Global Networks, Local Protests - Social Media and the Rise of Fridays for Future

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Abstract

How do global social media networks shape collective action? To answer this question, I study the diffusion of the Fridays for Future climate movement in Europe. I construct a weekly panel of local protests and exposure to protests in other European locations through social media connections. Using weather shocks as instruments, I find that increasing protest exposure by one standard deviation doubles the probability of local protest activity in the following week. This implies that, on average, a week of protests causes protests in .28 other locations in the sample through spillovers. Further evidence suggests that online networks can substitute previous political networks, improving local coordination and mobilizing new supporters. Moreover, I investigate how social exposure to protests shifts environmental voting. My findings highlight the role of global network effects in organizing collective action in the age of social media.

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1 Introduction

Social media has transformed political activism. Beyond local impact, viral content can cross regional boundaries and subsequently spark global activism, as illustrated by the MeToo or Black Lives Matter movements. Modern communication technologies have enabled novel horizontal information flows, through which individuals share information directly with each other in real time and independently of geographic distance. Such connections between peers are critical for the local coordination of collective action, such as protests (Barbera et al., 2020; González, 2020), and could similarly shape activism on a global level.[1]

Social media networks could further help resolve coordination problems in policymaking related to climate change. Climate change mitigation measures are difficult to implement since externalities - and the associated free-rider problem - occur on a global scale (Nordhaus, 2015). Individual support for environmental action often depends on the perception of social norms and the cooperation of others (Andre et al., 2022). Yet there is little systematic evidence on how global social media influences climate-related collective action.

In this paper, I study how global social networks shape collective action through social media. I do this in the context of the protests organized by Fridays for Future (FFF), a student-led climate movement, throughout Europe. Combining data on protest time and location with information on interregional connectedness via social media links, I trace the diffusion of the movement following protests in connected locations and analyze how exposure to protest shifted voting behavior.

Estimating the causal effects of social exposure to protests is challenging, particularly due to the likely presence of time-varying unobserved heterogeneity and correlated shocks. Similar locations are usually more connected (homophily), but shared characteristics and attitudes, such as preference for environmentalism, might also affect participation in FFF protests. Even when controlling for baseline characteristics, these attributes might drive a region's protest participation over time. To overcome this empirical challenge, I introduce exogenous variation in the social exposure to protests by using weather shocks (Madestam et al., 2013) to

[1] Social media not only eases global communication, but also facilitates local information sharing and protest organization (e.g., Fergusson and Molina, 2019; Enikolopov et al., 2020).

instrument for protest participation in connected locations. To further eliminate the potential presence of geographically related shocks and to isolate the channel of non-face-to-face interactions on social media, I focus on exposure to protests outside a location's country.

The Fridays for Future protests present an ideal setting to investigate the global network effects of social media. The movement quickly gained international traction after Greta Thunberg's initial protest, aimed at increasing environmental awareness in the upcoming Swedish national election in September 2018, went viral. Fridays for Future's strong social media presence[2] allows me to trace related social media activity in parallel to local protests. The majority of protesters were below voting age and had not been politically active before (Wahlström et al., 2019; De Moor et al., 2020), which highlights protests as an important form of political participation. This is critical in the context of climate action, where traditional politics struggle to address the intergenerational mismatch between decision-makers and younger generations most affected by climate change. Furthermore, the impact of perceived social norms on individual attitudes (Andre et al., 2022; Mildenberger and Tingley, 2019) and other coordination problems associated with the movement's goal of climate change mitigation make information about peers' activism particularly valuable, even when the links are relatively weak, indirect or to geographically distant areas. Such peer effects become even more salient in a setting without government repression and media censorship.[3] Overall, these factors make this a suitable context to study whether network effects of social media are capable of mobilizing supporters globally, which traditional modes of political participation tend to miss.

For my empirical analysis, I construct a weekly region-level panel of local protests and exposure to past protests through social connections between Septem-

[2] Greta Thunberg, the initiator and most prominent figure of the movement, had over 4 million followers on Twitter and nearly 10 million followers on Instagram in early 2020 (Jung et al., 2020). I also found almost 700 active accounts run by local FFF groups on Twitter.

[3] Censorship and government repression have been highlighted in the literature as important drivers of coordination of collective action (Cantoni et al., 2023). As it is more difficult to censor, social media is often the only source of information about discontent or demand for social change in the population, which can facilitate coordination. The fear of government repression instead increases the returns to coordination since larger group size and higher visibility can decrease the probability of negative consequences.

ber 2018 and December 2019.[4] I obtain information on protests from the organizers' records, containing the location and weekly attendance of 3177 European FFF protests. I further construct a time-varying measure of social protest exposure by combining information on protests in other locations with data on locations' interregional connectedness based on the bilateral probability of Facebook friendships, the Meta Social Connectedness Index (Bailey et al., 2018b).

This study presents three main findings. First, I document the importance of spillovers in social networks for organizing collective action. I find a significant effect of social exposure to protests in connected regions on the likelihood of future protests. In my preferred specification, increasing the social exposure to protests in the previous week by one standard deviation doubles the baseline probability of a local protest. This implies that an average protest week causes protest activity in .28 additional locations (equivalent to roughly 800 protesters) in Europe through online network spillovers in the following week. I further examine the channel of real-time information sharing via novel communication technologies by adding information on weekly Tweets related to FFF. I find that social network spillovers increase both with local Twitter activity and Twitter activity in connected regions.

Second, I highlight that social media's ability to overcome unfavorable local conditions allowed the FFF movement to reach new groups of supporters that local politics or movements could not. I show that online social networks mobilized protesters in areas with higher coordination cost and without a history of Green political activism. I find that the effect of spillovers is decreasing with the strength of local social networks (where coordination was already easier) and increasing with population size (which makes coordination more difficult). Looking at historical voting patterns, I find that effect sizes do not depend on the presence of a Green party (i.e., no politically organized environmentalism) or support for environmental parties in past elections. This suggests that online social networks can act as substitutes for local networks and previous political organization to enable collective action.

Third, I show that protest spillovers increased support for environmental par-

[4] While weekly time intervals might appear long, FFF organizes protests usually only on Fridays, i.e. in weekly intervals. In daily ACLED protest data of FFF protests from 2021, 88% of protests and 91% of attendance were recorded on Fridays.

ties, speaking to the role of global peer effects in addressing the coordination problems surrounding climate action. Using regional data on voting in the 2019 European Parliament election, I find that social exposure to FFF protests before the election increased voting for Green parties and parties that support environmentalism. These findings suggest that social exposure to protests not only facilitates the coordination of protests, but can further change political expression with the potential to influence policy in years to come.

My findings contribute to the literature on collective action in networks. Theoretical work on social movements has long emphasized the importance of social ties, e.g. to overcome the free-rider problem (Olson, 1965; Tilly, 1978; Granovetter, 1978).[5] Recent empirical literature provides some causal evidence on peer effects in protest settings. González (2020) shows that individuals' attendance at Chilean student protests increased with attendance in their network; Bursztyn et al. (2021) report similar findings from a field experiment with protesters in Hong Kong. Adding to this literature on local connections, I highlight the importance of weaker links, i.e. across long geographic distances or even indirect ties (since I consider aggregate geographic connectedness), and emphasize social networks' relevance beyond local coordination. The focus on non-face-to-face interactions further allows me to isolate the importance of information flows. In related work, García-Jimeno et al. (2022) show how the railroad and telegraph networks drove the diffusion of prohibition protests in the US in the 19th century. I demonstrate that peer effects can facilitate collective action also through modern social media. A different strand of this literature studies the evolution of protests and the role of peer effects on various social media platforms (González-Bailón et al., 2011; González-Bailón and Wang, 2016; Gromadzki and Siemaszko, 2023). However, these studies typically focus on activism on the platforms themselves instead of the (much costlier) participation in real-world protests.

Second, my results speak to the rich literature on behavioral spillovers and information sharing in social networks (Banerjee, 1992; Bikhchandani et al., 1992). The empirical literature documents how social spillovers arise in local settings (e.g., Banerjee et al., 2013; Gilchrist and Sands, 2016; Foster and Rosenzweig, 1995)

[5] Experimental work studying the role of strategic considerations in political activism does indeed find strategic substitutability, e.g. in the contexts of anti-government protests in Hong Kong Cantoni et al. (2019) and canvassing for a European party (Hager et al., 2023).

but similarly shows how peer effects occur across long geographic distances, for example in home buying (Bailey et al., 2018a), insurance decisions (Hu, 2022), or compliance with social-distancing rules during the COVID-19 pandemic (Bailey et al., 2020; Tian et al., 2022). A novel strand of this literature emphasizes how information technology can lead to almost real-time reactions. Du (2023) shows that aggressive behavior, caused by local pollution shocks, can spill over through Twitter networks and increase criminal assaults in connected regions. Yarkin (2023) documents that political events in migrants' home countries shape their individual political attitudes, and that this effect is amplified by Facebook connections. I show that these information flows can facilitate collective behaviour beyond private attitudes and decision-making.

Third, this study builds on the literature that explores the effects of communication technology on political mobilization. Compared to the vertical structure of traditional mass media, information technology emphasizing the horizontal sharing of information has been recognized for its potential to stimulate protests (Little, 2016; Barbera et al., 2020). The empirical literature mainly studies the impact of the roll-out of new types of information technologies, such as social media (Fergusson and Molina, 2019; Enikolopov et al., 2020; Casanueva-Artís et al., 2022), broadband internet (Amorim et al., 2022), or cell phones (Manacorda and Tesei, 2020). The inclusion of global network connections in this study adds novel evidence for the mechanisms underpinning these previous findings. My results further highlight the relevance of non-local outcomes to fully assess the impact of communication technology in this context. The latter finding also contributes to the literature studying the effects of protests and social movements (Madestam et al., 2013; Levy and Mattsson, 2023; Hungerman and Moorthy, 2023; Fabel et al., 2022). In ongoing work, Qin et al. (2021) document that following the expansion of bilateral social media links between Chinese cities, protests were more likely to spill over between them; the authors attribute this effect to tacit coordination and emotional reactions. Enikolopov et al. (2023) suggest that social image concerns, amplified by social media, were an important driver of individuals' participation in Russian anti-government protests. Relative to this previous work, my study also analyzes the effects of collective action through social networks on political outcomes.

Finally, this paper relates to the literature on the political economy of climate change. Collective action to manage the efficient use of common resources has been studied at least since Ostrom (1990). However, in the context of climate change mitigation, free-riding problems are severe due to the global scope of externalities, which make international coordination difficult, yet critical (Nordhaus, 2015). Efficient implementation of climate policies is further complicated by the heterogeneous distribution of local adaption costs and benefits, both on an international and subnational level (Carleton et al., 2022; Markkanen and Anger-Kraavi, 2019). The theoretical work by Besley and Persson (2023) emphasizes the importance of citizens' environmental values for a sustainable, green transition. Empirical literature studies the determinants of support for climate action (Dechezleprêtre et al., 2022; Whitmarsh and Capstick, 2018). While some papers show that environmental values can be unilateral, others emphasize (perceived) social norms and cooperation as key drivers of individual attitudes: Peers' willingness to contribute and the strength of social norms around climate action are often underestimated; correcting these beliefs can significantly raise individual willingness to support climate action (Mildenberger and Tingley, 2019; Bolsen et al., 2014; Andre et al., 2022). Building on this literature, which focuses on data collected in surveys,[6] my work provides novel evidence from the field that is consistent with the mechanisms highlighted by the survey-based evidence. Exposure to FFF protests, even across long distances, increases the willingness to engage in real-world support for environmentalism through local protest participation and in the voting booth.

The rest of the paper is structured as follows. Section 2 describes the study's setting and the data. Section 3 discusses the empirical framework and identification. Section 4 presents results on protest diffusion and explores underlying mechanisms. Section 5 investigates the spillover effects on environmental voting. Section 6 concludes.

[6] A related literature does study real-world actions, such as the adoption of Green technologies, but examines peer effects and collective behavior through direct interactions in local communities. Carattini et al. (2019) provide a summary.

2 Background and data

2.1 Setting

Fridays for Future is an international student-led climate movement. The movement's key demand is adherence to and implementation of the Paris 2015 agreement, in which many countries set the goal to limit global warming to 1.5°C. To publicly express their demands, local subgroups regularly organize protest marches, typically on Fridays. The majority of participants are high school or university students who skip class to attend (De Moor et al., 2020; Wahlström et al., 2019).

The movement was started by 15-year-old student Greta Thunberg in Stockholm in August 2018. Before the upcoming national election, she staged daily protests outside the Swedish parliament in demand of stronger political measures against climate change. She continued her protests on every Friday in the following months. Her continued action generated public attention and the Fridays for Future movement, named after one of the Hashtags used by Thunberg on social media, gained global traction in early 2019. Following four global calls to action in 2019, the movement was able to mobilize millions of protesters, such as 1.6 million protesters in March 2019 (Wahlström et al., 2019) and 7.6 million for its largest event in September (De Moor et al., 2020). However, the movement lost much of its momentum in 2020 when large gatherings were banned or discouraged in many countries due to the global COVID-19 pandemic.

The group was very successful in raising public awareness for environmental issues. [7] Greta Thunberg was invited to speak on 23 September 2019 at the UN's Climate Action Summit (UN News, 2019). The European Parliament declared climate emergency on 28 November 2019, calling for increased political and financial support to curb greenhouse gas emissions and limit global warming to 1.5°C (European Parliament Press Releases, 2019). This publicity also turned into political support for environmental parties in many countries, e.g. Fabel et al. (2022) show that protests in Germany increased local voting for the Green party.

The evolution of the movement in Europe closely mirrors its global trajectory.

[7]Collins Dictionary named "climate strike" their word of the year 2019. The band Coldplay skipped their 2019 world tour due to environmental concerns related to the travel.

I plot weekly attendance data in Appendix Figure A1. Participation spikes during global climate strikes and is overall driven by major events, but fitting a log-linear time trend reveals an overall growth during late 2018 and 2019.

To illustrate the role of social networks for FFF's geographical spread through Europe, I zoom in on its early stages before April 2019 when first-order network spillovers from the origin Stockholm were likely dominating. Figure 1 presents two maps that illustrate the relationship between connectedness to Stockholm and early FFF protest. Panel (a) plots the relative importance of Stockholm in a region's network. While geographic proximity is a clear driver of connectedness, certain regions, especially in Central, Western and Southern Europe, locally stand out. Panel (b) plots the number of FFF before 25 March 2019. Again, geographic proximity seems to be an important determinant, but the same regions, such as Berlin and Barcelona, stand out again. To formalize this this visual intuition a bit, I plot the same data in a binned scatterplot shown in Appendix Figure A2. It shows a strong positive correlation for between early protest and linkage with Stockholm, both for the full sample and a subsample excluding Sweden and its neighboring countries.

2.2 Data

I combine data from various sources described below. For the main analysis, I build a weekly panel of 1508 3rd-level administrative regions, as classified by the EU's Nomenclature of Territorial Units for Statistics (NUTS 3 regions),[8] containing detailed information on local protest incidence as well as the social exposure to protests abroad. It also contains various measures of the local weather and weather in connected regions. Since the movement stopped most of its activity due to COVID-19, I focus on the 71 weeks between September 2018 and December 2019. I present basic descriptive statistics in Table 1. To analyse the effect of social protest exposure on voting, I further use a cross-sectional subset of this data containing protests in the week before the 2019 European Parliament election on 23 - 26 May 2019; I discuss the construction of this sample in Section 5.

Protests: The data on the incidence of and attendance at climate strikes was

[8] This definition is equivalent to counties in the US and corresponds to districts (*Kreise*) in Germany and departments (*départements*) in France

shared by the FFF movement and comes from the movements global 'action map'.[9] Local FFF groups or individuals can organize and register local events by adding information about the time and location to increase their visibility to potential participants. After a registered event, the organizers can follow up and add information on the attendance. The data available to me contains the aggregated weekly attendance per location based on the data from confirmed events.

I geocode the location names in the original data using Nominatim and aggregate the data by NUTS 3 region, recording the number of locations with at least one protest and the total attendance at the protests. My final data contains information on 3177 records over my study period in 2056 different NUTS 3 region - weeks. As shown in Table 1, the baseline probability of observing at least one protest in a week and region is 1.92%, with an average attendance of 56 at baseline or 2900 participants conditional on protest activity.

Social connectedness: To measure social network connections between two regions I use Meta's Social Connectedness Index (SCI) (Bailey et al., 2018b). For every pair of regions (including the region itself), it measures the probability that two randomly chosen users from each region are connected on the social media platform Facebook.[10]. I use the SCI to construct my measure of social protest exposure, a connectedness-weighted sum of protests in other regions, as outlined in Section 3. I further construct the total SCI for every region (total connectedness), rescaled by the factor 1,000,000, and the within-region SCI (local connectedness), normalized by the total connectedness.

While the SCI is based on data collected in 2021, the underlying object is quite stable over time (Bailey et al., 2018b) and represents the fundamental geographic structure of social networks between locations.[11] Therefore, I assume for my analysis that the linkage intensity is constant for my study period and accurately measured by the SCI. [12]

[9]The current map can be found at: https://fridaysforfuture.org/action-map/map/

[10]Formally, social connectedness between locations i, j is defined as a rescaled measure of $SCI_{i,j} = \frac{Connections_{i,j}}{Users_i \times Users_j}$

[11]For example, the same data predicts today's trade flows just as well as trade in the 1980s (Bailey et al., 2021)

[12]I discuss concerns about the role of social media, as the SCI may not explicitly measure Facebook-specific links, in Section 4.4.

Weather data: I obtain daily historical weather data between 2008 and 2020 from Meteostat for 3028 different weather stations. The reported weather measures include average, minimum and maximum temperature, total precipitation and snow fall, wind speed and air pressure. I average the daily records from all stations within a NUTS 3 region, or use the reported values from the nearest station. I aggregate the 2008 - 2017 data to day-of-the-year averages as a baseline measure of expected weather on every day of the year and construct daily weather shocks for the sample period as the deviations from this 10 year historical average. The main local weather measures are the weekly averages of the weather shocks.

Tweets: Using the official Academic Research API, I scrape all posts from the micro-blogging platform Twitter (Tweets) that contain a hashtag related to the FFF movement during the study period, including information on the sender and the time of the post.[13] I geocode the self-reported user locations using Nominatim [14] and aggregate the number of FFF-related Tweets by region and week. On average, 1.3 Tweets are posted per week in every region and 18% of region-weeks see 2 or more weekly Tweets.

Elections and party ideology: I obtain NUTS 3-level election data for all national parliamentary elections between 2008 and 2017 from 22 countries (or 64% of all locations), as well as the European Parliament election on May 23 - 26, 2019 from The European NUTS-Level Election Database (Schraff et al., 2022). I use the partyfacts data (Bederke et al., 2021) to merge the party-level results with information from the Chapel Hill Expert survey (Jolly and Vachudova, 2022) on European parties' ideology. I use the data on parties' general left-right position, their environmentalism, the salience of environmentalism, and the parties' family to identify Green parties.

I combine this data to measure regional vote shares of the local Green parties. Since many countries do not have a relevant Green party, I construct an alternative measure of local environmental voting based on all parties' environmentalism score. I rescale the classification measure to percent and aggregate parties'

[13] The three hashtags are #fridaysforfuture, #climatestrike, and #gretathunberg

[14] Around 75% of Tweets have a non-empty location; however, this is not always a real location and I can place 49% of Tweets to a location. This share is comparable to that in similar studies in different settings (such as Gallotti et al., 2020), suggesting that users engaging with FFF are not systematically different in sharing their location.

environmentalism weighted by their local vote share, creating a measure of environmentalism of the average elected party.[15] On average, Green parties received 4.4 percentage points of votes in national elections; the average environmentalism of elected parties is 36.5% (Table 1).

Other data: I obtain regional socio-economic information from the Eurostat database. For 2019, I obtain quarterly information on local average Internet download speeds from Ookla's speedtest data.

3 Empirical framework

As a baseline, I describe my panel OLS strategy. I consider a set of locations (NUTS 3 regions) that are embedded in a social network and are connected to each other, measured by a fixed measure of linkage intensity. I use the linkage intensity to all other locations to construct the relative exposure to protests in the region's social network, excluding within-country links as outlined below. Consider $Protest_{j,t}$, the aggregate protest attendance in region j in week t, and $SCI_{i,j}$, the SCI between regions i and j. I define the social exposure to protest $Protest\_Exposure_{i,t}$ as:

$$Protest\_Exposure_{i,t} = \frac{\sum_j SCI_{i,j} \times Protest_{j,t}}{\sum_j SCI_{i,j}}, \qquad \forall j : country(j) \neq country(i)$$

I then estimate the my main panel specification as follows:

$$Y_{i,t} = \beta \times Protest\_Exposure_{i,t-1} + \theta_t + \theta_i + \epsilon_{i,t} \tag{1}$$

where $Y_{i,t}$ is a measure of local protest (either an indicator or a measure of attendance) in region i in week t, and $Protest\_Exposure_{i,t-1}$ is the lagged social exposure to protest. The coefficient β will pick up the strength of network spillovers due to the social exposure to protests. I include fixed effects for every time period θ_t that capture the overall trajectory of the movement and NUTS 3 region fixed effects θ_i that absorb all observable and unobservable baseline characteristics of

[15] Classification in the CHES data is performed on a national level with (potentially) different experts ranking every party. The measure is thus suitable for within-country comparison, but not necessarily accurate across countries.

each region, including its social network. I cluster my errors by NUTS 1 region, the first unit of administration, to account for possible local spillovers and serial correlation.[16] I focus on administrative regions since protesters might choose a location closer to their local administration.

3.1 Identification

While the correlation from the panel estimation of equation (1) is suggestive, it is subject to various endogeneity concerns. A common issue in the estimation of causal effects of social interactions is the reflection problem (Manski, 1993); however, it is no concern here due to the panel structure of my data. A more severe problem is the effect of unobserved heterogeneity and correlated shocks due to various factors. Proximity is a main determinant of connectedness (for descriptives of the SCI data, see Bailey et al., 2018b). However, local shocks or heterogeneity, e.g., due to underlying local environmental or political conditions, could lead to correlated behavior between nearby locations. Therefore, I focus on long-distance connections and drop observations from close location pairs, keeping only different-country links (Hu, 2022; Bailey et al., 2018a). Furthermore, this focus on long distances ensures that I am capturing effects going through the channel of social media and its underlying non-face-to-face interactions.

Other factors of unobserved heterogeneity could be similarly problematic. Typically, locations with similar characteristics and attitudes are more strongly connected (homophily). While the inclusion of location fixed effects will account for a location's own and also its network's baseline characteristics, these characteristics could have more dynamic effects: As the FFF movement gains traction, certain locations, e.g., with stronger preference for environmentalism, might react more strongly to the global trend of the movement. Thus, if regions with similar attitudes (and thus, similar reactions) are more connected, correlated behavior between connected regions could be driven by unobserved heterogeneity instead of the social spillover effects between activists.

To deal with this challenge, I employ an instrumental variable strategy using weather shocks to introduce exogenous variation in protest participation and therefore the subsequent social exposure. Since my sample covers a diverse set of

[16] I observe 121 NUTS 1 regions in my data

locations and spans all seasons, I focus on deviations from typical weather as my main weather measures. I define typical weather as the local 10-year mean on the same days of the year and construct my weather shocks as deviations from their historical averages. I show the robustness to using the absolute weather measures instead in section 4.1. I then construct social exposure to weather shocks for all of my weather variables $Weather^k$ described above as the same SCI-weighted sum as my social exposure to protest variable:

$$\omega_{i,t}^{k} = \frac{\sum_j SCI_{i,j} \times Weather_{j,t}^{k}}{\sum_j SCI_{i,j}}, \qquad \forall j : country(j) \neq country(i)$$

Since weather phenomena could be correlated between regions, e.g., rain in certain regions predicting rain in other regions a week later, I further include controls for local weather. The the effects of weather on protest participation are not necessarily linear. To capture more complicated weather interaction and to limit the degree of researcher discretion in instrument selection, I use LASSO (following the approach in Beraja et al., 2023) to select the optimal functional form of all my potential weather instruments. I similarly use LASSO to select local weather controls. Both for my local weather variables and social exposure to weather shocks, I consider the continuous and a discretized (quartile) form and all of their interactions. I then use Belloni et al. (2016)'s Post-Double-Selection method (in the implementation by Ahrens et al. (2018)) to select the relevant instruments and controls. I also show the results of a more traditional 2SLS regression based on a literature-guided choice of instruments in Section 4.1.

4 Results

I present the results of my baseline panel estimation of the main specification (equation (1)) in Table 2. To ease the interpretation, the measure of social protest exposure is standardized to have a mean of zero and a standard deviation (SD) of one. A one standard deviation increase in protest exposure is equivalent to average protest activity in 8% of a location's connectedness-weighted network. 8% is roughly the combined importance of the two regions that a location is most connected to.

In my preferred specification with my full set of fixed effects in column (3) of Table 2, I find that a one SD increase in social exposure to protest participation is associated with a 1.56 percentage point higher probability of at least one local protest in the subsequent week. My specification using the LASSO-selected weather instruments and controls in the bottom panel confirms this result; a one SD increase in social exposure to protest increases the likelihood of a protest in the following week by 2.25 percentage points or 117% of the average protest probability. Social protest exposure also has a significant positive impact on protest attendance across different outcome measures.

My coefficients imply that social media spillovers played a substantial role in the diffusion of the FFF movement. Given an average weekly protest exposure of .25 standard deviations (see Table 1), the coefficient in column (3) of Table 2 implies that average protest exposure increases the expected number of protest locations by 8.5 per week, or 29% of the baseline. This suggests that first-order effects accounted for roughly 600 additional location-weeks with protest activity over the full sample period.

My coefficient from column (3) further implies that an average week of protests increases the expected number of locations with protest incidence in the following week by .28.[17] Comparing this magnitude to the literature, I find that my number is similar to the effect size of reported by Qin et al. (2021), who study protest spillovers via social media connections between Chinese cities. They report that a protest in a given city in the last two days increases the expected number of cities with protest incidence by .25.[18] I also find an implied effect roughly twice as large as the spillovers found by García-Jimeno et al. (2022) who study protest diffusion via railroad networks in the 19th century US. This finding is consistent with modern social media being a more effective communication technology; however, the

[17]At a conditional weekly attendance average of 2900, this implies a total protest exposure of 12.26 standard deviations across all connected regions, which gives an expected number of regions recording protests overall by $12.26 \times .0225 = .28$. The baseline protest probability is 1.92% across 1508 regions, which yields an expected increase of $.28/(1508 \times .0192) = .01$

[18]Due to the substantially smaller network size, i.e. fewer locations, in Qin et al. (2021) (at 16% of the number of locations in this paper), the relative effect size in their context is substantially larger. This could be explained by differences in the setting, as Qin et al. (2021) include more types of protest, and focus on (presumably stronger) intra-national spillovers and short-term effects (within two days).

magnitudes may not be easily comparable due to different network structures.[19]

4.1 IV and robustness

I show a full first stage with all selected instruments and controls for the specification in column (3) in Appendix Table A1. The first-stage F statistic for all instruments is 17.7, which suggests a strong first stage. I also perform the same estimation using the double-orthogonalization approach by Chernozhukov et al. (2015) with both LASSO and post-LASSO (Belloni and Chernozhukov, 2013). Reassuringly, I find a very similar magnitudes of my coefficient using the alternative methodology, reported in Appendix Table A2. I also perform the weak-instrument robust sup-score test proposed in Chernozhukov et al. (2013) (again using the implementation by Ahrens et al. (2018) for all), which rejects the null hypothesis of a zero coefficient at $p < .05$.

To further check the robustness of my results and methods, I consider alternative specifications and perform Placebo checks. I use a more traditional 2SLS set-up, with instrumental variables based on the literature on weather shocks and protest participation (Madestam et al., 2013; Beraja et al., 2023). These variables include temperature measures and precipitation interacted with wind speed; again, I focus on the deviations from the historical means. The results can be found in Appendix Table A3 (columns (1) and (4)) and the associated first stage in Appendix Table A4). While the Kleibergen-Paap F-statistic of 19 already suggests a strong first stage, following the recommendation by Lee et al. (2022), I further perform a weak instrument-robust Anderson-Rubin test (Anderson and Rubin, 1949) which rejects my null hypothesis of a zero effect at $p < .05$ for the protest indicator and $p < 0.01$ for my attendance measure as the outcome. To account for the possibility of errors correlated with the network structure, in columns (2) and (5) of Appendix Table A3 I present my OLS and the 2SLS specifications with

[19] They report that an additional protest in a connected town, which on average represents 43% of a location's network, increases the likelihood of a protest in the next five days period by a factor of 5.6. In my setting, average protest activity in the previous 7 days in 43% of a location's network increases the likelihood of a protest by a factor of 12. However, a town in García-Jimeno et al. (2022) has on average only 2.3 connections, giving a single event a lot of presence in the network; in my data, a location's most strongly connected region represents on average 5% of the network. Due to the bigger networks, the presence of *one* event in a location's network would therefore imply a factor of (at most) 1.4 in my setting.

standard errors clustered by network network connectedness (Colella et al., 2019). Finally, I consider spatially clustered standard errors in columns (3) and (6) of the same table.

Next, in Appendix Table A5 I perform a Placebo check to test for the presence of residual unobserved heterogeneity. I repeat my main OLS and LASSO IV analyses but use exposure to protests one time period in the future as the main dependent variable.[20]. The idea of this Placebo test is that protests driven by time-varying unobserved heterogeneity, such as connected locations with shared characteristics protesting at similar times in response to a global trend, would lead to a correlation between future protest exposure and contemporaneous local protest. While I find small, but significant coefficients in some OLS specifications, I find null effects in my LASSO specifications, consistent with my identification strategy eliminating the effects of time-varying unobserved heterogeneity.

The small coefficients in the Placebo check of the OLS specification can also help explain why the coefficients in the LASSO IV specification are often larger than their OLS counterparts. This might initially seem surprising as one might expect a positive bias induced by unobserved heterogeneity. However, such bias is likely minor, as my Placebo check in the top panel in the Appendix Table A5 illustrates that correlation with exposure to future protests is small and, depending on the outcome, even zero. Therefore, the presence of time-varying unobserved heterogeneity appears to be small in my setting. Additionally, measurement error in the measured protest exposure may even induce a (downward) attenuation bias in my baseline OLS specification.

Finally, I consider different definitions of key variables and include further controls. In columns (1) - (4) of Appendix Table A6, I use population-normalized definitions of attendance to construct both my outcome variable and my main dependent variable. Additionally, I consider an alternative set of instruments and local weather controls based on the non-demeaned weather measures, shown in columns (5) and (6) of Appendix Table A6. To account for the role of regional characteristics on protests over time, I allow the time trends to vary by different baseline controls, adding interactions between a series of time-period fixed effects and population, population density, regional GDP per capita, unemployment, the

[20] And use future weather shocks as instruments

population share with tertiary education, and the average stance on environmentalism and position on the general left-right scale of the elected parties in the 2014 EP election. I report the results in columns (1) and (3) of Appendix Table A7. Next, to further control for the role of geographic proximity as a determinant of network links and potential non-social media interactions, I further account for the geographic spread of protests besides dropping same-country pairs. In columns (2) and (4) of Appendix Table A7, I include protest exposure weighted by proximity as a control.[21] Across all specifications based on alternative variable construction and including additional controls, I find significant positive spillover effects.

4.2 Network characteristics

To further investigate the mechanisms behind my findings, I evaluate the role of of a location's networks characteristics, namely total network size and the strength of local networks, which measure the local coordination costs. Adding an interaction term for total connectedness, i.e. the total SCI across all different-country links (i.e., the denominator of my protest exposure measure), I find no differential effects by network size (columns (1) and (4) of Table 3). This indicates that the network spillovers depend on the relative presence in the network and not the absolute number of connected peers. A non-negative number seems plausible. Smaller networks can generate stronger spillovers due to tighter connections (e.g., found by González, 2020); in my setting, however, all connections are relatively distant. The absence of increasing effects in network size suggests that motivations like social image concerns, which grow with the total number of connected peers, are less relevant in this context.

Instead of enabling long-distance collective action, networks might merely enable information flows which raise awareness for environmental issues. As an empirical test, I consider how spillovers differ by the strength of local connectedness. Since local connections also facilitate coordination, a stronger effect in locations with weak local networks would imply the presence of a collective action channel. Indeed, I find a negative and significant interaction effect between

[21] The formal definition is: $Protest\_proximity_{i,t} = \frac{\sum_j D_{i,j} \times Protest_{j,t}}{\sum_j SCI_{i,j}}, \forall j : country(j) \neq country(i)$, where $D_{i,j} = Distance_{i,j}^{-1}$, measured between region i and j's centroids in km.

social protest exposure and local network strength, both using protest probability and attendance as outcomes (columns (2) and (5)). This speaks to the importance of online social networks for the organization of collective action and underlines that online social networks can be substitutes for local structures.

To further test my hypothesis that social spillovers facilitate collective action, I analyze the effect size by local population. Coordination in high-population areas is more difficult, therefore, a stronger effect in these locations is consistent with social spillovers facilitating collective action at the local level (Enikolopov et al., 2020). An added interaction term with an indicator equal to one if a location is in the top population decile is significant and positive (columns (3) and (6) of Table 3). Compared to the bottom nine deciles, being in a highly-populated location roughly doubles the relative probability of protest activity in the subsequent week. I find similar effects on attendance. Note that this effect on attendance is not mechanically induced by the larger local population size, as there are similar effects on the per-capita attendance measures shown in Appendix Table A9.

4.3 Political environmentalism

Can online social networks help a movement reach new followers? To identify existing local support, I consider the previous strength of political environmentalism measured by vote shares for local Green parties in national elections for a subset of my data. To assess the effects more flexibly, I construct five bins around the quintiles of my measures within country. My lowest bin exclusively contains locations in countries with no Green party. This gives me two relevant margins of comparison. First, I can compare the spillovers based on the presence of a (relevant) Green party; its presence suggests that environmentalists were able to overcome the collective action problem to coordinate, organizing and sustaining an interest group. The absence of a Green party thus implies that previous political mobilization must have been below a critical threshold. Second, for countries with one or more Green parties, their aggregate vote share in elections is an important gauge of environmentalist attitudes in the population. If the strength of the response heavily depends on local environmentalism, this implies that social exposure to this novel movement mostly mobilizes existing supporters. To further test the latter channel, I consider a second, more general measure of the average environmentalism of all locally elected parties.

I modify my baseline specification by considering the spillover effects within each quintile bin by adding interaction terms.[22] I plot all five coefficients in Figure 2. In my baseline OLS, I find a strong response in regions with no Green party (first bin) and with the locally highest Green vote shares (fifth bin), and a slightly lower, yet still significantly positive response where Green parties were slightly less popular (panel (a)). However, this pattern is not present using the alternative, more general measure in panel (b). In my LASSO IV specification, the response is more stable across bins. I find no significant difference in spillover effects based on past votes for the Green party (panel (c)) or overall environmental voting (panel (d)). In Appendix Figure A3, I show the results from running the same specification with attendance measures as the outcome variable and find a very similar pattern. This indicates that social exposure to protests did not only motivate a small group of activist leaders to organize events in regions with previously weak political environmentalism, but that social spillovers helped mobilize a broad base of supporters across locations. Overall, online social networks allowed FFF to overcome a lack of earlier local activism and mobilize participants independently of previous local political support and structures.

4.4 Social media

My connectedness data is based on friendship data from the online social network Facebook; however, these links also represent underlying offline social connections that can promote other interactions, not necessarily via social media. While novel communication technologies do facilitate long-range information transmission and social spillovers, particularly in my setting of links across country borders, the effects could be driven by other interactions or technologies.

Therefore, I explicitly track social media activity related to FFF on the social media platform Twitter.[23] Similar to my measure of social exposure to protests, I construct a measure of social exposure to FFF Tweets based on my measures of

[22] Keeping other variable definitions from the main specification (1), for the 5 bins G_k the specification becomes: $Y_{i,t} = \sum_{k=1}^{5} \beta^k \times Protest\_Exposure_{i,t-1} \times \mathbb{1}(G_i = k) + \theta_t + \theta_i + \epsilon_{i,t}$.

[23] Ideally, I would use data from Facebook itself. However, suitable data, which contains user location and weekly activity, is not available. Furthermore, since the movement is present on many different social media channels, I use Twitter activity as a gauge of overall local social media activity rather than a platform-specific effect.

local Tweets; again standardizing my measure to have a mean of zero and SD of one for the analysis. To track local weekly Twitter use, I mainly rely on indicator variable which is equal to one if I observe two or more local Tweets, which is the case for 18.3% of my sample. For the empirical analysis, I augment my main specification with interaction terms with my Twitter activity measures.[24]

I present the results in Table 4. Social media activity, both local and in the social network, significantly amplifies the protest spillovers. At a given level of social exposure to protests, spillover effects increase by .35 percentage points for every 1 SD increase in social exposure to FFF Twitter activity. Similarly, protests spillovers grow by 1.7 percentage points when local users tweet more than once about FFF. These two channels have robust distinctive effects, as shown in columns (4) and (5), highlighting the role of both senders and receivers for the transmission of network effects.

In columns (6) to (8) of Table 4, I further show that social media spillovers are mainly driven by interactions between users of the platform. In column (6), I show that the effect of protest exposure alone is weak and not significant in my LASSO IV specification. However, the interaction effect between protest and Twitter activity in the location's network is highly significant across my two measures of local Twitter activity. This suggests that Twitter users' engagement is not explained by overall exposure to protest, but by protest that is also accompanied by activity on Twitter.

For robustness, I repeat my analysis with a general measure of Internet access and consider the responsiveness to social exposure to protests by local Internet speed.[25] In Appendix Table A8, I show that spillover effects on protests and local Twitter are increasing with local Internet quality, as measured by a high download speeds.

[24]For this specification and all following specifications which include interaction effects, in my LASSO IV specifications I add a set of my high-dimensional weather measures interacted with the respective variable(s) as instruments.

[25]This data is only available for a subset of countries and the year 2019, as described above.

5 Environmental voting

While I have shown how protest social connections shaped the diffusion of protests, it is unclear whether social exposure to protests can induce further political change. Moreover, focusing on protests alone might mask differential reactions in the wider population beyond a relatively small group of active participants. Therefore, I evaluate two additional outcomes. First, I analyze election results as a measure of political expression. Second, I examine underlying attitudes, measured by self-identification with environmentalism in individual survey data.

To assess the effect of social protest exposure on voting behavior, I mainly focus on the week of the European Parliament (EP) election on 23 - 26 May 2019 and the FFF protests on Friday, 24 May. I restrict my sample to 21 countries which voted on Saturday or Sunday (25 & 26 May) and for which NUTS 3-level election data is available[26]. Descriptive statistics for this sample are presented in Appendix Table A10. I adapt my main framework to the cross-sectional setting and estimate the following equation:

$$Y_i = \beta \times Protest\_Exposure_i + X_i \ + \tau_{r(i)} \ + \epsilon_i \tag{2}$$

where the outcome Y_i is a measure of environmental voting in region i in the 2019 EP election, $Protest\_Exposure_i$ is the social exposure to protest in the week of Friday, 24 May 2019, $\tau_{r(i)}$ are fixed effects for all NUTS 1 regions, and X_i contains controls for population, population density, regional GDP per capita, unemployment, the population share with tertiary education, and past election results measured by the average stance on environmentalism and position on the general left-right scale of the elected parties in the 2014 EP election.[27]. To account for party-level correlation, I cluster the standard errors at the national level. The coefficient β will then pick up the strength of spillovers of social exposure to climate protests on voting decisions.

Again, there might be identification concerns in this cross-sectional framework. Participation in FFF protests and green voting is likely correlated, e.g. due

[26]This excludes Belgium, Croatia, Slovenia (no elction data), UK, Netherlands (voted on 23 May), Ireland (voted on 24 May) and Austria (voted on 24 and 25 May).

[27]Information on regional GDP, unemployment and tertiary education share is only available at the NUTS 2 level. I cluster the standard errors at a higher level which nests the appropriate NUTS 2-level clustering.

to underlying ideology or local shocks; if these factors are also related to network connections, my estimates will be biased. I address these concerns in three ways: First, since I can no longer include fixed effects that control for regions' baseline characteristics, I include an array of controls to capture potential sources of unobserved heterogeneity. Second, I again exclude links to locations in the same country to account for geographically correlated shocks. Third, comparable to the identification in the previous section, I use weather shocks in region i's social network ω_i^k to instrument instrument for social exposure to protests. For my local weather variables and weather in the network, I consider the continuous and discretized form and all interactions between them, and use the post-double-selection method (Belloni et al., 2016) to select relevant instruments and local weather controls.

The results of estimating equation (2) can be found in Table 5. I standardize protest exposure within the week and report vote shares in percentage points. I find a strong positive effect of social exposure to FFF protests and environmental voting. In regions with a Green party, a 1 SD growth in protest exposure raises the vote share of the local Green party by 2.5 percentage points (column (1)). To put this magnitude into perspective, Green parties' vote share increased by over 6 percentage points compared to the previous EP election (in which I record a regional average of 10.4% in 2014). A 1 SD increase in protest exposure would therefore account for roughly 41% of this gain.

To further isolate the impact of social exposure, I run the same specification on the sub-sample of regions that did not experience any FFF protests before and during the EP election week. This yields a slightly smaller, yet still substantial and very significant coefficient, consistent with the presence of direct spillover effects. Finally, I investigate the time-horizon of spillovers on voting and examine the effects of social spillovers from 10 weeks earlier, the global climate strike on 15 March. I find a smaller coefficient than for the protests in the same week[28], which is still significant. This suggests that social protest exposure had not only a short-run impact on voting behavior but that information spillovers have a more substantial, long-run effect.

[28] Note that I standardize coefficients within-week. A 1 SD increase in exposure represents a non-standardized value that is roughly 3 times larger, as shown in Appendix Table A10.

I repeat this regression with my general measure of environmental voting, which allows me to include the full sample of countries, including those without a Green party. I find that the average voter chose a party that was roughly .8 percentage points higher on the environmentalism scale. I find similar effects in regions without any local protest and for the long-term effect of the protests in the week of 15 March.

These results demonstrate that social exposure to protests increased the willingness to vote for parties that promote environmental policies. This finding is consistent with different underlying mechanisms. First, exposure to protest could have persuasive effects and shift local attitudes towards environmentalism. Second, information about protests in the network could increase the willingness to support environmental policies, regardless of underlying attitudes. As Andre et al. (2022) point out, individuals often underestimate their peers' willingness to fight climate change, but become substantially more willing to contribute to climate action when their beliefs are corrected. Similarly, voters could be more willing to support green policies once they observe their peers' protest.

Overall, the evidence shows that protests' spillover effects do not only increase protest, but can further affect non-protest outcomes. Environmental voting increased with social protest exposure, even in areas without local FFF protests. While more work is needed to disentangle underlying mechanisms, it is clear that the FFF protests' spillovers shaped environmental policy making in the years to come.

6 Concluding remarks

In this study, I present evidence that online social networks facilitate collective action on a global scale. Using protest data on the climate movement Fridays for Future in Europe, I show how social exposure to protests drives the diffusion of the movement to connected locations. Spillover effects are stronger in regions where local coordination is more difficult and do not depend on the previous strength of political environmentalism, speaking to online social networks' role as substitutes for local structures and their capability to mobilize new followers. The effects of social protest exposure are not limited to the organization of protests, but also increase voting for environmental parties.

While online social networks can improve global coordination, they could simultaneously drive local polarization. When the strength of social network spillovers is constant, i.e. independent of local support, local fringe groups may disproportionately benefit relative to their popularity. Niche views, which were too extreme to receive local backing or which carried social stigma, can now draw upon a global base of potential support, therefore strengthening the expression of locally unpopular views and magnifying local polarization.[29] Such a mechanism could help understand the polarizing effects of the Internet and social media, which are often found in the literature (summarized by Zhuravskaya et al., 2020). While I present evidence from a single movement across different locations with varying starting conditions, evidence on more movements, ideally across a broad ideological spectrum, would be needed to generalize my findings.

Moreover, further investigation is needed on the mechanisms underlying online social networks' effects on collective action. Does social media solely reduce coordination costs or does is also increase the returns? International cooperation and a set of shared values are fundamental for social movements working towards a global goal like climate change mitigation. But movements centered around local concerns could also benefit from supra-regional coordination in many ways. A strong group identity, built by activism on social media around the world, may encourage local activism. Additionally, due to the importance of social media for online journalism (Hatte et al., 2021; Cagé et al., 2020), the global number of protests in reporters' networks, as opposed to local events alone, might determine coverage and subsequent visibility of local activism.

Overall, my paper shows that social media can fundamentally alter political participation by enabling worldwide horizontal information exchange. Enabling citizens to globally coordinate their attitudes and activism can be a crucial step towards the implementation of more effective climate action.

[29] Recent movements illustrate how the Internet can be used to leverage global support in response to controversial local policy issues. Leaked data from the fundraising platform GiveSendGo shows how the Canadian "Freedom Convoy" movement, a group of truckers protesting against the government's vaccine mandate in 2022, collected substantial contributions from international supporters, including thousands of donors from overseas.

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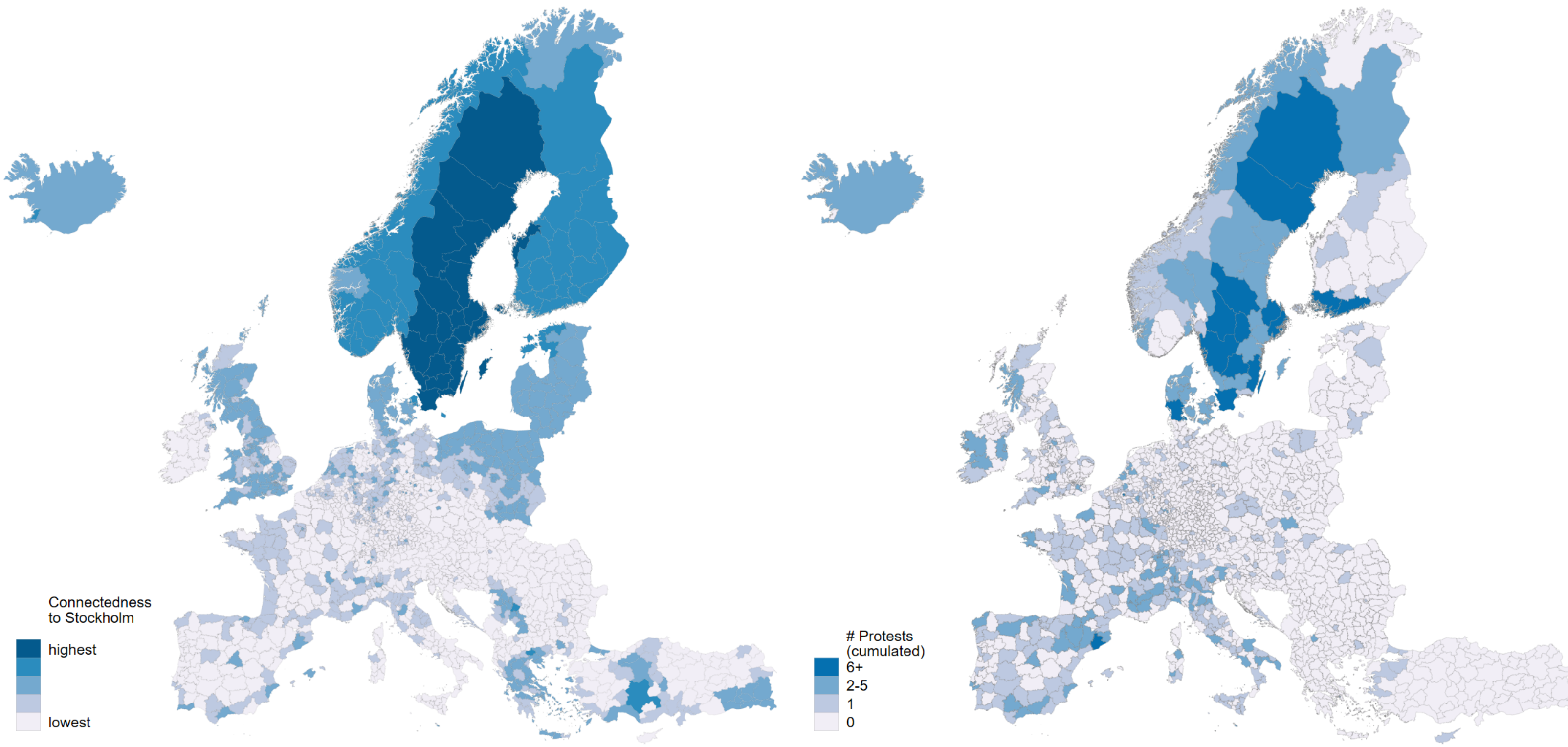
Figure 1: Connectedness to Stockholm and early FFF protests

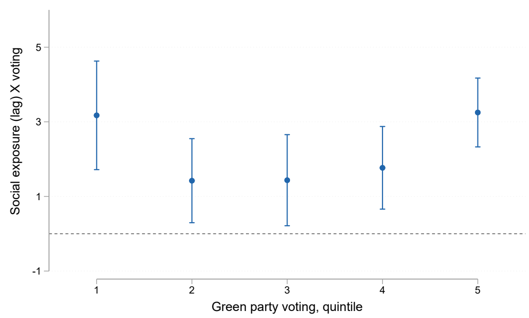
(a) Connectedness to Stockholm | (b) Protests before 25 March 2019



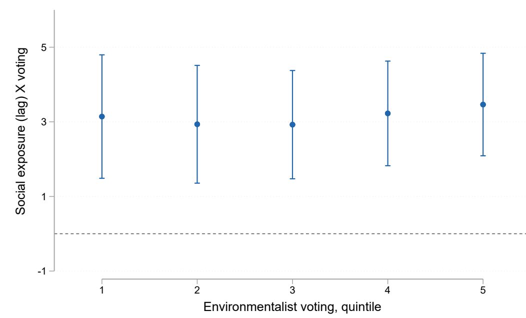
Panel (a) illustrates the relative connectedness of locations to Stockholm. Panel (b) records the number of recorded FFF protests until 24 March 2019, the week after the first global climate strike. Relative connectedness is defined as the Meta Social Connectedness Index (SCI, see Section 2.2 for more detail), normalized by the total SCI across all region in the sample. Raw correlation between relative connectedness and cumulative count of protests is $\rho = .608$

Figure 2: Spillovers by historical political environmentalism

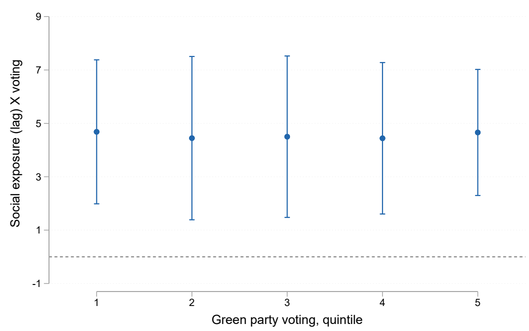
(a) OLS, Green party vote



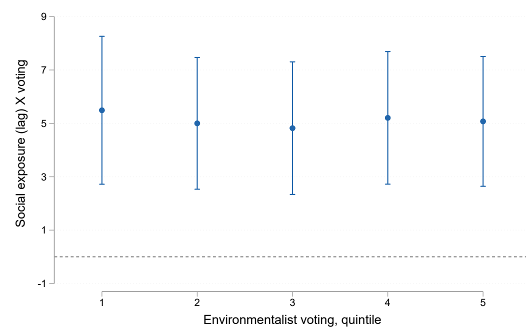
(b) OLS, environmental vote



(c) LASSO IV, Green party vote



(d) LASSO IV, environmental vote



This figure illustrates the protest spillovers by local environmental voting. In particular, I regress an indicator equal to one if at least one protest was recorded in a given region and week on the interaction between protest exposure, the standardized linkage-weighted exposure to protest attendance in the previous period, and a series of indicators for 5 bins which represent the strength of historical environmental voting. In panels (a) and (c), the bins are constructed based on the Green party vote share in national elections 2008-17. Category 1 represents regions without a Green party. Categories 2-5 represent country-specific quartiles of Green party vote share with a Green party. In panels (b) and (d), the bins are constructed as the country-specific quintiles of environmental voting, as defined in the text. The top panels (a) and (b) present correlations using an OLS estimation, while the bottom panels (c) and (d) present the results from an IV specification with LASSO-selected weather instruments and additional LASSO-selected local weather controls. All specifications include fixed effects for every region and every week in the sample. Note: N = 68657. 95% CIs indicated, SEs clustered by NUTS 1 region.

Table 1: Descriptive statistics

	Mean	SD	Median	Observations
FFF protests				
Protest attendance > 0 (percent)	1.92	13.72	0.00	107068
Attendance	55.70	2517.17	0.00	107068
Attendance, if protest > 0 (in 1000)	2.90	17.94	0.13	2056
Attendance > 2000 (percent)	0.25	4.98	0.00	107068
Protest exposure	59.21	236.57	0.24	107068
Connectedness				
Local connectedness	10.55	17.46	6.14	107068
Total connectedness	0.71	0.53	0.54	107068
Social media				
Local Tweets	1.32	2.20	1.00	107068
Local Tweets > 1 (percent)	18.33	38.69	0.00	107068
Tweet exposure	1.26	0.34	1.20	107068
Voting				
Green party vote, 2008-17 (percent)	4.44	4.76	3.54	68657
Environmental vote, 2008-17 (percent)	36.52	10.19	39.86	68657

Note: This table presents summary statistics on weekly aggregated FFF protest attendance, social protest exposure (as defined in Section 3), FFF-related Twitter activity, baseline connectedness measures and historical voting for 1508 NUTS 3 regions in the main sample.

Table 2: Social protest exposure and protest

	Protest probability			Attendance		
	$\mathbb{1}(Attendance > 0)$			Att. (1000)	IHS Att.	$\mathbb{1}(Att. > 2k)$
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS					
Protest exposure$_{t-1}$	1.607***	1.538***	1.579***	0.312**	0.031***	0.842***
	(0.265)	(0.264)	(0.427)	(0.130)	(0.010)	(0.294)
	LASSO IV					
Protest exposure$_{t-1}$	1.490***	1.378***	2.251**	0.367***	0.043***	1.113**
	(0.244)	(0.241)	(0.898)	(0.127)	(0.014)	(0.446)
NUTS 3 region FE		X	X	X	X	X
Week FE			X	X	X	X
Observations	105560	105560	105560	105560	105560	105560

This table shows the relationship between protest exposure in the previous period and local current-period protest activity. The variable *Protest exposure*$_{t-1}$ measures linkage-weighted exposure to protest attendance in the previous period as described described in the text and is standardized to have a mean of zero and SD of one. The top panel presents correlations using an OLS estimation, while the bottom panel presents the results from an IV specification with LASSO-selected weather instruments and additional LASSO-selected local weather controls. Coefficients in columns (1) - (3) and (6) are rescaled by the factor 100 to represent percentages. In columns (1) - (3), the outcome variable is an indicator equal to one if at least one protest was recorded in a given region and week. The outcome variables in columns (4) - (6) are different measures of attendance, specifically, the total weekly attendance in 1000s in column (4), the arcsinh-transformed weekly attendance in column (5), and an indicator equal to one if the total attendance exceeded 2000 in that week in column (6). Column (1) estimates specifications which include no fixed effects. Column (2) adds fixed effects for every NUTS 3 region. Columns (3) - (6) include fixed effects for every region and every week in the sample. Note: *** p<0.01, ** p<0.05, * p<0.10. SEs are clustered by NUTS 1 region.

Table 3: Effect of local network characteristics

	Protest incidence			Attendance		
	$\mathbb{1}(Attendance > 0)$			IHS Attendance		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS					
Protest exposure$_{t-1}$	1.643***	1.780***	1.216***	0.138***	0.141***	0.096***
	(0.538)	(0.437)	(0.407)	(0.047)	(0.039)	(0.033)
Protest exposure$_{t-1}$ X Total connectedness	-0.091			-0.015		
	(0.295)			(0.024)		
Protest exposure$_{t-1}$ X Local connectedness		-0.019***			-0.001***	
		(0.005)			(0.000)	
Protest exposure$_{t-1}$ X Population top decile			1.284***			0.110***
			(0.360)			(0.034)
	LASSO IV					
Protest exposure$_{t-1}$	1.921**	2.464***	2.249***	0.177***	0.207***	0.202***
	(0.841)	(0.878)	(0.843)	(0.063)	(0.065)	(0.061)
Protest exposure$_{t-1}$ X Total connectedness	0.199			0.020		
	(0.424)			(0.030)		
Protest exposure$_{t-1}$ X Local connectedness		-0.024***			-0.002***	
		(0.006)			(0.000)	
Protest exposure$_{t-1}$ X Population top decile			1.094**			0.092**
			(0.444)			(0.038)
Observations	105560	105560	105560	105560	105560	105560

This table shows the relationship between local characteristics, protest exposure in the previous period and local current-period protest activity. The top panel presents correlations using an OLS estimation, while the bottom panel presents the results from an IV specification with LASSO-selected weather instruments and additional LASSO-selected local weather controls. The variable *Protest exposure*$_{t-1}$ describes linkage-weighted exposure to protests in the previous period and is standardized to have a mean of zero and SD of one. *Total connectedness* is the sum of a regions total SCI across connected locations. *Local connectedness* is a regions SCI with itself, normalized by total connectedness. *Top decile population* is an indicator equal to one if a region is in the highest decile of local population (or has a population larger than 763441). Coefficients in columns (1) - (3) are rescaled by the factor 100 to represent percentages. In column (1) - (3), the outcome variable is an indicator equal to one if at least one protest was recorded in a given region and week. The outcome variable in columns (4) - (6) is the arcsinh-transformed weekly attendance. All columns include fixed effects for every region and every week in the sample. Specifications with interaction terms include the respective variables as a controls. Note: *** p<0.01, ** p<0.05, * p<0.10. SEs clustered by NUTS 1 region.

Table 4: Twitter and protest spillovers

	Local Protest					Local Twitter		
	$\mathbb{1}(Attendance > 0)$				IHS Attendance	$\mathbb{1}(Tweets > 1)$		IHS Tweets
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS							
Protest exposure$_{t-1}$	1.579***	-0.280	0.969***	-0.552*	-0.048	0.778***	0.027	-0.004
	(0.427)	(0.331)	(0.369)	(0.333)	(0.029)	(0.397)	(0.397)	(0.006)
Protest exposure$_{t-1}$ X Twitter exposure$_{t-1}$		0.314***		0.261**	0.024**		0.165**	0.004***
		(0.103)		(0.101)	(0.010)		(0.077)	(0.001)
Protest exposure$_{t-1}$ X High Twitter			1.862***	1.629***	0.117***			
			(0.286)	(0.261)	(0.024)			
	LASSO IV							
Protest exposure$_{t-1}$	2.251**	0.148	1.055	-0.825	-0.044	0.653	-1.461	0.035
	(0.898)	(1.122)	(0.961)	(1.168)	(0.098)	(0.860)	(1.000)	(0.091)
Protest exposure$_{t-1}$ X Twitter exposure$_{t-1}$		0.346**		0.357**	0.028*		0.377***	0.026*
		(0.160)		(0.161)	(0.014)		(0.140)	(0.014)
Protest exposure$_{t-1}$ X High Twitter			1.682***	2.134***	0.152***			
			(0.380)	(0.373)	(0.034)			
Observations	105560	105560	105560	105560	105560	105560	105560	105560

This table shows the relationship between FFF-related social media activity, protest exposure in the previous period and local current-period protest activity. The top panel presents correlations using an OLS estimation, while the bottom panel presents the results from an IV specification with LASSO-selected weather instruments and additional LASSO-selected local weather controls. The variable *Protest exposure*$_{t-1}$ (*Twitter exposure*$_{t-1}$) describes linkage-weighted exposure to protest attendance (number of Tweets) in the previous period and is standardized to have a mean of zero and SD of one. *High Twitter* is an indicator equal to one if a region saw more than one local tweet in a week. Coefficients in columns (1) - (4) and (6) - (7) are rescaled by the factor 100 to represent percentages. Columns (1) - (5) present the role of social media on protest spillovers. In column (1) - (4), the outcome variable is an indicator equal to one if at least one protest was recorded in a given region and week. The outcome variable in column (5) is the arcsinh-transformed weekly attendance. Columns (6) - (8) present the effect of protest exposure and social media on local Twitter activity. In column (6), (7), the outcome variable is an indicator equal to one if a region saw more than 1 local tweet in a week. The outcome variable in column (8) is the arcsinh-transformed number of weekly Tweets. All columns include fixed effects for every region and every week in the sample. Specifications with interaction terms include the respective variables as a controls. Note: *** $p<0.01$, ** $p<0.05$, * $p<0.10$. SEs are clustered by NUTS 1 region.

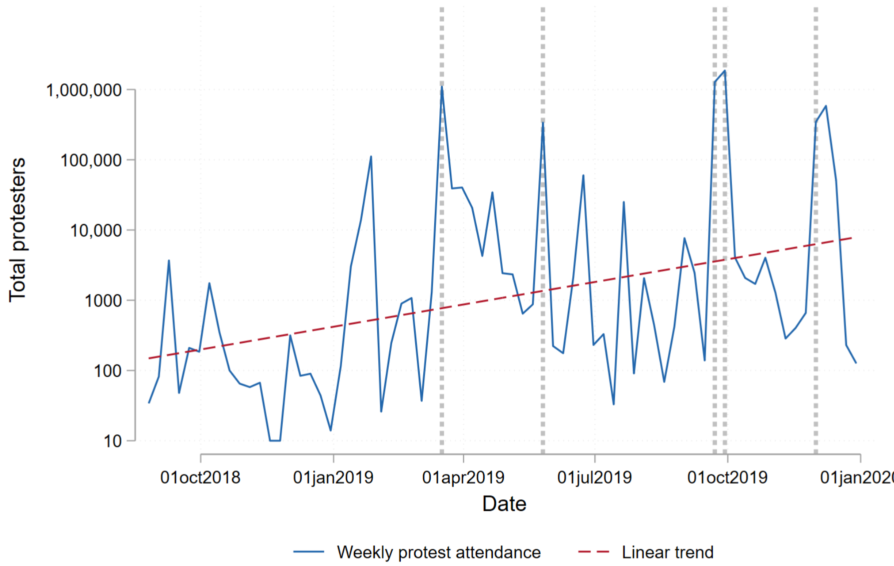
Table 5: Social protest exposure and voting in the 2019 European Parliament Election

	Green vote			Environmental vote		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS					
24 May protest exposure	1.275***	1.135***		0.583**	0.792***	
	(0.282)	(0.300)		(0.240)	(0.208)	
15 March protest exposure			0.686**			0.512***
			(0.267)			(0.121)
	LASSO IV					
24 May protest exposure	2.520***	1.778***		0.824*	1.129***	
	(0.960)	(0.170)		(0.477)	(0.263)	
15 March protest exposure			1.174***			1.021***
			(0.149)			(0.289)
Sample	Green	Green & no protest	Green	Full	No protest	Full
NUTS1 FE	X	X	X	X	X	X
Population controls	X	X	X	X	X	X
Education and Economy	X	X	X	X	X	X
Past voting	X	X	X	X	X	X
Observations	541	412	541	1016	662	1016

This table shows the relationship between protest exposure in selected previous periods and voting in the 2019 European election. The top panel presents correlations using an OLS estimation, while the bottom panel presents the results from an IV specification with LASSO-selected weather instruments and additional LASSO-selected local weather controls. The variable *Protest exposure* describes linkage-weighted exposure to protest attendance and is standardized to have a mean of zero and SD of one. *24 May protest exposure* measures exposure in the week before 26 May; *15 March protest exposure* measures exposure in the week of the first global climate strike on 15 March. In column (1) - (3), the outcome variable is the local vote share of Green parties in the 2019 EP election, as classified by the CHES, in percent. The outcome variable in columns (4) - (6) is EP 2019 vote share-weighted average environmentalism of local parties, as classified by the CHES, in percent. The sample in columns (1) and (3) includes only regions where at least one relevant Green party was present. The sample in column (2) further excludes regions that recorded at least one FFF protest before 2 June 2019. Columns (4) and (6) include the full sample as described in the text, column (5) excludes regions that recorded at least one FFF protest before 2 June 2019. All columns include fixed effects for first-level administrative region (NUTS 1) and controls for the logarithm of population, logarithm of population density per km^2, population share with tertiary education, population share in employment, logarithm of regional gdp, environmental voting and right-wing voting in the 2014 EP election. Note: *** p<0.01, ** p<0.05, * p<0.10. SEs clustered by country.

A Additional Tables and Figures

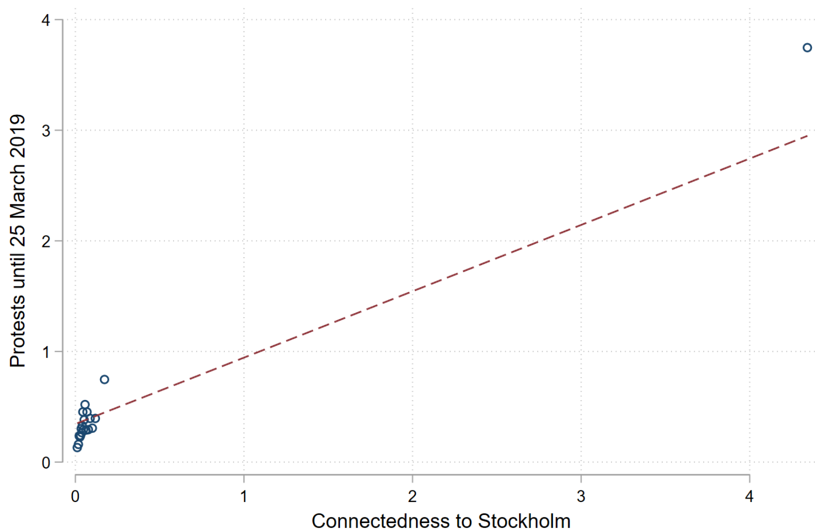
Figure A1: Weekly protests in Europe



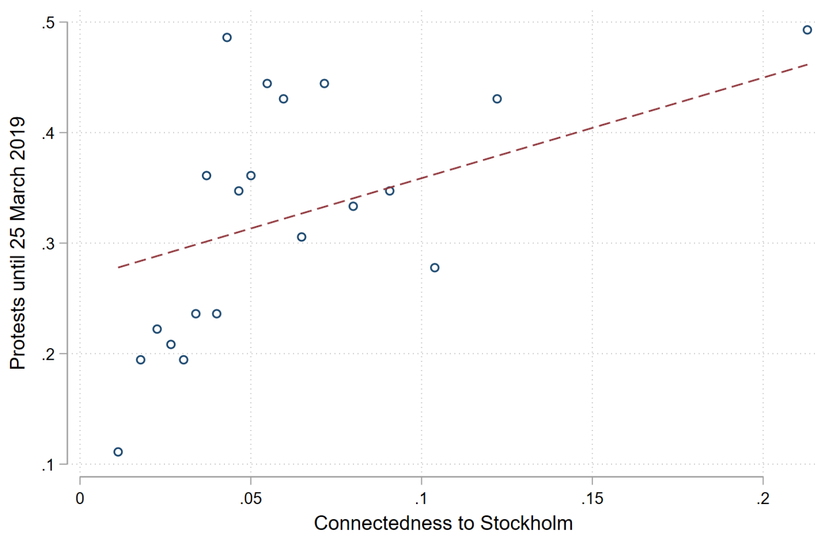
This figure illustrates the weekly protest attendance on a logarithmic scale. The red line illustrates the (log-) linear time trend from a linear fit. Grey vertical lines highlight weeks with global climate strikes, which were held on 25 March, 24 May, 20&27 September, 29 November.

Figure A2: Early FFF protests and connectedness to Stockholm

(a) Protest and connectedness

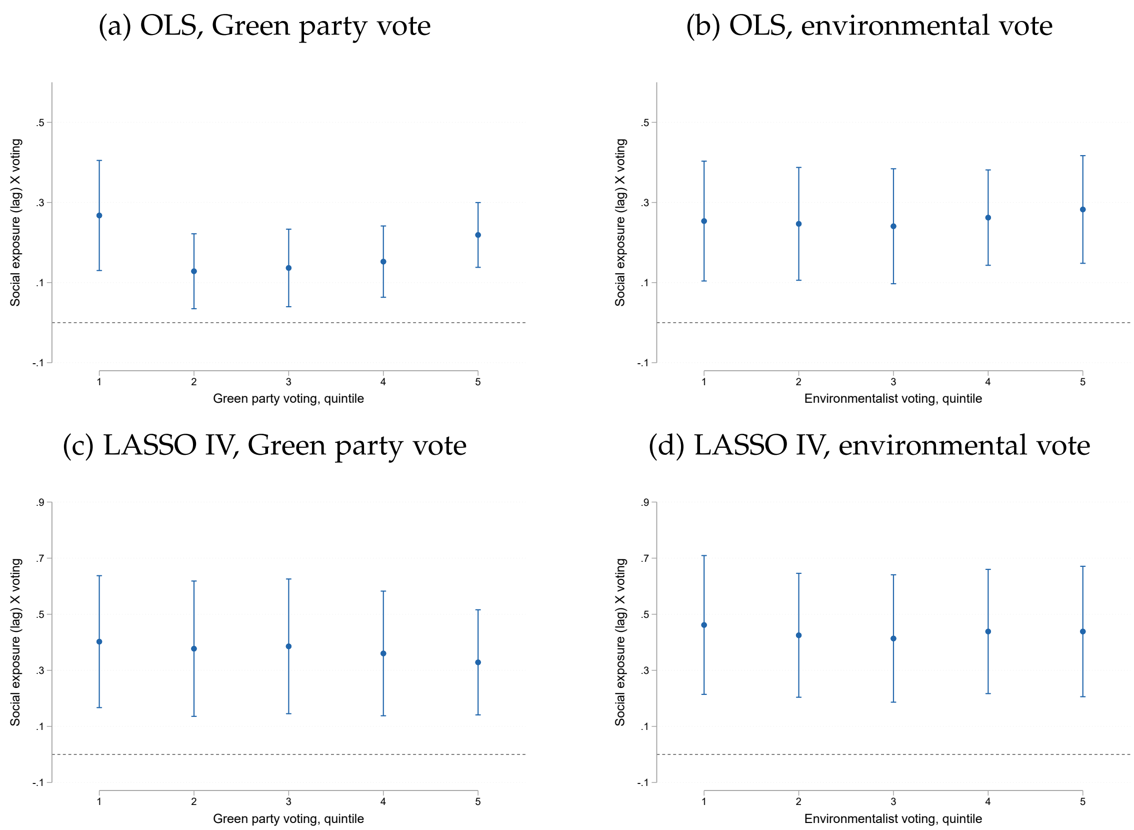


(b) Protest and connectedness, excl. neighboring countries



This figure illustrates the relationship between early FFF protests and relative connectedness to Stockholm, averaged within 20 vintiles of relative connectedness to Stockholm. Early FFF protests are the number of recorded FFF protests until 24 March 2019, the week after the first global climate strike. Relative connectedness is defined as the Meta Social Connectedness Index (SCI, see Section 2.2 for more detail), normalized by the total SCI across all region in the sample. Panel (a) presents the correlation for the full sample of 1508 regions. Panel (b) excludes all regions from Sweden and neighboring Scandinavian countries Finland, Norway, Denmark, cutting down the sample to 1439 regions. The dashed red line indicates the linear fit from a regression of protests on relative connectedness.

Figure A3: Spillovers by historical political environmentalism, attendance



This figure illustrates the protest spillovers by local environmental voting. In particular, I regress the arcsinh-transformed protest attendance on the interaction between protest exposure , the standardized linkage-weighted exposure to protest attendance in the previous period, and a series of indicators for 5 bins which represent the strength of historical environmental voting. In panels (a) and (c), the bins are constructed based on the Green party vote share in national elections 2008-17. Category 1 represents regions without a Green party. Categories 2-5 represent country-specific quartiles of Green party vote share with a Green party. In panels (b) and (d), the bins are constructed as the country-specific quintiles of environmental voting, as defined in the text. The top panels (a) and (b) present correlations using an OLS estimation, while the bottom panels (c) and (d) present the results from an IV specification with LASSO-selected weather instruments and additional LASSO-selected local weather controls.
Note: N = 68657. 95% CIs indicated, SEs clustered by NUTS 1 region.

Table A1: First stage, LASSO-selected instruments and controls

	Protest exposure$_{t-1}$	
	(1)	
	Coefficient	SE
Air pressure X Wind speed	0.000	0.000
Wind speed quart.= 4 X Air pressure	0.003	0.001
Wind speed quart.= 4 X Snow quart.= 2	-0.031	0.009
Wind speed quart.= 4 X Min. temp. quart.= 3	-0.018	0.009
Wind speed exp. quart.$_{t-1}$ = 2	-0.023	0.008
Precipitation exp. quart.$_{t-1}$ = 3	0.024	0.014
Air pressure exp. quart.$_{t-1}$ = 2 X Wind speed exp. quart.$_{t-1}$ = 4	-0.026	0.008
Air pressure exp. quart.$_{t-1}$ = 4 X Max. temp. exp. quart.$_{t-1}$ = 2	-0.011	0.007
Air pressure exp. quart.$_{t-1}$ = 4 X Min. temp. exp. quart.$_{t-1}$ = 3	-0.077	0.014
Precipitation exp. quart.$_{t-1}$ = 3 X Air pressure exp.	-0.006	0.002
Air pressure exp. X Precipitation exp.$_{t-1}$	0.001	0.000
Min. temp. exp. quart.$_{t-1}$ = 4 X Air pressure exp.$_{t-1}$	0.007	0.002
Wind speed exp. quart.$_{t-1}$ = 2 X 3Snow exp. quart.$_{t-1}$	-0.062	0.013
Wind speed exp. quart.$_{t-1}$ = 4 X Snow exp.$_{t-1}$	-0.001	0.000
Wind speed exp. quart.$_{t-1}$ = 4 X Precipitation exp.$_{t-1}$	-0.009	0.003
Wind speed exp. quart.$_{t-1}$ = 3 X Max. temp. exp. quart.$_{t-1}$ = 4	0.124	0.025
Wind speed exp. quart.$_{t-1}$ = 3 X Max. temp. exp.$_{t-1}$	0.014	0.003
Wind speed exp. quart.$_{t-1}$ = 2 X Min. temp. exp. quart.$_{t-1}$ = 4	0.099	0.022
Wind speed exp. quart.$_{t-1}$ = 2 X Min. temp. exp.$_{t-1}$	0.016	0.005
Wind speed exp. quart.$_{t-1}$ = 2 X Mean temp. exp. quart.$_{t-1}$ = 2	-0.037	0.014
Precipitation exp. quart.$_{t-1}$ = 4 X Wind speed exp.$_{t-1}$	-0.029	0.009
Wind speed exp. X Precipitation exp.$_{t-1}$	0.004	0.001
Snow exp. quart.$_{t-1}$ = 3 X Snow exp.$_{t-1}$	0.001	0.000
Snow exp. quart.$_{t-1}$ = 4 X Min. temp. exp. quart.$_{t-1} = 4$	-0.112	0.023
Snow exp. quart.$_{t-1}$ = 3 X Mean temp. exp. quart.$_{t-1} = 2$	-0.076	0.018
Precipitation exp. quart.$_{t-1}$ = 3 X Precipitation exp.	0.030	0.017
Precipitation exp. quart.$_{t-1}$ = 3 X Min. temp. exp. quart.$_{t-1}$ = 3	0.111	0.020
Precipitation exp. quart.$_{t-1}$ = 3 X Mean temp. exp.$_{t-1}$	0.018	0.004
Max. temp. exp. quart.$_{t-1}$ = 2 X Min. temp. exp. quart.$_{t-1}$ = 4	-0.128	0.029
Max. temp. exp. quart.$_{t-1}$ = 4 X Mean temp. exp. quart.$_{t-1}$ = 2	-0.514	0.090
Mean temp. exp. quart.$_{t-1}$ = 2 X Max. temp. exp.$_{t-1}$	-0.059	0.012
Min. temp. exp. quart.$_{t-1}$ = 2 X Min. temp. exp.$_{t-1}$	0.097	0.018
Min. temp. exp. quart.$_{t-1}$ = 3 X Mean temp. exp.$_{t-1}$	0.039	0.009
Constant	0.019	0.008
F-stat Instruments	17.73	

Note: This table presents the first stage of the IV estimation with LASSO-selected controls and instruments presented in column (3) of Table 2. Air pressure the weekly average sea-level air pressure in hPa, Wind speed is weekly average wind speed in km/h, Precipitation is average daily total precipitation in mm, Snow is average daily total snow depth in mm, Min., Max., and Mean. temp. are average daily minimum, maximum and average temperature in °C. Quart. refers to quartiles of these variables. The subscript $t-1$ refers to lagged variables. Exp. refers to weather measures in other regions, weighted by connectedness, as described in Section 3. SEs are clustered by NUTS 1 region. All columns include fixed effects for every region and every week in the sample.

Table A2: Alternative LASSO IV approaches

	$\mathbb{1}(Attendance > 0)$ (1)	IHS Attendance (2)
	OLS	
Protest exposure$_{t+1}$	1.579^{***}	1.579^{***}
	(0.427)	(0.427)
	LASSO-orth.	Post-LASSO-orth.
Protest exposure$_{t+1}$	2.081^{**}	2.226^{***}
	(0.905)	(0.900)
Observations	105560	105560

Note: This table shows the robustness of the main result reported in Table 2, column (3), to alternative methodologies incorporating high-dimensional instruments and controls. The bottom panel presents results from the "double-orthogonalization" method by Chernozhukov et al. (2015), based on the LASSO-selected (column (1)) and post-LASSO-selected (column (2)) instruments and controls. This table shows the relationship between protest exposure in the previous period and local current-period protest activity. The variable *Protest exposure*$_{t-1}$ measures linkage-weighted exposure to protest attendance in the previous period as described described in the text and is standardized to have a mean of zero and SD of one. The outcome variable is an indicator equal to one if at least one protest was recorded in a given region and week. All columns include fixed effects for every region and every week in the sample. Note: *** p<0.01, ** p<0.05, * p<0.10.SEs are clustered by NUTS 1 region.

Table A3: 2SLS estimation

	$\mathbb{1}(Att. > 0))$			IHS Att.		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS					
Protest exposure$_{t-1}$	1.579***	1.579***	1.579***	0.031***	0.031**	0.031***
	(0.427)	(0.402)	(0.214)	(0.010)	(0.013)	(0.005)
	2SLS					
Protest exposure$_{t-1}$	5.402**	5.402*	5.402***	0.079***	0.079**	0.079***
	(2.701)	(3.016)	(1.874)	(0.023)	(0.034)	(0.019)
First-stage F-Stat.	19.352	12.280	38.011	19.352	12.280	38.011
Clustering	NUTS 1	Network	Distance	NUTS 1	Network	Distance
Observations	105560	105560	105560	105560	105560	105560

This table shows the robustness to alternative definitions of my protest, protest exposure and weather measures. The variable *Protest exposure*$_{t-1}$ measures linkage-weighted exposure to protest attendance in the previous period as described described in the text and is standardized to have a mean of zero and SD of one. Coefficients in columns (1) - (3) are rescaled by the factor 100 to represent percentages. The top panel presents correlations using an OLS estimation, while the bottom panel presents the results from an IV specification using the interaction between wind speed and precipitation in the network and minimum, maximum, average temperature in the network as instruments and controls for local average, minimum, maximum temperature and an interaction between wind and precipitation. First-stage results for column (1) are presented in Appendix Table A4. In columns (1) - (3), the outcome variable is an indicator equal to one if at least one protest was recorded in a given region and week. The outcome variable in columns (4) - (6) is the arcsinh-transformed weekly attendance. All columns include fixed effects for every region and every week in the sample. Note: *** p<0.01, ** p<0.05, * p<0.10. SEs are clustered by NUTS 1 region in columns (1) and (4); SEs are clustered by network structure in columns (2) and (5); SEs are clustered by geographic distance in columns (3) and (6).

Table A4: First stage, 2SLS estimation

	(1) Protest exposure$_{t-1}$
Wind shock exposure$_{t-1}$ X Precipitation shock exposure$_{t-1}$	-0.004***
	(0.001)
Mean temperature shock exposure$_{t-1}$	0.070**
	(0.033)
Max. temperature shock exposure$_{t-1}$	-0.029
	(0.019)
Min. temperature shock exposure$_{t-1}$	-0.013
	(0.021)
Wind shock X Precipitation shock	-0.000
	(0.000)
Mean temperature shock	-0.005**
	(0.002)
Max. temperature shock	0.005***
	(0.001)
Min. temperature shock	-0.000
	(0.002)
Observations	105560

This table shows the first stage of columns (1) and (2) in Appendix Table A3. The outcome variable *Protest exposure*$_{t-1}$ measures linkage-weighted exposure to protest attendance in the previous period as described described in the text and is standardized to have a mean of zero and SD of one. Instruments are the interaction between lagged wind speed and precipitation in the network and lagged minimum, maximum, average temperature in the network; controls are local average, minimum, maximum temperature and an interaction between wind and precipitation. All columns include fixed effects for every region and every week in the sample. Note: *** p<0.01, ** p<0.05, * p<0.10. SEs are clustered by NUTS 1 region..

Table A5: Future protest exposure and local protest

	$\mathbb{1}(Attendance > 0)$	IHS Attendance
	(1)	(2)
	OLS	
Protest exposure$_{t+1}$	0.111	0.010***
	(0.225)	(0.003)
	LASSO IV	
Protest exposure$_{t+1}$	-0.482	0.006
	(0.390)	(0.004)
Observations	105560	105560

This table shows the relationship between future protest exposure and local current-period protest activity. The variable *Protest exposure*$_{t+1}$ measures linkage-weighted exposure to protest attendance in the following period as described described in the text and is standardized to have a mean of zero and SD of one. Coefficients in column (1) are rescaled by the factor 100 to represent percentages. The top panel presents correlations using an OLS estimation, while the bottom panel presents the results from an IV specification with LASSO-selected weather instruments and additional LASSO-selected local weather controls. In column (1), the outcome variable is an indicator equal to one if at least one protest was recorded in a given region and week. The outcome variable in column (2) is the arcsinh-transformed weekly attendance. All columns include fixed effects for every region and every week in the sample. Note: *** p<0.01, ** p<0.05, * p<0.10. SEs are clustered by NUTS 1 region.

Table A6: Alternative variable definitions

	Per-capita measures				Non-demeaned weather	
	$\mathbb{1}(Att. > 0)$	IHS Att.	IHS Att. p/c		$\mathbb{1}(Att. > 0)$	IHS Att.
	(1)	(2)	(3)	(4)	(5)	(6)
			OLS			
P/C-protest exposure$_{t-1}$	2.592***	0.055***	0.178***			
	(0.566)	(0.015)	(0.043)			
Protest exposure$_{t-1}$				0.099***	1.579***	0.031***
				(0.030)	(0.427)	(0.010)
			LASSO IV			
P/C-protest exposure$_{t-1}$	2.243**	0.041***	0.150***			
	(0.903)	(0.013)	(0.051)			
Protest exposure$_{t-1}$				0.153***	3.387***	0.284**
				(0.054)	(1.309)	(0.115)
Observations	105560	105560	105560	105560	105560	105560

This table shows the robustness to alternative definitions of my protest, protest exposure and weather measures. The variable *Protest exposure*$_{t-1}$ (*P/C-Protest exposure*$_{t-1}$) measures linkage-weighted exposure to protest attendance (protest attendance normalized by local population (in 100,000)) in the previous period as described described in the text and is standardized to have a mean of zero and SD of one. Coefficients in columns (1) and (5) are rescaled by the factor 100 to represent percentages. The top panel presents correlations using an OLS estimation, while the bottom panel presents the results from an IV specification with LASSO-selected weather instruments and additional LASSO-selected local weather controls. In column (1), the outcome variable is an indicator equal to one if at least one protest was recorded in a given region and week. The outcome variable in column (2) is the arcsinh-transformed weekly attendance. In columns (3) and (4), the outcome variable is the arcsinh-transformed weekly attendance normalized by local population (in 100,000). In columns (5) and (6), the weather controls and weather instruments in the bottom panel are selected from a set of non-demeaned weather measures. In column (5), the outcome variable is an indicator equal to one if at least one protest was recorded in a given region and week. The outcome variable in column (6) is the arcsinh-transformed weekly attendance All columns include fixed effects for every region and every week in the sample. Note: *** p<0.01, ** p<0.05, * p<0.10. SEs are clustered by NUTS 1 region.

Table A7: Additional controls

	$\mathbb{1}(Att. > 0)$		IHS Attendance	
	(1)	(2)	(3)	(4)
	OLS			
L.Protest exposure	2.134***	1.618***	0.042***	0.033***
	(0.482)	(0.438)	(0.011)	(0.011)
	LASSO IV			
L.Protest exposure	3.713**	2.441***	0.083***	0.047***
	(1.474)	(0.937)	(0.023)	(0.015)
Controls	Het. trends	Protest dist.	Het. trends	Protest dist.
Observations	74550	105560	74550	105560

This table shows the robustness to alternative definitions of my protest, protest exposure and weather measures. The variable *Protest exposure*$_{t-1}$ (*P/C-Protest exposure*$_{t-1}$) measures linkage-weighted exposure to protest attendance (protest attendance normalized by local population (in 100,000)) in the previous period as described described in the text and is standardized to have a mean of zero and SD of one. Coefficients in columns (1) and (2) are rescaled by the factor 100 to represent percentages. The top panel presents correlations using an OLS estimation, while the bottom panel presents the results from an IV specification with LASSO-selected weather instruments and additional LASSO-selected local weather controls. In columns (1) - (2), the outcome variable is an indicator equal to one if at least one protest was recorded in a given region and week. The outcome variable in column (3) - (4) is the arcsinh-transformed weekly attendance. Columns (1) and (3) add further controls for heterogeneous time trends in the form of interactions between a series of time-period fixed effects and population, population density, regional GDP per capita, unemployment, the population share with tertiary education, and the average stance on environmentalism and position on the general left-right scale of the elected parties in the 2014 EP election. Columns (2) and (4) add further controls for nearby protests in the form of the inverse-distance weighted protests in other locations, as described in Section 4.1. All columns include fixed effects for every region and every week in the sample. Note: *** p<0.01, ** p<0.05, * p<0.10. SEs are clustered by NUTS 1 region.

Table A8: Social exposure and local Internet speed

	Protest incidence		Attendance		Local Twitter	
	$\mathbb{1}(Attendance > 0)$		IHS Attendance		$\mathbb{1}(Tweets > 1)$	IHS Tweets
	(1)	(2)	(3)	(4)	(5)	(6)
			OLS			
Protest exposure$_{t-1}$	1.435***	0.691	0.119***	0.071	-0.270	-0.012***
	(0.428)	(0.675)	(0.038)	(0.056)	(0.334)	(0.004)
Protest exposure$_{t-1}$ X Download speed		0.015**		0.001*	0.015***	0.000***
		(0.007)		(0.001)	(0.005)	(0.000)
			LASSO IV			
Protest exposure$_{t-1}$	1.718*	0.532	0.167**	0.087	-0.153	-0.017*
	(0.939)	(0.990)	(0.067)	(0.074)	(0.811)	(0.009)
Protest exposure$_{t-1}$ X Download speed		0.025***		0.001**	0.020*	0.001***
		(0.009)		(0.001)	(0.011)	(0.000)
Observations	74001	74001	74001	74001	74001	74001

This table shows the relationship between local Internet quality, protest exposure in the previous period and local current-period protest activity in the year 2019 for a subsample of countries. The variable *Protest exposure*$_{t-1}$ measures linkage-weighted exposure to protest attendance in the previous period as described in the text and is standardized to have a mean of zero and SD of one. *Download speed* measures average quarterly broadband download speed in MBit/s. Coefficients in columns (1),(2) and (5) are rescaled by the factor 100 to represent percentages. The top panel presents correlations using an OLS estimation, while the bottom panel presents the results from an IV specification with LASSO-selected weather instruments and additional LASSO-selected local weather controls. In columns (1) and (2), the outcome variable is an indicator equal to one if at least one protest was recorded in a given region and week. The outcome variable in columns (3) and (4) is the arcsinh-transformed weekly attendance. In column (5), the outcome variable is an indicator equal to one if a region saw more than 1 local tweet in a week. The outcome variable in column (6) is the arcsinh-transformed number of weekly Tweets. All columns include fixed effects for every region and every week in the sample. Specifications with interaction terms include the respective variables as a controls. Note: *** p<0.01, ** p<0.05, * p<0.10. SEs are clustered by NUTS 1 region.

Table A9: Per-capita protest by local population

	(1) IHS Att. p/c	(2) Att. p/c
	OLS	
Protest exposure$_{t-1}$	0.081***	9.350**
	(0.028)	(4.408)
Protest exposure$_{t-1}$ X Population top decile	0.063**	27.824**
	(0.024)	(10.643)
	LASSO IV	
Protest exposure$_{t-1}$	0.157***	33.038***
	(0.050)	(11.273)
Protest exposure$_{t-1}$ X Population top decile	0.051*	22.590**
	(0.028)	(11.505)
Observations	105560	105560

This table shows the relationship between local Internet quality, protest exposure in the previous and local protest attendance per capita. The top panel presents correlations using an OLS estimation, while the bottom panel presents the results from an IV specification with LASSO-selected weather instruments and additional LASSO-selected local weather controls. The variable *Protest exposure*$_{t-1}$ describes linkage-weighted exposure to protests in the previous period and is standardized to have a mean of zero and SD of one. *Top decile population* is an indicator equal to one if a region is in the highest decile of local population (or has a population larger than 763441). In column (1) , the outcome variable is the arcsinh-transformed weekly attendance normalized by local population (in 100,000). The outcome variable in column (2) is the weekly attendance normalized by local population (in 100,000). All columns include fixed effects for every region and every week in the sample. Note: *** p<0.01, ** p<0.05, * p<0.10. SEs are clustered by NUTS 1 region.

Table A10: Descriptive statistics, EP 2019 sample

	Mean	SD	Median	Observations
Voting				
Green party vote, if present, 2019 EP (percent)	16.76	8.22	17.38	541
Environmental vote, 2019 EP (percent)	35.85	10.77	38.10	1016
FFF protests				
Local protest before 26 May	0.29	0.45	0.00	1016
24 May protest exposure	279.26	125.57	246.30	1016
15 March protest exposure	759.47	321.25	684.79	1016

Note: This table presents summary statistics the data used to analyze the effects of social exposure on voting in the 2019 European parliament election.