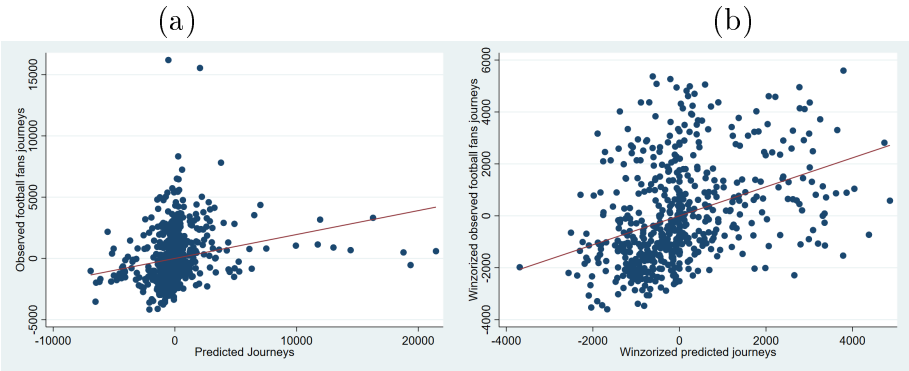


Figure B.2. Validation, soccer fans journeys
Observed football fans journeys are the observed number of supporters of the away team that attend the match (`fuballmafia.de`). Predicted journeys are the mobile phone based predicted excess journeys from the county of the away team to the county of the home 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.

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