Did COVID-19 Boost Populism? Evidence from Early super spreader Events*

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Abstract

We examine whether right-wing populists benefited from the profound societal upheaval brought about by the COVID-19 pandemic. Drawing on a unique panel of Twitter data, we use an innovative instrumental variable approach to measure the causal impact of the pandemic on online support for right-wing populist political parties and their leaders in five Western European states. The results show that regions with higher COVID-19 cases experienced increases in online populist support. We further demonstrate the implications for political behavior, showing that super spreader events increased Rassemblement National vote share in French municipal elections held in March 2020 and that the pandemic contributed to support for right-wing populists at the ballot box in the UK and the Netherlands. We argue that increased online media use, anxiety, and declining trust in institutions during the pandemic are responsible for the shifts toward right-wing populism.

Keywords: populism, COVID-19, social media, super spreader events, voting behavior
JEL Codes: D72, D91, I12

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1 Introduction

The emergence of the COVID-19 pandemic profoundly reorganized social, economic, and political life across the globe. We examine whether right-wing populists may have benefited from these intersecting crises. The literature on this question so far reports correlations rather than causally identified effects (Guriev and Papaioannou, 2022). In this paper, we provide causal evidence that right-wing populism saw an increase in support during the early phase of the pandemic. Drawing on a unique panel of Twitter data, we use an innovative instrumental variable approach following Avetian et al. (2021) to measure the impact of the pandemic on online support for populism. Further, we demonstrate that the pandemic contributed to support for right-wing populists at the ballot box and argue that increased online media use, declining trust in institutions, and rising anxiety due to COVID-19 are the main facilitators of the continuing rise of right-wing populism as seen in recent elections in France, Italy, and Sweden.

At the beginning of the pandemic, it was unclear how the emerging public health crisis would become politicized. There were many instances of public displays of unity and solidarity, like daily festivities to celebrate healthcare workers. We have since seen how unprecedented shutdowns of public life and practices like mask-wearing and vaccination have become hotly contested, partisan issues in many contexts. In many cases, right-wing populists have strongly opposed these measures, viewing them as attempts by liberal elites to consolidate their power over social, cultural, and political institutions (Stavrakakis and Katsambekis, 2020).

There are several theoretical arguments to be made in favour or against COVID-19 pushing right-wing populism (Morelli, 2020). On the one hand, the sudden arrival of COVID-19 increased confidence in most governments, triggering a 'rallying around the flag' effect (Bobba and Hubé, 2021). As an external crisis with nobody directly to blame, populists could not easily politicize the pandemic. Indeed, polls in Europe showed no increased support for populists during the pandemic (Bobba and Hubé, 2021). If in power, populists were slower to enact protective measures and their mishandling of the crisis could have led to a backlash (Bayerlein et al., 2021; Kavakli, 2020). Finally, COVID-19 called for supranational collaboration and touched all groups of society, potentially halting a cultural identification process that facilitated the rise of populism (Bonomi et al., 2021).

On the other hand, COVID-19 has led to severe drops in interpersonal and institutional trust due to economic insecurity and health concerns (Daniele et al., 2020; Brück et al., 2020), which is usually fertile ground for populism (Algan et al., 2017). Survey data from the Eurobarometer series highlight significant shifts in European public opinion across Europe since the onset of the pandemic. Figure 1 shows a sharp pandemic-era decline both in respondents' feelings of attachment to their local and national communities (left column) and in their assessment of their country's general and economic situation (middle column).[1] Interestingly, these trends have been accompanied by an acceleration in reported usage of online social networks (right column). Guriev et al. (2020) suggest that populists might benefit from increased internet access, an effect that accelerates the dispersion of beliefs about the pandemic and mechanisms of anxiety as documented by Fetzer et al. (2020). Data from Facebook and Twitter show that populist parties tended to receive higher rates of engagement in 2020 compared to 2019. Figure 2 shows evidence of statistically-significant increases in five out of six kinds of engagement among parties considered populist by an expert survey (Rooduijn et al., 2019), with the largest increases in populist support on Facebook. Finally, populists could also have benefited from changes in turnout of differently educated citizens Morelli et al. (2020).

We examine the relationship between the emergence of the COVID-19 pandemic and support for populism using three different sets of empirical analyses. First, we use geo-located data from Twitter to measure engagement with populist political parties and their leaders. Using both OLS and instrumental variable approaches, we find evidence of a strong, positive relationship: increases in cases result in higher rates of mentioning, retweeting, and liking populists. We demonstrate that the effect is specific to right-wing populists and that non-populist parties and leaders receive less engagement with increasing COVID-19 cases. Second, we use the same approach to analyze the results of the first-round of the French municipal election held in March 2020. We choose this election as it is the only election in Europe during the first six months of 2020 and because the right-wing populist *Rassemblement National* (RN, formerly the *Front National*) is one of the leading right-wing populist parties in Europe. We find that communes with proximate to super spreader events tended to favor right-wing populist RN candidates and that our Twitter measures are associated with voting behavior. Nationally-represented survey data from the United Kingdom and the Netherlands provide further evidence of an association between COVID-19 and intent to vote for right-wing populists. Finally, we use these surveys to explore individual-level mechanisms. The results suggest that increased social media use and anxiety might be key mechanisms driving the effect.

Our work relates to different strands of literature. First, we contribute to the growing evidence on the determinants of right-wing populism (Guriev and Papaioannou, 2022; Guriev, 2018). Second, we speak to the abundant literature on the socio-economic effects of COVID-19.[2] Third, we contribute to research on socio-political and psychological effects of online media use by using Twitter data and

[1] The data were accessed from the GESIS Leibniz Institute for the Social Sciences data archive (`https://www.gesis.org/en/eurobarometer-data-service/search-data-access/data-access`). In each wave, respondents are randomly selected by address clusters after stratification by the distribution of each country's population in terms of metropolitan, urban, and rural areas. Online Appendix 1 provides evidence of growing social alienation as well as mistrust of democracy from the European Values Study, which employs a similar sampling procedure but contains substantially fewer responses for 2019 and 2020.

[2] For example, see `https://cepr.org/publications/covid-economics-papers` for CEPR's Covid Economics Papers.

complementing our analysis with survey data (Allcott et al., 2022; Levy, 2021; Allcott et al., 2020).

The paper is structured as follows. section 2 provides a brief background on COVID-19 and right-wing populism, section 3 details the identification strategy using early super spreader events, and section 4 provides information on data. subsection 4.1 and subsection 4.2 present the main results and robustness of evidence using Twitter data. section 5 show results of COVID-19 for voting behaviour, section 6 discusses mechanisms, and section 7 concludes.

2 Background: The COVID-19 Pandemic and Right-Wing Populism

In early 2020, several media organizations speculated the COVID-19 would weaken the recent advances of populism, as the bluster of populist leaders like Donald Trump would be no match for the hard, scientific expertise needed to reign in the virus (Stavrakakis and Katsambekis, 2020). Scholarly research still debates whether COVID-19 damaged Trump (Clarke et al., 2021; Noland and Zhang, 2021) or aided him (Lake and Nie, 2021). Moments of crisis often induce a "rally-around-the-flag" effect, particularly when governments can demonstrate competence and action (Chowanietz, 2011). There is some evidence this occurred at the onset of the pandemic, with some governemtns experiencing increases in support (Bobba and Hubé, 2021). Nonetheless, the pandemic presented a challenge, as political actors across the spectrum had to respond to the unprecedented crisis. Governments had to grapple with the need to control the spread of the virus without undermining core democratic principles (Engler et al., 2021).

For incumbents, the pandemic posed a serious challenge, but for challengers, the pandemic provided an opportunity to be exploited for political gain. From the supply-side, populist discourses and political positions are conducive to anti-government positions. Populism is characterized by anti-elitist/anti-establishment stance, the notion of the sovereignty of the people, and a Manichean outlook that simplifies political problems, juxtaposing a "corrupt" elite against the "pure" people (Mudde, 2004). Populists could criticize state-directed responses to the pandemic as top-down, technocratic solutions that imposed restrictions on people and their freedoms. At the same time, however, the policies of right-wing populist parties often have more authoritarian dimensions (Müller, 2016) that could be sympathetic to the kinds of restrictions imposed on civil society in attempts to limit the spread of the virus. Indeed, in some cases such as the Netherlands, populists criticized the government for not taking strong enough measures against the virus (Stavrakakis and Katsambekis, 2020). While this suggests heterogeneity across countries, it also highlights the flexibility of populism, illustrating how populist challengers could criticize elites both for doing too much or too little. In addition to their hostility towards elites, right-wing populism is typified by an "exclusionary" dimension, often directing public ire against minority groups (Mudde and Rovira Kaltwasser, 2013). The origins of the virus in China, which led to racist hostility against Asians in Europe and elsewhere, clearly resonated with the xenophobic positions of right-wing populists, with parties including the French National Rally and Italian Northern League quickly connecting the virus to the issue of immigration (Stavrakakis and Katsambekis, 2020; Froio, 2022). The pandemic therefore presented an opportunity for populists to attack internal elites for their actions and inaction and present the virus as a foreign enemy.

Turning to the demand-side, voters for populist parties not only tend to subscribe to this Manichean worldview, but tend to have low trust in political institutions (Akkerman et al., 2013; Geurkink et al., 2019), making it likely that they would be skeptical of the top-down pandemic control measures. The salience of these anti-elite attitudes likely increased as governments were perceived has mishandling their responses to the pandemic (Stavrakakis and Katsambekis, 2020). Populist voters are also more likely to endorse conspiracy theories (Castanho Silva et al., 2017), including those propagated around the pandemic (Eberl et al., 2021; Stecula and Pickup, 2021), in part due to their distrust of political and scientific institutions. During the early stages of the pandemic, conspiracies spread across social media and online news sites, promoting the idea that the virus manufactured or exploited by elites for ulterior motives, like the use of 5G broadband towers for mind control or to justify the expansion of government powers (Theocharis et al., 2021).

3 Identification Strategy: Exploiting Early super spreader Exposure

We measure local support for populism using data from Twitter described in the following section. A first simple approach to estimate the effect of COVID-19 cases on right-wing populism is:

$$Y_{it} = \beta_0 + \beta_1 \text{COVID-19}_{it} + \mathbf{X}'_{c(i)t}\gamma_{\text{x}} + \delta_t + \phi_c + \epsilon_{it} \tag{1}$$

where the dependent variable Y_{it} is either mentions, likes, or retweets for populist leaders or parties on Twitter in region i and country $c(i)$ on day t. COVID-19$_{it}$ are log daily new cases per 10,000 inhabitants, $X_{c(i)t}$ is a time-varying control variable for lockdown stringency , and δ_t and ϕ_c are day and country fixed effects respectively.

We use three different dependent variables because they capture different kinds of interactions with populists. Mentions of populists can be made at any time but could indicate either favourable or critical engagement, making them more ambiguous. Retweets and likes can only be made in response to tweets by populists, but provide a clear measure of support, indicating that users are choosing to share or endorse statements made by politicians.

A natural source of omitted variable bias for the relationship between COVID-19 cases and populist support comes from the different degrees to which lockdown measures are implemented. To tackle this concern, we add a time-varying control for the stringency of lockdown measures at the daily level (Hale et al., 2021). We also add day fixed effects to capture general dynamics of COVID-19 cases, as well as country fixed effects to account for any unobserved time-constant heterogeneity across countries. We further report results of an even more demanding specification with country times day fixed effects, as well as a results from Poisson regressions. In all cases, standard errors are clustered at the NUTS-3 region level.

Despite the host of fixed effects, it is still plausible that time-varying confounders bias our estimates. For example, reverse causality might be present: higher support for populists on social media could affect perceptions of the risk of COVID-19 and ultimately the behaviour of people, even given the same lockdown measures. Such changes in behaviour can plausibly translate into changes in COVID-19 cases. Other unobserved time-varying factors impacting the interplay between local COVID-19 cases and individual attitudes and behaviour will also lead to biased estimation of β_1. This is possible even if we control for the stringency of so-called lockdown measures aimed at containing transmission of COVID-19, which could themselves be affected by local political climates or virus transmission.

Our principal strategy for addressing this endogeneity threat is an instrumental variables approach based on the timing of super spreader events. Given the high degree of overdispersion and idiosyncrasy in COVID-19 transmissions (Chen et al., 2021), we argue that, in the early phase of the pandemic, the timing of super spreader events in nearby regions is plausibly orthogonal to factors influencing populist support. The starting point of our strategy is the high degree of overdispersion and idiosyncrasy in COVID-19 transmissions. Chen et al. (2021) write that "poorly ventilated, crowded spaces with susceptible individuals facilitate superspreading, but whether a virus tends to transmit via large clusters in the first place seems to be intrinsic to that viral infection." In fact, about eighty percent of COVID-19 transmission has been caused by only ten percent of the infected individuals (Endo et al., 2020). These features lead us to argue that occurrence of super spreader events in the early phase of the pandemic is as-good-as random. Note that our argument for the exclusion restriction does not hinge on geographic location. Instead, our identifying assumption is that, in a given region and across comparable lockdown stringency, the timing of additional local COVID-19 infections due to early super spreader events is exogenous to factors also contributing to populist support on Twitter. To address concerns related to geography, we also omit regions with super spreader events such that COVID-19$_{it}$ is instrumented with exposure to super spreader events from nearby regions only. Our preferred instrument has a specification which allows super spreader events to time-varyingly impact local COVID-19 cases up to 60 days after the event, with a linear geographic decline until 800km distance. Appendix subsection 2.2 shows that results are generally robust to various choices of instrument specifications.

We restrict our analysis to the first half of 2020. In this early phase of the pandemic, the coronavirus had not yet disseminated into all regions, and was characterised by clusters and hotspots. Super spreader events were the driving force behind coronavirus transmission in the early phase of the pandemic (Galvani and May, 2005). We use a database on super spreader events from Swinkels et al. (2021) which itself is built on four existing databases, as well as other contributions.[3] Based on these data, we limit our analysis to countries in Europe which have prominent right-wing populist political parties and with several recorded super spreader events between 1st February 2020 and 30th June 2020: France, Germany, Italy, the Netherlands, and the United Kingdom.

We project the locations and date indicators of the super spreader events on a shapefile of NUTS-3 regions from Eurostat (2020). As Swinkels et al. (2021) note, the exact number of people infected in super spreader events is not exactly known, making direct quantitative comparisons between super spreader events problematic. For this reason, we design our instrument using the time and location of super spreader events. We also use the day chosen or estimated by Swinkels et al. (2021) for events which last several days or where exact dates are unknown. The locations of the super spreader events are approximate within cities, but are arguably precise when situated within broader NUTS-3 regions.

We construct an instrumental variable that captures exposure to super spreader events in nearby regions. We report robustness of our results to various specifications of this exposure instrument, but use as our preferred measure a time-varying specification which allows super spreader events to impact local COVID-19 cases up to 60 days after the event with a linear geographic decline until 800km distance.[4] This specification better represents the transmission dynamics of super spreader events than a time-constant exposure given the incubation period of SARS-COV-2 and its pattern of exponential growth in the early phase.

The first stage of our approach is thus:

$$\text{COVID-19}_{it} = \varphi_0 + \varphi_1 \mathrm{Z}_{it} + \mathbf{X}'_{c(i)t}\varphi_{\mathrm{x}} + \xi_t + \mu_i + \nu_{it} \tag{2}$$

where

$$\mathrm{Z}_{it} = \begin{cases} \sum_{k=1}^{K}(1 - \frac{\Omega_{k-i}}{\Phi})\lambda, & \text{if } \phi < \Phi \quad \text{and} \quad \tau \leq \mathrm{T} \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

Our instrument Z_{it} is a weighted sum over all super spreader events, where Ω_{k-i} is the Vincenty distance between the centroid of NUTS-3 region $i = 1...N$ and super spreader events $k = 1...K$ and Φ is a normalization parameter for the maximum radius from the event. It is equal zero for NUTS-3 regions where the distance from the super spreader event, ϕ, is $\Phi = 800$ or more, or the days since

[3] The database is publicly available and accessible on `https://covid19settings.blogspot.com/p/about.html`.

[4] See Appendix subsection 2.2 for more details.

the event, τ, exceeds $\mathrm{T} = 60$. We also use temporal weights λ to capture first the increasing and then decreasing effect of super spreader events on COVID-19 cases due to the incubation period of SARS-COV-2 of around 5.7 days (Salzberger et al., 2021). In Appendix subsection 2.2 we show results of first stages with different choices of Φ and T. We also discuss the weight λ and present first-stage results with and without this adjustment.

The second stage can be written as:

$$Y_{it} = \beta_0 + \beta_1 \widehat{\text{COVID-19}}_{it} + \mathbf{X}'_{c(i)t}\gamma_{\mathbf{x}} + \delta_t + \alpha_i + \epsilon_{it} \tag{4}$$

where $\widehat{\text{COVID-19}}_{it}$ is isolated variation in log COVID-19 cases per 10,000 population due to temporal and geographic proximity to super spreader events.

Data on COVID-19 cases at the sub-national level come from the COVID-19 European regional tracker (Naqvi, 2021). We also add our data with a measure of lockdown stringency at the country-day level from Hale et al. (2021). Our final data is a panel of 792 NUTS-3 regions for five European countries (DE, IT, FR, NL, UK) observed for 151 days between 1st February 2020 and 30th June 2020. The data has 119,520 region-day observations and is weakly unbalanced since in 72 instances (0.06% of data) COVID-19 daily cases are not reported (Naqvi, 2021).[5]

4 Geographically Locating Populist Support on Social Media

We use data collected from social media as a proxy for populist support, focusing on interactions between social media users and populist politicians and political parties. Unlike conventional surveys, social media are "always on" (Salganik, 2017), allowing us to track shifts in engagement with populists in high-resolution across multiple countries. For our main empirical analyses, we use data collected from Twitter to measure the relationship between exposure to COVID-19 and support for right-wing populism at the local level. Facebook was also widely used across the countries considered, and, as Figure 2 showed, populists were particularly popular on the platform during the pandemic. However, the platform no longer provides access to any data on individual users, making such regional or individual analyses impossible.

We focus on the period from January through July 2020, when the nascent pandemic was a nexus for political conflict. We selected five countries to analyze: France, Germany, Italy, the Netherlands, and the UK. These cases were chosen because all five countries experienced a set of super spreader

[5] We further replace log daily cases per 10,000 population with zero for the 282 instances (0.24% of data) where official reported daily cases are negative. Naqvi (2021) note that "negative changes in daily cases exist in the raw files and are mostly likely corrections to the data."

events during the period considered, an important feature of our empirical strategy discussed in the following section. For each country considered, we collected all tweets that mentioned right-wing populist political parties or party leaders during the period and recorded every user who liked or retweeted one of these accounts. For supplementary analyses, we also collected mentions of major non-populist parties and politicians. All data were collected using the Twitter Academic API and the associated software developed by Barrie and Ho (2021).

Our goal is to use these data to measure sub-national variation in support for right-wing populists. Prior work has used geo-tags that users can associate with particular tweets, but this functionality tends to be biased towards urban areas (Hecht and Stephens, 2014) and only a small percentage of tweets are geo-tagged (Liu et al., 2014). While several machine-learning based methods for inferring locations have been proposed (Ajao et al., 2015), we elected to use a more parsimonious approach by using self-reported location text from their Twitter profiles. Most users provide some information in this field. Across the five countries, approximately three-quarters of users who mentioned a populist had provide a location. This information varied from general locations, such as country or region, to more specific geographical indicators like names of towns and villages. Some users also use this space to write nonsense, fictional places, or include unrelated information (e.g. "Somewhere over the rainbow") and it is plausible that some intentionally list misleading or incorrect locations (Hecht et al., 2013). Although these data are somewhat noisy, we are interested in general trends across time and space, and we have no reason to expect that any errors in this field should systematically vary according to the geographical areas or periods considered. Since we are interested in precise, sub-national geographic variation, any locations that only consisted of the country name or broad regions (e.g. Wales, Süddeutschland) were manually removed.[6] The Google Geolocation API was then used to retrieve locations and coordinates for the remaining locations. The API takes a name of a location and returns an address and coordinates where relevant. These locations do not typically correspond to the residential address of Twitter users but to the centroid of the city, town, or village where they reside.

The location data was spatially-joined to shapefiles for each country provided by Eurostat, enabling us to locate each user to within a NUTS-3 region.[7] We removed any users whose locations were outside the country associated with the politician they were interacting with, including those located within other countries considered in our analysis (e.g. A user located in France who mentioned a German politician would be excluded). After the extracting the coordinates and merging them with the shapefiles we were able to match the majority of users who provided location data to a location. For example, from the users who mentioned a politician and provided some location data ($n = 20,110$),

[6]We iteratively developed a keyword lexicon for each country using by evaluating the most frequently occurring locations, which tended to be these broad geographic areas.

[7]The NUTS 2021 shapefile was downloaded from the European Commission website: `https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/administrative-units-statistical-units/nuts`

69% were matched to a NUTS-3 region. Overall, we were able to infer locations for 52% of all users who mentioned a populist politician or party, ranging from 42% in Italy to 68% in Germany.[8]

This information was then used to construct several measures of engagement with populists over time and across locations. For each NUTS-3 unit, we measure the daily number of times right-wing populists are mentioned, liked, and retweeted, as well as the number of unique users who made each type of engagement in each region-day. These Twitter data were then merged with information on daily COVID-19 cases at the NUTS-3 level for all countries from Naqvi (2021). Table 1 reports summary statistics.

4.1 Results

Table 2 shows first results as described in Equation 1 of section 3. Column 1 reports that, in a simple model, a one percent increase in COVID-19 cases per 10,000 inhabitants is associated with 0.172 more mentions, 4 more retweets, and 7.3 more likes for populist leaders. These associations are statistically significant at the 1 percent level.

It can be expected that some of the association is driven by varying lockdown measures. Right-wing populist leaders generally responded critically to lockdown measures, albeit not always in a consistent direction (Stavrakakis and Katsambekis, 2020). Appendix Table A1 confirms that an increase in lockdown stringency is robustly associated with an increase in mentions, retweets, and likes for populist leaders. As these responses are likely to trigger reactions on social media and could be influenced by the timing of super spreader events, we include a time-varying control for lockdown stringency in column 2. As expected, the coefficient of interest decreases by 33 percent (mentions), 41 percent (retweets), and 29 percent (likes).

The association between local COVID-19 cases and support of populists on Twitter could be driven by macro-effects such as country-specific timing of coronavirus "waves". In columns 3-5 we subsequently add country fixed effects, day fixed effects, or their interaction, to rule out this possibility. The result remains qualitatively unchanged: higher numbers of COVID-19 cases are statistically significantly related to more engagement with and support of populists on Twitter. Moreover, given that the dependent variables are counts with high shares of zeros, column 6 confirms that Poisson estimation does not yield qualitatively different results.

To arrive at a causal estimate, we exploit the arguably random timing of early COVID-19 super

[8]A potential concern is that users who provide valid locations behave differently to those who do not share location information or cannot be precisely located. To assess this possibility, we compare the language used in their tweets that mention politicians and political parties. Analyzes using structural topic models reported in Online Appendix 4 do not show any evidence of differences in tweet content attributable to the propensity to reveal location information in users' profiles. This implies that users who add a location to their profile are representative of the wider population of Twitter users who mention politicians with respect to the kinds of topics they discuss in their tweets.

spreader events in nearby regions. Table 3 shows instrumental variable estimates where exposure to super spreader events of nearby regions is used as an instrument for local COVID-19 cases. Panel A uses the same dependent variables (and data) as Table 2. The F-statistics provide strong support to our argument that super spreader events are relevant for local COVID-19 cases (Stock and Yogo, 2005). Coefficients in Panel A indicate that a one percent increase in COVID-19 cases per 10,000 inhabitants due to early super spreader events in nearby regions leads to 0.31 more mentions, 11.5 more retweets, and 6.9 more likes for populist leaders.

Is this effect specific to the personalities of populist leaders? Panel B shows results for mentions, retweets, and likes of Twitter accounts of populist political parties. Coefficients of interest are considerably smaller, but remain statistically significant. The effect thus suggests that increases in local COVID-19 cases causally lead to more support on Twitter not only of populist politicians, but also the political parties they belong to.

Given the diversity of populist parties and leaders in the countries of our sample, we investigate whether the effect is different across countries. Table 4 shows that the observed relationship is present and statistically significant for all countries in our sample (the Netherlands in column 1 being the only exception). Interaction effects vary in size, with Italy showing slightly lower coefficients and France consistently highest. We turn to an in-depth analysis of the French case in section 5. Apart from differing population sizes across NUTS-3 regions, lower coefficient sizes for Italy could be explained by Italy's special experience as the first country in Europe heavily hit by SARS-COV-2.

4.2 Robustness: Individual-level analyses and overall political engagement

To corroborate the causality of the effect even further, we conduct a within-individual analysis on those who mentioned populist leaders or parties at any time during the period. We then carry out our analysis with a dataset of 1,258,222 observations on the author-day level, instead of the region-day level. This data structure allows us to add Twitter author fixed effects and hold constant any time-constant unobserved heterogeneity not only with respect to NUTS-3 regions, but also with respect to Twitter users. Table 5 reports results of this highly-demanding specification with 8,190 Twitter user fixed effects. Still using our instrumental variable approach, we find that it takes a roughly eight percent increase in local COVID-19 cases per 10,000 inhabitants to induce a Twitter user to post a Tweet mentioning a populist leader.

A valid question is whether there might be also an increase in engagement with non-populists on Twitter due to COVID-19. Table 6 shows that mentions of non-populist leaders and parties decrease substantially with increasing COVID-19 cases (column 2). The relative increase of engagement with populists over non-populists is positive and statistically significant (column 3). Thus, our findings are not driven by an overall increase in the use of social media for political discussion during the pandemic.

Finally, we provide robustness checks for different choices of instruments capturing exposure to super spreader events. Figure A2 in the Online Appendix shows that estimates are in general unchanged when different maximum distances, different days of exposure, or different temporal weights are employed to construct the instrument.

5 Voting Behavior: Electoral and Survey Evidence

Was increased engagement with populists on social media in the early stages of COVID-19 accompanied by stronger support for them at the ballot box? In this section, we investigate the pandemic's consequences for voting behavior, drawing on evidence from the 2020 French municipal elections — one of the few European elections to be held in the first months of COVID-19 — as well as from surveys conducted in the Netherlands and the United Kingdom around this time. First, using our super spreader event instrument, we show that French municipalities that were more exposed to COVID-19 before the elections saw higher levels of support for the *Rassemblement National*, France's leading right-wing populist party. Second, we confirm that the RN's vote share is also positively associated with local Twitter mentions of the party in the run-up to the elections, indicating a connection between social media engagement and voting behavior. Third, we extend our analysis to the individual level using a well-established British electoral survey, finding that respondents in localities with greater exposure to COVID-19 in 2020 were more likely to vote for a populist party. Fourth, we present concordant individual-level evidence from a Dutch survey that captures respondents' personal exposure to COVID as well as their voting intentions.

5.1 Populist Performance in the 2020 French Municipal Elections

The first round of the 2020 French municipal elections was held on 15 March amid growing concerns about the spread and implications of COVID-19 — worries that led to the postponement of the second round until 28 June.[9] Due to financial problems linked to the unexpected recall of a Russian loan, the *Rassemblement National* (RN) (formerly known as *Front National*) was forced to focus its efforts on 262 races, compared to 369 in the previous (2014) municipal elections (Lichfield, 2020). As a result, the party fared worse overall than in 2014, winning approximately 40 percent fewer council seats. Insofar as resource constraints and negative publicity might be expected to harm the RN's performance at the local level, the 2020 elections represent a difficult test for the COVID-populism hypothesis. What is

[9] We do not include the second round in our analysis because it excluded party lists that did not receive at least 10 percent in the first round.

more, some analysts have posited a link between the RN's low vote share and COVID-19, which, they suggest, may have disproportionately suppressed turnout among its older and more risk-averse voter base (e.g., Conley, 2020; Leromain and Vannoorenberghe, 2022).

In the approximately 10,000 municipalities (or *communes*) with more than 1,000 inhabitants, councilors are elected by proportional representation from complete (and unalterable) party lists. Following Noury et al.'s (2021) analysis of COVID-19's impact on turnout in the 2020 elections, we exclude both municipalities with smaller populations, which employ a different electoral system involving non-proportional block voting and *panachage*, and French overseas territories, which are not covered by our super spreader event instrument. Our outcome variable, the RN's vote share in a given municipality, is defined by:

$$V_m = \frac{\sum_{j_m=1}^{J_m} vj_m}{R_m} \tag{5}$$

where vj_m is the number of votes received by candidate j from RN's list in municipality m, J_m is the number of candidates on RN's list in m, and R_m is the number of votes cast in m. Data come from France's Ministry of the Interior (Ministère de l'Intérieur, 2020).

As French health authorities do not release statistics on COVID-19 cases at the *commune* level, our main treatment variable is a modified version of our super spreader exposure instrument, which was earlier shown to be a strong predictor of such cases at the NUTS-3 level: the sum of inverse kilometer distances from a given municipality to all early super spreader events that occurred prior to the 2020 election wave, that is,

$$Z_m^{fr1} = \sum_{s=1}^{S} \theta D_{m,s}^{-1} \tag{6}$$

where $D_{m,s}$ is the Vincenty distance between the centroid of municipality m and super spreader event s, S is the total number of super spreader events that occurred within 800km of m's centroid before 15 March 2020, and θ is a weight initially set to 1. To account for the possibility that support for the RN varies with the length of time since m experienced a COVID-19 shock, we additionally employ two time-specific variants of instrument that assign lower and higher weights to more recent super spreader events.[10] These variables, Z_m^{fr2} and Z_m^{fr3}, are constructed by setting θ in Equation 6 to the number of days between s and 15 March 2020 and to the inverse of this number, respectively. Figure 4 displays the location of all pre-election super spreader events (represented by large circles) in France and neighboring countries.

We control for NUTS-3 fixed effects, the RN's vote share in the previous (2014) municipal elec-

[10]Theoretically, the implications of such variation are not obvious. While a longer period since m gives RN politicians more time to mobilize political support, for instance, a shorter period could elicit a stronger populist response from the electorate.

tions, and several municipality-level demographic and socioeconomic characteristics — measured at the end of 2019 — that could plausibly affect both support for the RN and distance from super spreader events: total population (in thousands); population density, i.e., population divided by area (in squared kilometers); the proportion of the population under 30 years old; the proportion of individuals over 14 years old with no elementary school diploma; and the unemployment rate.[11] These variables are measured with census, tax, and employment compiled by France's national statistics bureau (INSEE, 2022). Our specification is thus:

$$V_m = \beta_0 + \beta_1 \begin{cases} Z_m^{fr1} \\ Z_m^{fr2} \\ Z_m^{fr3} \end{cases} + \alpha V_{m,2014} + \mathbf{X}_m + \gamma_d + \epsilon_m \tag{7}$$

where V_m is the RN's vote share in municipality m (as defined in Equation 5), $V_{m,2014}$ is the RN's vote share in m in the 2014 elections, Z_m^{fr1}, Z_m^{fr2}, Z_m^{fr3} are the three variants of our super spreader exposure instrument described above, $\mathbf{X}_m$ is a vector of municipality-varying controls listed above, and γ_d are NUTS-3 (or *départements*) fixed effects. Huber-White standard errors are clustered at the NUTS-3 level.

The results, reported in Table 7, reveal a positive and relatively strong relationship between exposure to pre-election super spreader events and support for the RN. The treatment coefficient on the time-invariant measure of exposure falls just short of significance (column 1), while those on the time-varying measures are significant at the five percent level. The late-weighted measure has a substantially larger estimate (column 2) than the early-weighted measure (column 3), suggesting that super spreader occurring closer to the elections delivered a more sizable electoral boost to the RN. More precisely, a 100-kilometer reduction in a municipality's aggregate distance from super spreader events is associated with a 0.6-percentage-point increase in the RN's vote share. Table A3 in Online Appendix 5 shows that these results are robust to a variety of alternative controls, including longer trends in the RN's vote share, the proportion of workers in industrial and manual occupations, and the proportion of residents who moved to their current municipality within the past year.

In sum, municipalities that were more exposed to super spreader events before the 2020 elections saw higher levels of support for the RN. An interesting implication of this finding is that, rather than contributing to the RN's inferior overall performance in 2020, COVID-19 may have helped to *mitigate* the impact of electoral headwinds then facing the party (such as its financial difficulties).

[11] We do not pursue a difference-in-differences strategy comparing the 2020 and 2014 municipal election results both because the RN did not exist (in its present form) in 2014 and because it competed in a substantially smaller set of municipalities in 2020. More generally, the lengthy gap between the two contests would create a serious risk of temporal confounding.

5.2 Vote Shares and Twitter Engagement

Before turning to survey evidence, we note an interesting implication of the findings thus far. We have shown that local exposure to COVID-19 in the opening months of 2020 predicts both electoral support for the RN and positive engagement with European populist parties on social media. We might also expect, therefore, to observe a positive association between the RN's popularity among social media users and performance in the 2020 municipal elections.

Figure 4 provides initial plausibility for this implication. French municipalities with more than 1,000 inhabitants are shaded by the RN's vote share in the left panel and by the combined number of Twitter mentions, retweets, and likes of the party or its leader between 1 January 2020 and the elections, normalized by municipality population, in the right panel. Municipalities with high RN vote shares are concentrated close to super spreader events prior to the election — most notably in the northeastern Alsace region bordering Germany and the southeastern Provence region bordering Italy and the Mediterranean Sea — and they overlap substantially with those where the RN saw the strongest engagement on Twitter.

To more precisely gauge this relationship, we regress the RN's vote share in each municipality on two sets of Twitter engagement measures: (1) the per capita number of mentions, retweets, and tweet-likes of the RN or its leader prior to the elections; (2) the per capita number of unique users who mentioned, retweeted or liked tweets by the RN or its leader before the elections. We disaggregate each measure by engagement type, include the same set of controls (excluding population) and fixed effects as in the previous analysis, and cluster standard errors at the NUTS-3 level.

As shown in Table 8, the RN's vote share is positively predicted by both sets of engagement measures.[12] The coefficients on the retweets- and tweet-likes-based measures are statistically significant at the five percent level, while those on the mentions-based measures fall marginally short of significance. Given that there are far fewer mentions than likes by an order of magnitude, it is not surprisingly that it is more difficult to detect an effect. The effect sizes are not insubstantial. For example, an additional 1,000 pre-election tweet-likes of the RN or its leader within a given municipality is attended by an increase in the RN's vote share of 0.03 percentage points; an additional 1,000 unique Twitter users engaging in such activity comes with a 0.05-percentage-point rise.

In short, the results point to a link between engagement with populists on Twitter and electoral support for them in the initial stages of the COVID-19, and suggest that such engagement may have constituted an important channel through which COVID-19 improved the RN's performance in the 2020 municipal elections.

[12] In Table A4 of Online Appendix A3, we show similar results when the mentions-based measures are instead normalized by the number of mentions (for the first measure) or unique users that mention (for the second measure) *non-populist* parties or their leaders.

5.3 Local COVID Exposure and Populist Voting: British Survey Evidence

To assess whether evidence of a link between exposure to COVID-19 and populist voting extends to the individual level, we draw on two nationally-representative surveys fielded in our countries of interest. The first is the British Election Study (BES), a long-standing longitudinal survey with rich individual socio-political information including the location of survey respondents at the local authority (353 levels). We compare responses of 28,745 individuals across seven survey waves between March 2019 and May 2021 (waves 15 to 21).

We merge the survey data at the local authority level with data on official cumulative COVID-19 cases as of 1st June 2020 and 1st June 2021 (UK Health Security Agency, 2022). Unfortunately, in June 2020 COVID-19 cases are only available for 22 local authorities (wave 20) in which 2,396 respondents were surveyed. However, for May 2021 (wave 21) COVID-19 statistics are available for all 353 local authorities (28,745 individuals). We assign observations in waves 15-19 (March - December 2019) zero COVID-19 cases.

Our empirical setup is a standard two-way fixed effects design:

$$Y_{ilt} = \beta_0 + \beta_1 \text{COVID-19}_{lt} + X'_{ilt}\gamma + \alpha_i + \phi_l + \xi_t + \epsilon_{ilt} \tag{8}$$

where the dependent variable Y_{ilt} is a response to a survey question of individual i in local authority l at survey wave t. COVID-19$_{lt}$ are log cumulative cases per 10,000 inhabitants, X_{ilt} are individual-level controls, and α_i, ϕ_l, and ξ_t are individual, local authority, and survey wave fixed effects respectively. Controls include ethnicity, education, religion, homeownership, and gross personal income. We cluster standard errors at the level of the local authority.

Table 9 shows results for two key questions. A one percent increase in cumulative local COVID-19 cases per 10,000 inhabitants decreases the reported likelihood to vote on average by 0.02 percentage points and increases the reported likelihood to vote for right-wing populist UKIP or Reform party by 0.06 percentage points. These effect sizes might seem small, but they stem from a model with several thousand individual fixed effects and a location-specific treatment. What is more, they are statistically significant at the one percent level and far from negligible given that cumulative COVID-19 cases per 10,000 inhabitants saw increases of up to 42 percent between June 2020 and May 2021. For example, our model predicts that COVID-19 cases in the local authority of Ceredigion in Wales resulted in a 2.52 percentage points increase in the likelihood to vote UKIP or Reform party.

In summary, we find evidence that individuals living in areas with higher COVID-19 cases per capita are significantly more likely to abstain from voting, or to choose the right-wing populist option. This link is highly statistically significant despite the inclusion of several thousand individual fixed effects, as well as controls for a host of individual-level characteristics.

5.4 Individual COVID Exposure and Populist Voting: Dutch Survey Evidence

The second survey we utilize is the Longitudinal Internet Studies for the Social Sciences (LISS) panel survey on the "consequences of COVID for the quality of society," which was administered online to a random sample of approximately 2,000 individuals across the Netherlands in three waves from July 2020 to July 2021.[13] To our knowledge, this was the only questionnaire undertaken repeatedly in our five countries of interest during 2020 that investigates both personal exposure to COVID-19 and political preferences. A limitation of the LISS survey is that it neither identifies respondents by location nor asks questions about specific political parties after the July 2020 wave, preventing us from using our super spreader instrument or within-respondent variation over time to make credible causal inferences. Nevertheless, a positive association between COVID-19 exposure and populist voting preferences in the July 2020 wave is consistent with a pandemic-induced boost in populism, and the survey's examination of individual exposure to COVID-19 helpfully complements our previous focus on local exposure.

Specifically, the July 2020 wave asks respondents which party they would vote for if *Tweede Kamer* (House of Representatives) elections were to be held right now, whether they have been infected with COVID-19, and how people close to them have been affected by the disease.[14] We use responses to these questions to estimate two logistic models. The outcome variable in both models is a dummy for whether respondents would vote for *Forum voor Democratie* (FvD) or *Partij voor de Vrijheid* (PVV), the two right-wing populist parties in the Netherlands. In the first model, the treatment variable is a dummy for whether respondents report that they are or were previously been infected with COVID-19 (whether this was confirmed by a test or not). In the second model, it is a dummy for whether respondents report that a family member or someone in their household has been severely ill or died as a result of COVID-19. We control for a host of demographic characteristics, including respondent gender, age, educational level, and occupation.

Table 10 presents odds ratios from each model (with 95 percent confidence intervals). The ratio for both treatment variables substantially exceeds 1 and is statistically significant at the five percent level. On average, respondents who have been infected with COVID-19 are roughly twice as likely to express the intention to vote for the FvD or the PVV. Respondents with a household or family member who has suffered severe illness or death due to COVID-19 are 88 percent more likely. Thus, the results offer evidence that the likelihood of voting for a populist party increases with exposure to COVID-19

[13] The sample was drawn from population registers in collaboration with the Dutch statistics authority (Centraal Bureau voor de Statistiek); individuals without a computer or internet connection were provided with one. The average response rate across the three waves was 80 percent. LISS surveys are administered by CentERdata, a research institute based in Tilburg.

[14] Full questions and response options for all the survey items discussed in this section, as well as further details on how we construct our variables, are provided in Online Appendix 6.1.

at the individual as well as the local level.

6 Mechanisms

Why did early exposure to COVID-19 boost public engagement with and support for right-wing populists? This section explores the causal mechanisms behind our previous findings using Dutch and British survey data, presenting a link between exposure to COVID-19 and four variables known to be closely associated with support for populism at the individual level: (1) weak confidence in political and social institutions; (2) concerns about personal finances and the broader economic situation; (3) feelings of anxiety and social isolation; and (4) opposition to COVID-induced lockdowns. In the second part, we substantiate this evidence on mechanisms, but show that underlying populist attitudes did not change.

6.1 Individual COVID-19 Exposure and Populist Attitudes: Evidence from the Netherlands

In addition to asking respondents about their exposure to COVID-19 and inclination to vote for a populist party, the LISS survey on the societal consequences of COVID-19 contains questions on a range of personal attitudes, beliefs, and characteristics that could plausibly drive the relationship between these two variables. These questions shed light on six distinct types of mechanisms, which we summarize as *confidence in institutions*, *economic situation*, *social isolation*, *anxiety*, *opposition to government response*, and *out-group hostility*.[15] The first wave of the survey, conducted in July 2020, contains questions on all six types; the second and third waves, conducted in October 2020 and July 2021, respectively, only cover the first four types. We estimate two sets of models, both of which regress responses to mechanism-relevant questions on the two measures of COVID-19 exposure from Section 5.4 (in separate models).[16] The first set restricts the sample to the July 2020 wave and includes the same demographic control variables as Table 5.4's analysis. The second set encompasses all three waves, controls for respondent fixed effects, and clusters standard errors by respondent, thereby exploiting variation *within* respondents *between* waves.[17] Given the relatively short time between the first and last waves — during which only 417 respondents became infected and 915 had a family member or who became severely ill or died due to COVID-19 — this is a much more demanding specification.

[15]These categories are not mutually exclusive, and some variables straddle more than one. Nonetheless, we believe that they are helpful for distinguishing between mechanistic logics.

[16]See Online Appendix 6 for the questions' full text and answer categories.

[17]We exclude respondents who provide inconsistent answers to the two questions on COVID-19 exposure (for example, reporting that they have previously been infected with COVID-19 in the first wave of the survey but not in the last wave).

Standardized coefficients from the two sets of models (with 95 percent confidence intervals) are plotted alongside each other in Figure 5. In the first-wave models (left column), the *confidence in institutions* and *out-group hostility* mechanisms receive the strongest backing: infection with COVID-19 is negatively and significantly associated with confidence in government, the parliament, the lower house, the police, and the media and with support for assisting refugees and other pandemic-hit countries. It has a similar, albeit slightly weaker, association with the belief that people should follow COVID-19 restrictions even if they disagree with, are disadvantaged by, and do not understand them and that the government is failing to protect people with vulnerable health, providing evidence for the opposition to government response mechanism. The coefficients on the household or family exposure treatment, in contrast, are small and non-significant. The results for the *economic situation*, *social isolation*, and *anxiety* mechanisms are more mixed. Although most estimates are small and statistically indistinguishable from zero, a few are both significant and in the expected direction, such as the negative coefficient on the infection treatment when spare financial resources is the outcome and the positive coefficient on house or family exposure treatment when anxiety about COVID-19's economic consequences is the outcome.

The panel models (right column), which do not test the *opposition to government response* and *out-group hostility* mechanisms, again provide broad support for the *confidence in institutions* channel. Unlike in the first-wave models, however, both the coefficients on both treatment variables are negative and statistically significant in most models, implying that such confidence is damaged by family and household — not just individual — exposure to COVID-19. As before, treatment coefficients mostly fail to reach significance and have theoretically inconsistent signs when a proxy for *economic situation*, *social isolation*, and *anxiety* is the outcome variable. The only exceptions are the models in which family or household exposure is the treatment and worries about COVID-19's health and economic effects are the outcomes, in which coefficients are negative — that is, the opposite of what the *anxiety* mechanism leads us to expect.

Taken together, therefore, the two sets of estimates suggest that that reduced trust in political and social institutions was a key mechanism linking exposure to COVID-19 with populist support in the Netherlands, while offering suggestive evidence that opposition to the government's handling of the pandemic and hostility toward out-groups also played an important mediating role.

6.2 Anxiety, Social Media Use, and Underlying Populist Attitudes: Evidence from the UK

To substantiate evidence on the mechanism through which COVID-19 affects right-wing populist tendencies, we also present cross-sectional evidence using questions specific to COVID-19 from the

British Election Study waves 20 (June 2020) and 21 (May 2021). As a first plausibility check that survey responses are in general not independent from officially reported COVID-19 cases, Table 11 demonstrates that people seem to be aware of higher levels of local per capita COVID-19 cases in May 2021, providing strong evidence that the survey data capture something about there local COVID-19 rates. Respondents in areas with high COVID-19 cases per capita are more likely to suspect that they themselves, their family members, or their close friends had COVID. Interestingly, higher levels of per capita cases do not increase the likelihood of being vaccinated. Still, people in places with higher number of per capita cases feel more badly affected from COVID than people from places with lower numbers of per capita cases.

Complementing our analysis on mechanisms from subsection 6.1, we present evidence that can differentiate between different COVID-19 related psychological reactions and outcomes. Using the June 2020 cross-section from the British Election Study, Table 12 shows that – in the early phase of the pandemic – worries about COVID-19 are associated with higher levels of anxiety, depression, and lower levels of happiness and life satisfaction. The questionnaire in this wave allows us to differentiate between three types of worries emerging from the COVID-19 pandemic: (i) a personal health-related worry to catch the virus, (ii) a broader worry about the economic impact of COVID, and (iii) a general worry about COVID's impact on the way of life. We test the impact of each of these three types of worries on outcomes of anxiety and life satisfaction. To ease comparison of coefficients, we standardise the outcome variables.[18] It is interesting to see that the first, health-related worry is significantly and substantially related to anxiety (column 1) and current levels of personal depression (column 2). The second, economic worry has a negligible influence and does not seem to consistently relate to anxiousness or life satisfaction. In fact, at a given degree of worrying about catching COVID and about COVID's impact on the way of life, worrying more about the economy seems to be a luxury worry as it is positively associated with life satisfaction (column 3). The third, general worry about COVID's impact on the way of life dominates and has the largest association with all outcomes.

Having shown evidence of increased support of right-wing populist politicians and parties on social media due to COVID-19, a natural question is to which degree COVID-19 worries are associated with media use. Columns 6-8 of Table 12 show that media use in general increases if worries about the coronavirus are stronger.[19] Notably, all types of worry positively and significantly correlate with the time politics are followed on the internet. Yet, stronger worries about COVID-19 are also correlated with more time spent reading newspapers and – in the case of worrying about the economy – listening

[18] All outcomes are based on questions with a scale between 0 (not at all worried/anxious etc.) to 10 (extremely worried/anxious etc.), except personal depression today which has a 1-5 scale.

[19] The coefficients are not directly interpretable since outcome variables are categorical with (1) "None, no time at all", (2) "Less than 1/2 hours", (3) "1/2 hour to 1 hour", (4) "1 to 2 hours", (5) "More than 2 hours". Standard deviation of the variables are 1.34 (newspapers), 1.19 (radio), 1.34 (internet).

to political news on the radio. Taken together, especially additional online media use of people worried about the impact of COVID-19 on their way of life might have opened up a window of opportunity for right-wing populists to gain attention and facilitate electoral support.

Although COVID-19 has prompted changes in society on many levels and – as we argue – boosted right-wing populism, it would be surprising if underlying and slow-moving individual attitudes changed as promptly, too. Previous research has found that slow-moving underlying attitudes which favour the rise of right-wing populism can be "activated" by certain events (Bartels, 2017; Bonikowski, 2017; Cantoni et al., 2019). In Table 13 we show that slow-moving underlying attitudes remain stable in the face of fast-moving local COVID-19 cases. Measures of underlying populist attitudes (columns 1-5), as well as general left-right self-assessment (column 6), satisfaction with democracy, anti-intellectualism (column 8), and trust in general (column 10) do not seem affected by changes in COVID-19 per capita cases.

7 Conclusion

Our results provide robust evidence that right-wing populists benefited from the onset of the COVID-19 pandemic. Using fine-grained data from social media, and an innovative instrumental variables strategy, we show that the spread of the virus led people to turn to populists on social media, mentioning them in tweets and liking and retweeting their content. This support extended offline, as we see in the first round of the French municipal elections, when communes with more proximate to super spreader events voted for *Rassemblement National* candidates at a higher rate. The election data also correlates with Twitter engagement, suggesting that the online data do proxy real-world political behavior. Individual survey data from the UK shows evidence that local COVID-19 cases are associated with declines in general voting intention and increases in intent to vote for right-wing populist parties. Data from the Netherlands demonstrate the significance of personal exposure, as both individual and household exposure to COVID-19 predict vote intention for right-wing populist parties. Overall, these results all point in a consistent direction: right-wing populist parties in Western Europe saw an increase in public support during the early phase of the pandemic.

We use the survey data from the United Kingdom and the Netherlands to reveal the mechanisms linking the pandemic to increased support for populism. The British Election Study shows evidence of associations between COVID-19 worries, anxiety, and the online consumption of political media. The evidence from the Netherlands show how both individual and familiar exposure to COVID-10 can damage confidence and trust in political and social institutions. These data provide a stronger defense against reverse causality since they allow us to capture individual-level changes after exposure to COVID-19.

Further work is needed to understand how the politicization of the pandemic unfolded over time. In particular, it is important to understand the relationship between the top-down, elite-led communications and bottom-up public concerns. Were people engaging with populists and supporting them at the ballot box due to the populists' stance towards the pandemic? Or did populists experience a surge in bottom-up support as their positions resonated with the emerging concerns of an electoral experiencing existential uncertainty? Or are the observed relationships attributable to another source, like a general decline in trust in government due to failures to contain the pandemic, leading people to support lend their support to outsiders and challengers? Additionally, we need further work to understand the long-term implications of these shifts. Populists have not uniformly benefited from the pandemic, although major electoral gains have been made in countries including Italy, France, and Sweden. Will the pandemic result in lasting political realignments or will we return to previous equilibria as COVID-19 fades away from the public consciousness and becomes endemic?

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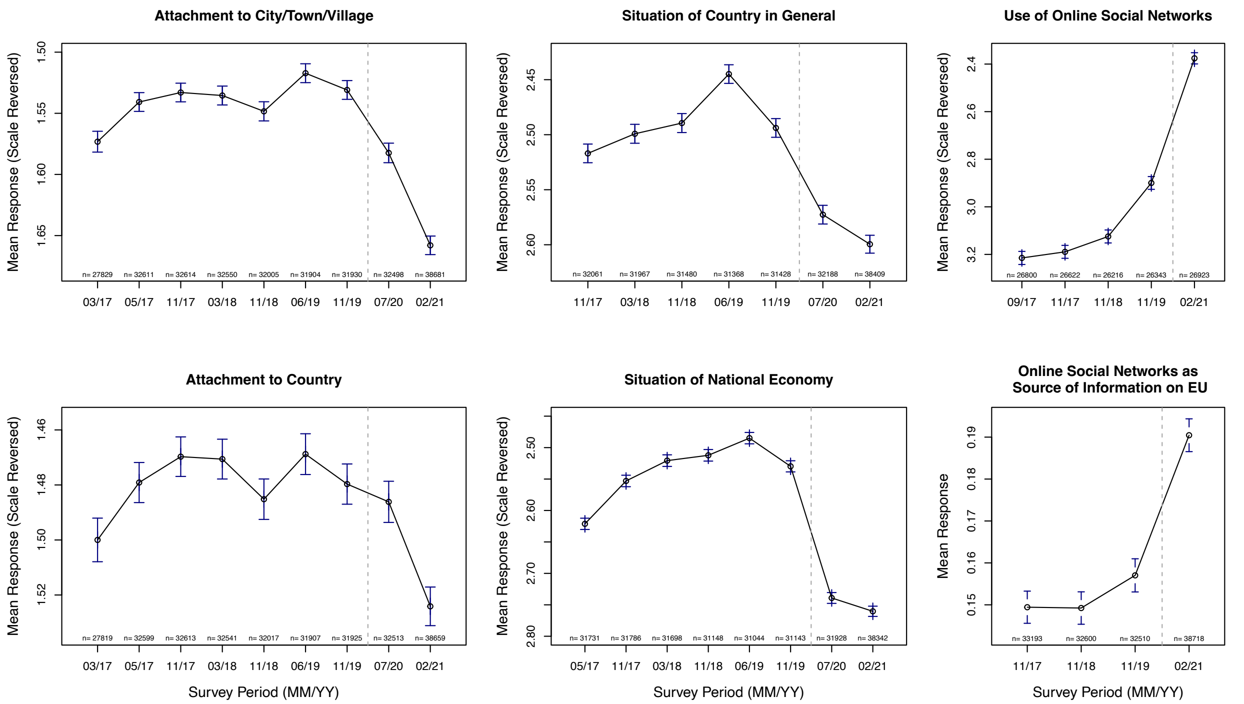
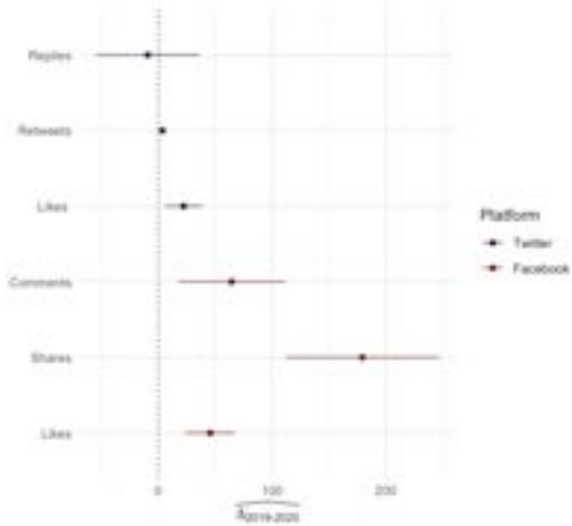
Figures and Tables

FIGURE 1. Stylized Facts: Eurobarometer Survey Trends, 2017-2021



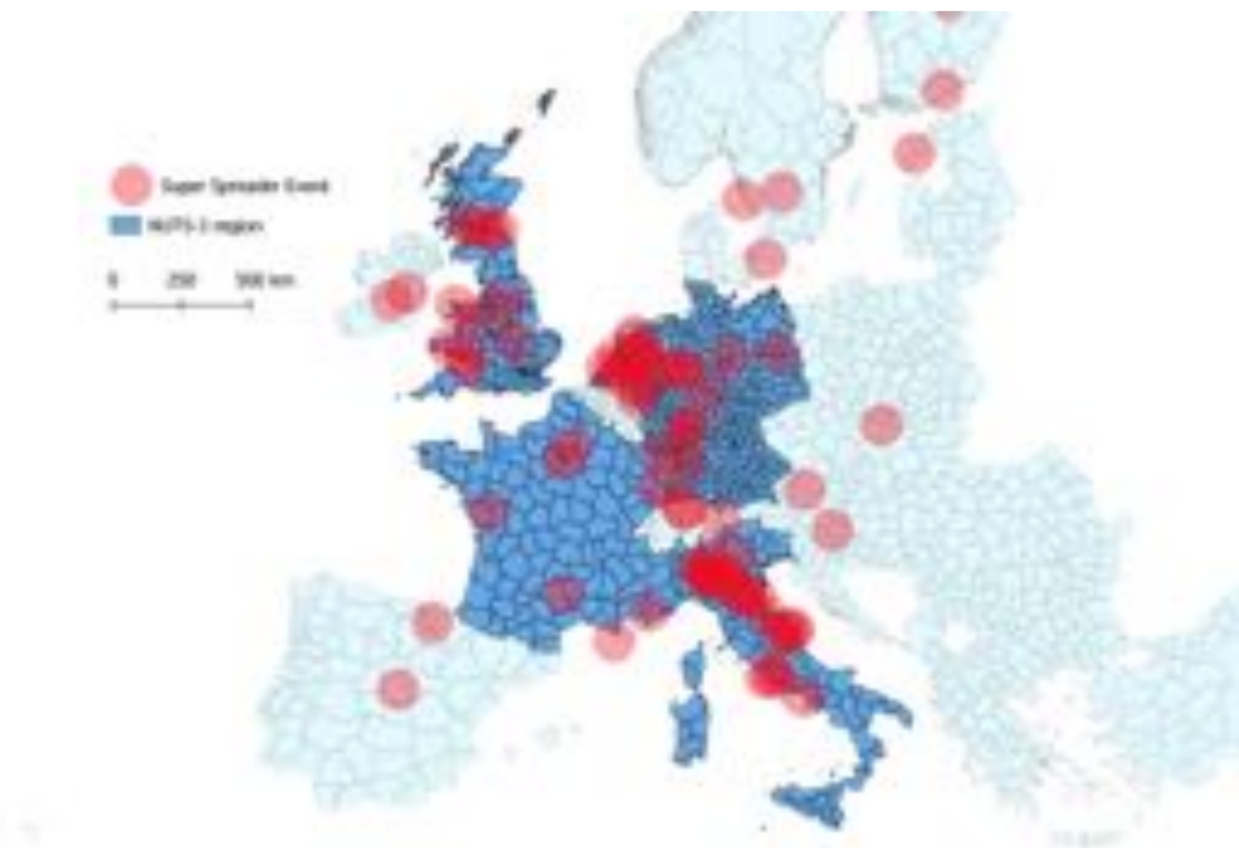
Notes: The figure displays the mean value of responses to six questions (shown in separate panels) in the Eurobarometer survey between March 2017 and early 2021; bars represent 95% confidence intervals. The full questions and response options are listed in Online Appendix 1. Values corresponding to responses of "Don't know" are excluded. The small text above the X-axis shows the number of responses. The dotted line denotes the onset of the COVID-19 pandemic.

FIGURE 2. Effect of populism change in social media engagement rate, 2019-2020



Notes: Estimates from OLS regression with country fixed-effects, including controls for ideology, incumbency (cabinet membership), most recent vote share, and whether elections held in 2019 or 2020. The Twitter data consists of 230 parties in 27 countries and Facebook 338 parties in 28 countries. All estimates are positive and statistically-significant except for Twitter replies. Full regression results are reported in 3.

FIGURE 3. Early Superspreader Events in Five European Countries



Notes: The map displays 793 NUTS-3 regions and 99 early superspreader events (between 1st February 2020 and 30th June 2020) across five European countries (DE, IT, NL, UK, FR). Data on superspreader events from Swinkels et al. (2021).

TABLE 1. Summary Statistics

	(1) Mean	(2) Std.Dev.	(3) Min	(4) Max	(5) Obs.
Panel A: *Twitter outcomes*					
Mentions populist leaders	0.19	1.10	0	89	119520
Retweets populist leaders	3.98	14.75	0	952	119520
Likes populist leaders	6.90	30.52	0	4042	119520
Mentions populist parties	0.08	0.70	0	60	119520
Retweets populist parties	1.13	5.34	0	642	119520
Likes populist parties	1.10	5.68	0	222	119520
Mentions non-populist leaders	1.04	5.82	0	530	119520
Mentions non-populist parties	0.29	1.51	0	126	119520
Relative mentions of populist leaders	0.97	0.80	0	45	119520
Relative mentions populist parties	0.99	0.58	0	32	119520
Panel B: *COVID-19 related variables*					
Lockdown Stringency	56.22	27.20	0.00	93.52	119520
Log Daily New Cases per 10,000 population	0.13	0.22	0.00	2.91	119520
Super Spreader Exposure	2.10	1.75	0.00	7.65	119520

Notes: Table reports summary statistics of Twitter and COVID-19 related variables. Data is a panel of 793 NUTS-3 regions for five European countries (DE, IT, NL, UK, FR) observed for 134 days between 1st February 2020 and 30th June 2020 from Naqvi (2021), Hale et al. (2021), and Swinkels et al. (2021).

TABLE 2. COVID-19 Exposure and Populist Social Media Engagement: Naïve Specification

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dependent Variable: Mentions of Populist Leaders, mean 0.19						
Log Daily New Cases per 10,000 population	0.172***	0.115***	0.065*	0.113***	0.113***	0.432***
	(0.032)	(0.034)	(0.034)	(0.035)	(0.042)	(0.152)
Observations	119520	119520	119520	119520	119520	107747
Panel B: Dependent Variable: Retweets for Populist Leaders, mean 3.98						
Log Daily New Cases per 10,000 population	3.996***	2.352	2.881*	4.394**	5.046**	0.932***
	(1.459)	(1.486)	(1.498)	(1.811)	(2.101)	(0.258)
Observations	119520	119520	119520	119520	119520	119520
Panel C: Dependent Variable: Likes for Populist Leaders, mean 6.90						
Log Daily New Cases per 10,000 population	7.339***	5.196**	4.079	5.758*	9.034**	0.890***
	(2.607)	(2.639)	(2.656)	(3.171)	(3.706)	(0.233)
Observations	119520	119520	119520	119520	119520	94955
Lockdown Control		✓	✓	✓		
Country FE			✓	✓		
Day FE				✓		
Country × Day FE					✓	✓
Poisson						✓

Notes: Table reports coefficients and standard errors from OLS regressions, with the exception of column 6 reporting coefficients from poisson regresison. Dependent variables as indicated in panel headers. Regressions include controls and fixed effects as indicated at the bottom of the table. Data is a panel of 793 NUTS-3 regions for five European countries (DE, IT, NL, UK, FR) observed for 134 days between 1st February 2020 and 30th June 2020 from Naqvi (2021), Hale et al. (2021), and Swinkels et al. (2021). Standard errors are clustered at the NUTS-3 level. One, two and three stars represent significance at the 10%, 5%, and 1% levels respectively.

TABLE 3. Instrumental Variables Approach: Leveraging Varying Exposure to Superspreader Events

	(1) Mentions of Populists	(2) Retweets for Populists	(3) Likes for Populists
Panel A: Party Leaders			
Log Daily New Cases per 10,000 population	0.310**	11.459***	6.896**
	(0.145)	(2.954)	(2.697)
Lockdown Control	✓	✓	✓
NUTS-3 FE	✓	✓	✓
Day FE	✓	✓	✓
Observations	119520	119520	119520
F-Statistic	17.50	33.19	42.78
Mean Dep.Var.	0.19	3.98	6.90
Panel B: Parties			
Log Daily New Cases per 10,000 population	0.179*	2.388***	2.265***
	(0.106)	(0.788)	(0.641)
Lockdown Control	✓	✓	✓
NUTS-3 FE	✓	✓	✓
Day FE	✓	✓	✓
Observations	119520	119520	119520
F-Statistic	2.56	7.74	6.50
Mean Dep.Var.	0.08	1.13	1.10

Notes: Table reports coefficients and standard errors from instrumental variable regression. All regressions include day and NUTS-3 fixed effects. The dependent variable are mentions of populist party or leader twitter handles on geo-tagged tweets in columns 1, the number of retweets of tweets by right-wing populists in column 2, and the number of likes for tweets from right-wing populists in column 3. Data is a panel of 793 NUTS-3 regions for five European countries (DE, IT, NL, UK, FR) observed for 134 days between 1st February 2020 and 30th June 2020 from Naqvi (2021), Hale et al. (2021), and Swinkels et al. (2021). Instrument is exposure to super spreader event using 60 days after the event in wave shock time specification, 800km maximum distance, and linear geographic decline. Standard errors are clustered at the NUTS-3 level. One, two and three stars represent significance at the 10%, 5%, and 1% levels respectively.

TABLE 4. Country Heterogeneity

	(1) Mentions of Populist Leaders	(2) Retweets for Populist Leaders	(3) Likes for Populist Leaders
COVID-19 × Germany	0.545***	15.642***	22.194***
	(0.124)	(4.109)	(5.332)
COVID-19 × England	0.873***	23.192***	43.461***
	(0.150)	(5.801)	(8.605)
COVID-19 × France	2.369***	85.837***	105.982***
	(0.666)	(18.394)	(24.058)
COVID-19 × Italy	0.506*	16.636***	22.487***
	(0.266)	(3.469)	(4.665)
COVID-19 × Netherlands	0.232	32.891***	48.518***
	(0.509)	(6.498)	(8.875)
COVID-19 × Scotland	0.678***	16.760***	25.264***
	(0.213)	(4.222)	(5.175)
Lockdown Control	✓	✓	✓
NUTS-3 FE	✓	✓	✓
Day FE	✓	✓	✓
Observations	119520	119520	119520

Notes: Table reports coefficients and standard errors from instrumental variable regressions. All regressions include day and NUTS-3 fixed effects. The dependent variable are mentions of populist party or leader twitter handles on geo-tagged tweets in columns 1, the number of retweets of tweets by right-wing populists in column 2, and the number of likes for tweets from right-wing populists in column 3. Independent variables are interactions between the log daily new cases per 10,000 inhabitants ("COVID-19") and country dummies. Data is a panel of 793 NUTS-3 regions for five European countries (DE, IT, NL, UK, FR) observed for 134 days between 1st February 2020 and 30th June 2020 from Naqvi (2021), Hale et al. (2021), and Swinkels et al. (2021). Instrument is exposure to super spreader event using 60 days after the event in wave shock time specification, 800km maximum distance, and linear geographic decline. Standard errors are clustered at the NUTS-3 level. One, two and three stars represent significance at the 10%, 5%, and 1% levels respectively.

TABLE 5. Main Results: Individual Twitter User Fixed Effects

	(1)	(2)
Log Daily New Cases per 10,000 population	0.128***	0.123***
	(0.032)	(0.031)
Lockdown Control	✓	✓
Region FE	✓	
Day FE	✓	✓
Author FE		✓
Observations	1258222	1258222
F-Statistic	9.71	10.65
Mean Dep.Var.	0.03	0.03

Notes: Table reports coefficient and standard error from instrumental variable regression including twitter User ID and day fixed effects. The dependent variable are mentions of populist party or leader twitter handles on geo-tagged tweets. Data is a panel of 8,190 twitter users in 793 NUTS-3 regions for five European countries (DE, IT, NL, UK, FR) observed for 134 days between 1st February 2020 and 30th June 2020 from Naqvi (2021), Hale et al. (2021), and Swinkels et al. (2021). Instrument is exposure to super spreader event using 60 days after the event in wave shock time specification, 800km maximum distance, and linear geographic decline. Standard errors are clustered at the NUTS-3 level. One, two and three stars represent significance at the 10%, 5%, and 1% levels respectively.

TABLE 6. Robustness to overall increase in twitter use

	(1) Mentions of Populists	(2) Mentions of Non-Populists	(3) Relative Mentions of Populists
Panel A: Party Leaders			
Log Daily New Cases per 10,000 population	0.310**	-5.579***	0.560***
	(0.145)	(1.092)	(0.118)
Lockdown Control	✓	✓	✓
NUTS-3 FE	✓	✓	✓
Day FE	✓	✓	✓
Observations	119520	119520	119520
F-Statistic	17.50	22.81	17.12
Mean Dep.Var.	0.19	1.04	0.97
Panel B: Parties			
Log Daily New Cases per 10,000 population	0.179*	-0.447*	0.832***
	(0.106)	(0.242)	(0.195)
Lockdown Control	✓	✓	✓
NUTS-3 FE	✓	✓	✓
Day FE	✓	✓	✓
Observations	119520	119520	119520
F-Statistic	2.56	2.75	9.15
Mean Dep.Var.	0.08	0.29	1.00

Notes: Table reports coefficients and standard errors from instrumental variable regression. All regressions include day and NUTS-3 fixed effects. The dependent variable are mentions of populist party or leader twitter handles on geo-tagged tweets in columns 1, mentions for non-populist parties or leaders in column 2 and for their quotient in column 3. Data is a panel of 793 NUTS-3 regions for five European countries (DE, IT, NL, UK, FR) observed for 134 days between 1st February 2020 and 30th June 2020 from Naqvi (2021), Hale et al. (2021), and Swinkels et al. (2021). Instrument is exposure to super spreader event using 60 days after the event in wave shock time specification, 800km maximum distance, and linear geographic decline. Standard errors are clustered at the NUTS-3 level. One, two and three stars represent significance at the 10%, 5%, and 1% levels respectively.

FIGURE 4. French Municipalities and Pre-Election Superspreader Events: Super Spreader Events, Right-Wing Populist Vote Share, and Engagement on Twitter

Notes: Maps display 9,825 French municipalities with more than 1,000 inhabitants as of the 2020 municipal elections (on 15 March 2020) and superspreader events in and near France prior to the election. Municipalities are shaded according to the RN's vote share in the elections in left figure and according to engagements (mentions, likes, retweets) with RN politicians on Twitter between 1st February and 15th March 2020 in the right figure (as indicated in the legend).

TABLE 7. COVID-19 Exposure and Populist Support in French Municipal Elections

Outcome variable: RN Vote Share 2020	(1)	(2)	(3)
Proximity to Superspreader Events	0.014		
(Time-Invariant)	(0.010)		
Proximity to Superspreader Events		0.001**	
(Early-Weighted)		(0.001)	
Proximity to Superspreader Events			0.006**
(Late-Weighted)			(0.003)
Front National Vote Share 2014	0.357***	0.356***	0.356***
	(0.048)	(0.048)	(0.048)
NUTS-3 FE	✓	✓	✓
Demographic & Socioeconomic Controls	✓	✓	✓
Observations	9,306	9,306	9,306
R^2	0.313	0.313	0.313
Mean Outcome Variable	0.005	0.005	0.005

Notes: This table presents OLS estimates of the association between French municipalities' exposure to superspreader events and support for the *Rassemblement National* (RN) in the first round of 2020 French municipal elections. The outcome variable is the RN party list's total vote share in each municipality. The treatments measure the sum of inverse distances from each commune to all pre-election superspreader events, with no adjustment for event timing in column 1, higher weights assigned to earlier events in column 2, and higher weights assigned to more recent events in column 3. The sample comprises French municipalities with more than 1,000 inhabitants. Controls: total population, population density, young population share, uneducated population share, unemployment rate. Huber-White standard errors, in parentheses, are clustered at the NUTS-3 level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

TABLE 8. Populist Support and Twitter Engagement in French Municipal Elections

Outcome Variable: RN Vote Share 2020	(1)	(2)	(3)
Panel A. Treatments: Twitter Engagement with RN			
Per Capita Mentions of RN	0.0002		
	(0.001)		
Per Capita Retweets of RN		0.00002**	
		(0.00001)	
Per Capita Tweet-Likes of RN			0.00003**
			(0.00001)
Front National Vote Share 2014	0.367***	0.367***	0.367***
	(0.044)	(0.044)	(0.044)
Panel B. Treatments: Unique Twitter Users Engaging with RN			
Per Capita Mentions of RN	0.001		
	(0.001)		
Per Capita Retweets of RN		0.00006**	
		(0.00003)	
Per Capita Tweet-Likes of RN			0.00005**
			(0.00002)
Front National Vote Share 2014	0.367***	0.367***	0.367***
	(0.049)	(0.049)	(0.048)
NUTS-3 FE	✓	✓	✓
Demographic & Socioeconomic Controls	✓	✓	✓
Observations	9,306	9,306	9,306
Mean Outcome Variable	0.005	0.005	0.005

Notes: This table presents OLS estimates of the association between Twitter engagement with the *Rassemblement National* (RN) and this party's vote share in the first round of 2020 French municipal elections. The outcome variable is the RN candidates' aggregate vote share in a given municipality. In Panel A, the treatment variables are the number of pre-election mentions (column 1), retweets (column 2), and likes (column 3) of the RN or its leader normalized by the population of each municipality. In Panel B, the treatments are identical except that they measure numbers of unique Twitter users participating in each form of engagement. Controls are the same as in Table 7 (minus population). The sample is a cross-section of approximately 9,000 municipalities. Huber-White standard errors, in parentheses, are clustered at the NUTS-3 level.
**Significant at the 5 percent level.
***Significant at the 1 percent level.

TABLE 9. COVID-19 Exposure and Populist Voting: British Survey Evidence

	(1) Likelihood to vote	(2) Likelihood to vote UKIP or Reform
Log Cases per 10,000 population	-0.0233***	0.0578***
	(0.0072)	(0.0111)
Wave FE	✓	✓
Individual FE	✓	✓
Local Authority FEs	✓	✓
Observations	67162	89342
R Squared	0.71	0.42
Mean Dep.Var.	0.82	0.03

Notes: Table reports coefficients and standard errors from two-way fixed effects linear regressions. Dependent variables are indicated in column headers. All regressions include individual, survey wave, and local authority fixed effects, as well as controls (if time-varying) for ethnicity, education, religiosity, homeownership, and gross personal income. Data is a panel from British Election Study waves 15-21 (March 2019 - May 2021) merged with data from Naqvi (2021) on the local authority level. Likelihood to vote is a dummy variable defined as answering "very likely that I would vote" to a question on turnout intention. Likelihood to vote for UKIP or Reform is defined as answering either UKIP or Reform to the question "And if there were a UK General Election tomorrow, which party would you vote for?". Standard errors are clustered at the local authority level. One, two and three stars represent significance at the 10%, 5%, and 1% levels respectively.

TABLE 10. COVID-19 Exposure and Populist Voting: Dutch Survey Evidence

Outcome variable: Populist Voting Intention	(1)	(2)
Infected with COVID-19	1.975**	
	(0.987, 3.744)	
Family or Household Affected by COVID-19		1.882**
		(1.055, 3.230)
Demographic Controls (Age, Gender, Education, Occupation, Household Role)	✓	✓
Observations	1,310	1,459
Log Likelihood	-393.414	-449.323
Akaike Information Criterion	840.827	952.646
Mean Outcome Variable	0.109	0.114

Notes: This table presents odds ratios from logistic regressions modeling an individual's probability of intending to vote for a populist party, given their exposure to COVID-19. Parentheses report 95 percent confidence intervals. The sample is a cross-section of Dutch citizens randomly selected for participation in a LISS panel survey in July 2020. The outcome variable is a dummy for whether respondents would vote for *Forum voor Democratie* or *Partij voor de Vrijheid* if parliamentary elections were held today (responses of "I don't know yet" are excluded). The treatment variables are dummies for whether respondents report that they have been infected with COVID-19 (column 1) or that a member of their family or household has been severely ill or died as a result of COVID-19 (column 2).

**Significant at the 5 percent level.

TABLE 11. Local cases and COVID-19 personal impacts

	(1) Suspect you had COVID (0-1)	(2) Suspect family member had COVID (0-1)	(3) Suspect close friend had COVID (0-1)	(4) Acquaintant died from COVID (0-1)	(5) Vaccinated (0-1)	(6) Severity COVID self (std.)	(7) Severity COVID family member (std.)	(8) Severity COVID close friend (std.)
Log Cases per 10,000 population	0.040***	0.069***	0.039***	0.053***	0.004	0.273**	-0.035	0.038
	(0.012)	(0.018)	(0.014)	(0.015)	(0.011)	(0.112)	(0.069)	(0.090)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Region FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	7752	7752	7752	8253	8579	1107	2067	988
R Squared	0.04	0.02	0.01	0.02	0.18	0.06	0.03	0.04

Notes: Table reports coefficients and standard errors from OLS regressions. The dependent variables are as indicated in the column header. All regressions include controls as well as region fixed effects. Controls consist of the following variables: age, gender, education, homeownership, religion, gross personal income. Data comes from the British Election Study wave 21 (May 2021) merged with data from Naqvi (2021) on the local authority level. Standard errors are clustered at the local authority level. One, two and three stars represent significance at the 10%, 5%, and 1% levels respectively.

TABLE 12. COVID-19, Anxiety, and Media Use

	Anxiety					Media		
	(1) Life anxious scale [std.]	(2) Personal depression today [std.]	(3) Life satisfaction scale [std.]	(4) Life worthwile scale [std.]	(5) Life happy scale [std.]	(6) Time follows politics in newspapers [std.]	(7) Time follows politics in radio [std.]	(8) Time follows politics on the internet [std.]
Worry: catching COVID [0-10]	0.049***	0.041***	-0.010	-0.004	-0.010	0.036***	0.001	0.013***
	(0.007)	(0.009)	(0.007)	(0.008)	(0.007)	(0.003)	(0.003)	(0.003)
Worry: economic impact of COVID [0-10]	-0.000	0.016	0.003	-0.006	-0.008	0.038***	0.026***	0.024***
	(0.010)	(0.013)	(0.010)	(0.010)	(0.010)	(0.005)	(0.005)	(0.005)
Worry: COVID's impact on way of life [0-10]	0.066***	0.037***	-0.072***	-0.038***	-0.065***	0.012***	0.002	0.011***
	(0.009)	(0.011)	(0.009)	(0.009)	(0.009)	(0.004)	(0.004)	(0.004)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Region FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3093	1676	3103	3064	3110	12290	12290	12290
R Squared	0.12	0.12	0.11	0.09	0.09	0.09	0.03	0.06

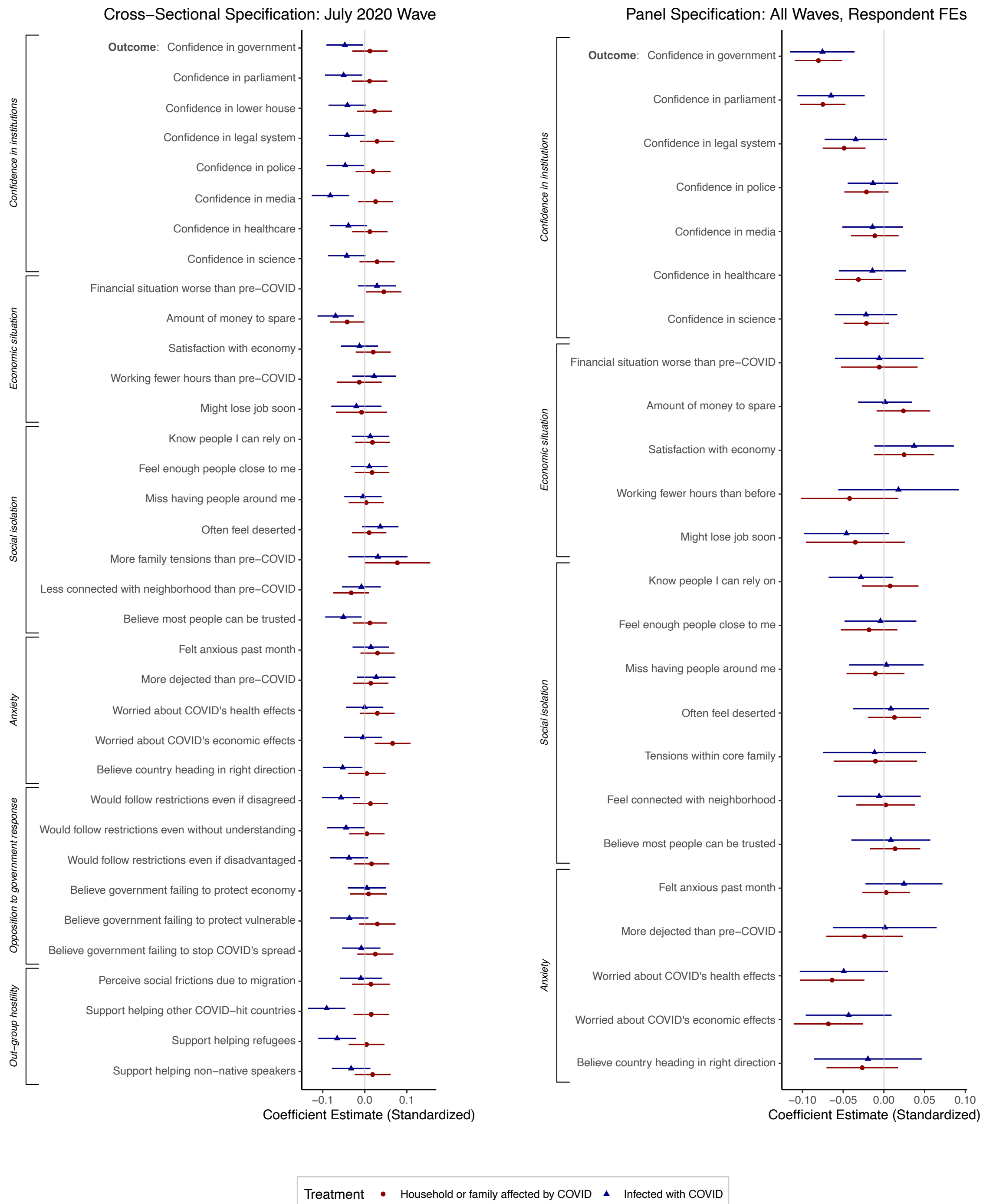
Notes: Table reports coefficients and standard errors from OLS regressions. The dependent variables are as indicated in the column header. All regressions include controls as well as region fixed effects. Controls consist of the following variables: age, gender, education, homeownership, religion, gross personal income. Data comes from the British Election Study wave 20 (June 2020). Standard errors are clustered at the regional level. One, two and three stars represent significance at the 10%, 5%, and 1% levels respectively.

TABLE 13. No Effect on Underlying Attitudes

	(1) Politicians should follow the People	(2) People should decide	(3) Citizen representation better	(4) Officials talk too much	(5) Compromise sells out principles	(6) Left-Right Self-Assessment	(7) Satisfaction with Democracy	(8) Against Intellectuals	(9) General Trust
Log Cases per 10,000 population	0.1766	0.0464	-0.0105	0.1834	-0.1330	0.0037	0.0167	0.0034	0.0019
	(0.1201)	(0.0983)	(0.1049)	(0.1132)	(0.1004)	(0.0116)	(0.0249)	(0.0234)	(0.0204)
Wave FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Local Authority FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4820	4565	4162	4785	4423	72509	65007	49517	37459
R Squared	0.80	0.78	0.78	0.76	0.77	0.91	0.67	0.77	0.74
Mean Dep.Var.	0.07	0.06	0.09	0.08	0.04	0.00	-0.02	0.08	0.00

Notes: Table reports coefficients and standard errors from two-way fixed effects linear regressions. All regressions include individual, survey wave, and local authority fixed effects. Dependent variables aren standardised and indicated in column headers. Data is a panel from British Election Study waves 15-21 (March 2019 - May 2021) merged with data from Naqvi (2021) on the local authority level. Standard errors are clustered at the local authority level. One, two and three stars represent significance at the 10%, 5%, and 1% levels respectively.

FIGURE 5. MECHANISMS: ANALYSIS OF DUTCH SURVEY RESPONSES



Notes: The figure plots OLS estimates of the association between exposure to COVID-19 and a range of populist attitudes and characteristics. Dots represent coefficients, horizontal bars 95 percent confidence intervals. Outcome variables are listed to the left of each set of estimates (see Online Appendix 6.1 for details). In the left column, the treatment variables, controls, and sample are the same as in Table 10. In the right column, the treatments are the same but all three waves of the LISS survey and respondent fixed effects are included, with Huber-White standard errors clustered by respondent.

Online Appendices for: Did COVID-19 Boost Populism? Evidence from Early Superspreader Events

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October 20, 2022

Contents

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1 Additional Stylized Facts: European Survey Trends

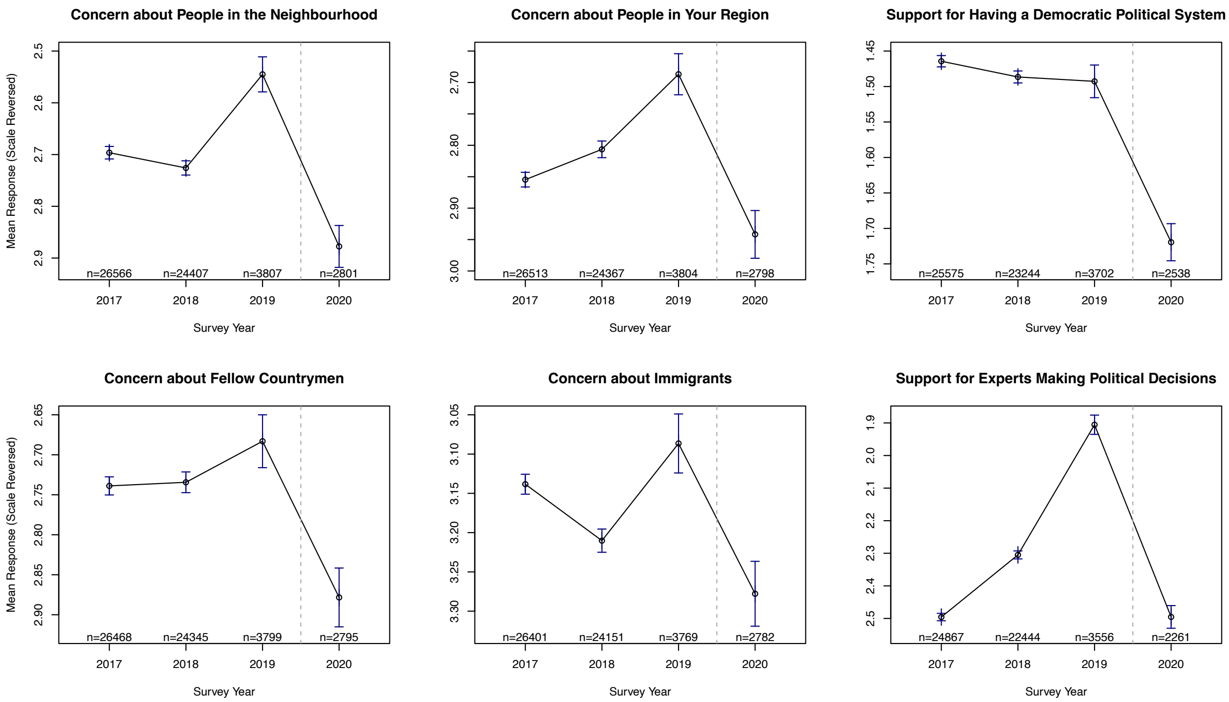
1.1 Eurobarometer

The full questions that provide the basis for Figure 1 are:

- Upper left panel: "Please tell me how attached you feel to your city / town / village." Answer scale: 1-4 categorical, where 1 = Very attached; 2 = Fairly attached; 3 = Not very attached; 4 = Not at all attached; 5 = Don't know (excluded from figure). Scale reversed in figure.
- Lower left panel: "Please tell me how attached you feel to [our country]." Answer scale: 1-4 categorical, where 1 = Very attached; 2 = Fairly attached; 3 = Not very attached; 4 = Not at all attached; 5 = Don't know (excluded from figure). Scale reversed in figure.
- Upper middle panel: "How would you judge the current situation in each of the following?...The situation in [our country] in general." Answer scale: 1-4 categorical, where 1 = Very good; 2 = Rather good; 3 = Rather bad; 4 = Very bad; 5 = Don't know (excluded from figure). Scale reversed in figure.
- Lower middle panel: "How would you judge the current situation in each of the following?...The situation of the [national] economy." Answer scale: 1-4 categorical, where 1 = Very good; 2 = Rather good; 3 = Rather bad; 4 = Very bad; 5 = Don't know (excluded from figure). Scale reversed in figure.
- Upper right panel: "Could you tell me to what extent you use online social networks?" Answer scale: 1-6 categorical, where 1 = Everyday/Almost everyday; 2 = Two or three times a week; 3 = About once a week; 4 = Two or three times a month; 5 = Less often; 6 = Never; 7 = No access to this medium (SPONTANEOUS); 8 = Don't know. Scale reversed in figure.
- Lower right panel: "When you are looking for information about the EU, its policies, its institutions, which of the following sources do you use?...Online social networks." Answer scale: 0-1 binary, 0 = Not mentioned; 1 = Mentioned.

1.2 European Values Study

The full questions that provide the basis for Figure A1 (main text) are:



Notes: The figure plots the mean value of responses to six questions (separated by panel) in the European Values Study over several waves conducted between 2017 and 2021. See the accompanying text for full questions and response options. Values corresponding to responses of "Don't know" are excluded from the graphs. The smaller text above the X-axis indicates the number of responses. The bars above and below each mean represent 95% confidence intervals. The dotted gray line denotes the onset of the COVID-19 pandemic.

FIGURE A1. Additional Survey Trends from the European Values Study Trends, 2017-2021

- Upper left panel: "To what extent do you feel concerned about the living conditions of: People in your neighbourhood?" Answer scale: 1-5 categorical, where 1 = Very much; 2 = Much; 3 = To a certain extent; 4 = Not so much; 5 = Not at all; -1 = Don't know (excluded from figure). Scale reversed in figure.

- Lower left panel: "To what extent do you feel concerned about the living conditions of: Your fellow countrymen?" Answer scale: 1-5 categorical, where 1 = Very much; 2 = Much; 3 = To a certain extent; 4 = Not so much; 5 = Not at all; -1 = Don't know (excluded from figure). Scale reversed in figure.

- Upper middle panel: "To what extent do you feel concerned about the living conditions of: The people of the region you live in?" Answer scale: 1-5 categorical, where 1 = Very much; 2 = Much;

3 = To a certain extent; 4 = Not so much; 5 = Not at all; -1 = Don't know (excluded from figure). Scale reversed in figure.

- Lower middle panel: "To what extent do you feel concerned about the living conditions of the following groups living in your country?...Immigrants in your country" Answer scale: 1-5 categorical, where 1 = Very much; 2 = Much; 3 = To a certain extent; 4 = Not so much; 5 = Not at all; -1 = Don't know (excluded from figure). Scale reversed in figure.
- Upper right panel: "I'm going to describe various types of political systems and ask what you think about each as a way of governing this country. For each one, would you say of governing this country?...Having a democratic political system." Answer scale: 1-4 categorical, where 1 = Very good; 2 = Fairly good; 3 = Fairly bad; 4 = Very bad; -1 = Don't know. Scale reversed in figure.
- Lower right panel: "I'm going to describe various types of political systems and ask what you think about each as a way of governing this country. For each one, would you say of governing this country?...Having experts, not government, make decisions according to what they think is best for the country." Answer scale: 1-4 categorical, where 1 = Very good; 2 = Fairly good; 3 = Fairly bad; 4 = Very bad; -1 = Don't know. Scale reversed in figure.

2 Additional Figures and Tables

2.1 Lockdown Effects

	(1) Mentions of Populists	(2) Retweets for Populists	(3) Likes for Populists
Panel A: Party Leaders			
Lockdown Stringency	0.006***	0.140***	0.188***
	(0.001)	(0.018)	(0.020)
NUTS-3 FE	✓	✓	✓
Day FE	✓	✓	✓
Observations	124948	124948	124948
R Squared	0.19	0.61	0.46
Mean Dep.Var.	0.19	4.16	7.19
Panel B: Parties			
Lockdown Stringency	0.001	0.009**	-0.001
	(0.001)	(0.004)	(0.004)
NUTS-3 FE	✓	✓	✓
Day FE	✓	✓	✓
Observations	124948	124948	124948
R Squared	0.20	0.49	0.70
Mean Dep.Var.	0.09	1.17	1.20

Notes: Table reports coefficients and standard errors from OLS regressions. Dependent variables as indicated in panel headers. Regressions include fixed effects as indicated at the bottom of the table. Data is a panel of 793 NUTS-3 regions for five European countries (DE, IT, NL, UK, FR) observed for 134 days between 1st February 2020 and 30th June 2020 from Naqvi (2021), Hale et al. (2021), and Swinkels et al. (2021). Standard errors are clustered at the NUTS-3 level. One, two and three stars represent significance at the 10%, 5%, and 1% levels respectively.

TABLE A1. Lockdown Effects

2.2 Exposure Instrument Construction and Robustness Checks

This section gives details on how we construct the exposure instrument for increased COVID-19 cases due to temporal and geographical proximity to early super spreader events.

We provide first and second stage results for specifications with different temporal and geographic maximum distances, as well as different temporal weight specifications. Figure A1 shows coefficients and confidence intervals on different exposure instruments in first stage linear regressions with NUTS-3 and day fixed effects, as well as lockdown stringency controls. We compare relevance of instruments which allow super spreader events to influence log COVID-19 cases per 10,000 population in nearby NUTS-3 regions to a maximum of 30, 40, 50, and 60 days. We also compare relevance of instruments for four different choices of maximum radius, which are less than 300, 400, 600, or 800 km distances. We also compare coefficients for specifications with constant temporal treatment weights and what we call *wave specifications*. The *wave specifications* use temporal weights that try to mimic a first increasing and then decreasing effect of super spreader events on COVID-19 cases. The theoretical explanation for this is that, first, exponential growth of cases will be likely to take off only after a certain amount of time due to the incubation period of SARS-COV-2 of around 5.7 days (Salzberger et al., 2021). Thus, exposure to nearby super spreader events should be weighted less heavily in the first days after the super spreader events. Second, after a peak of exposure at a certain point in time, the diffusion of SARS-COV-2 from early clusters into different regions across time means that exposure instruments should be weighted less heavily the further away the super spreader event happened in time. To be specific, we construct the instrument as follows.

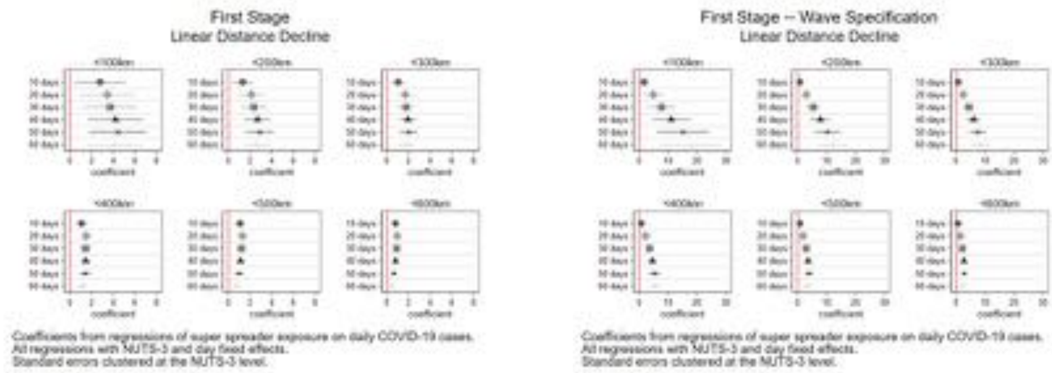
For NUTS-3 regions $i = 1...N$ at day $t = 1...T$ and excluding NUTS-3 regions with super spreader events $k = 1...K$, we construct the exposure instrument to all super spreading events depending on a maximum geographical distance parameter Φ and maximum temporal distance to super spreader event parameter T, as

$$\mathrm{Z}_{it} = \sum_{k=1}^{K}(1 - \frac{\Omega_{k-i}}{\Phi}) \tag{A1}$$

where Ω_{k-i} is the geographic distance between the centroid of NUTS-3 region i and k. We set Z_{it} equal zero for NUTS-3 regions farther away than Φ or for days further apart than T.

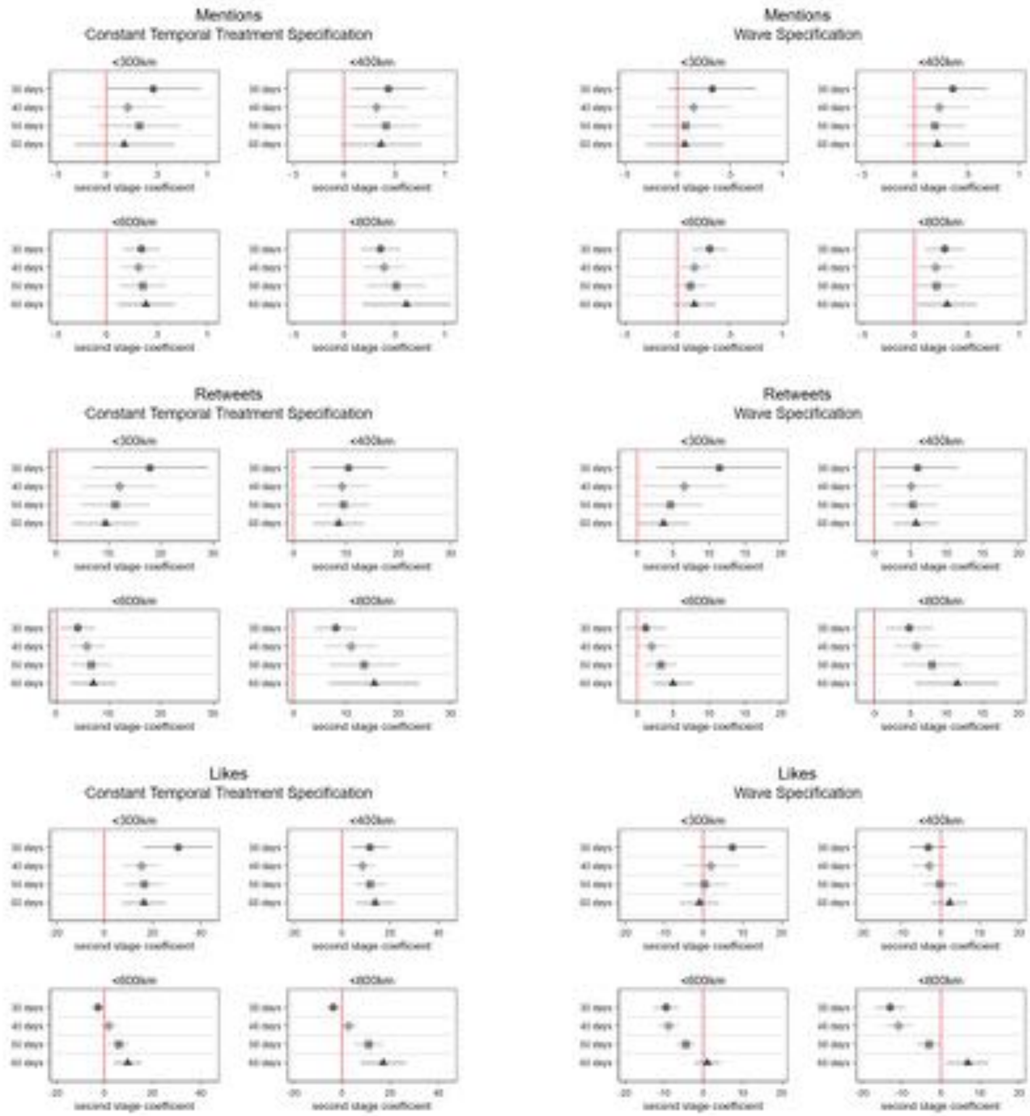
For the *wave specifications* of our instruments, we add temporal weights with a density $\lambda = 10\mathcal{N}(0, \frac{\Phi}{5})$ where the peak of the weight is assigned to $\frac{\mathrm{T}}{2}$.

In our preferred specification, we allow for the exposure to be time-varying as described above and set $\Phi = 800$ and $\mathrm{T} = 60$.



Notes: Graphs show coefficients and 95 percent confidence intervals from linear regressions. All regressions use NUTS-3 and day fixed effects and cluster standard errors at the NUTS-3 region. Data for five European countries (DE, IT, NL, UK, FR) between 1st February 2020 and 30th June 2020 from Naqvi (2021) and Swinkels et al. (2021).

FIGURE A1. First Stage Results



Notes: The figure plots coefficients and 95% confidence intervals of instrumental variable regressions with different exposure instruments for super spreader events. Dependent variable as indicated in title. All regressions include NUTS-3 and day fixed effects, as well as a control for lockdown stringency. Standard errors are clustered at the NUTS-3 level. Data is a panel of 793 NUTS-3 regions for five European countries (DE, IT, NL, UK, FR) observed for 134 days between 1st February 2020 and 30th June 2020 from Naqvi (2021), Hale et al. (2021), and Swinkels et al. (2021). One, two and three stars represent significance at the 10%, 5%, and 1% levels respectively.

FIGURE A2. Robustness of IV results: Mentions, Retweets, and Likes

3 Social Media and Populist Popularity, 2019-2020

Did populist actors see increased levels of engagement during the COVID-19 pandemic? We compare hundreds of political parties across Europe to examine the relationship between populism and social media engagement.

Data on political parties in Europe was collected from ParlGov. These data were merged with information collected from social media for all parties for which we could retrieve active social media accounts. We used the Twitter Academic API to collect all posts made by each party in 2019 and 2020 and counted the number of likes, retweets, and replies these posts received. We used CrowdTangle to do the same for Facebook, collecting the number of likes, comments, and shares each party received each year. This results in a total sample of 338 political parties active on Facebook and 230 active on Twitter during the period considered.

The dependent variables in the following analyses consist of the party-level difference in engagement rate for each type of engagement between 2019 and 2020. Here $\Delta_{i,k}$ is the difference for party i and engagement j. Subscript k indexes a post, $e_{i,j,k}$ corresponds the the number of engagements of type j on post k, and N_{year} is the total number of posts by party i in a given year.

$$\Delta_{i,j} = \frac{\sum_{k=1}^{N_{2020}} e_{j,k}}{N_{2020}} - \frac{\sum_{k=1}^{N_{2019}} e_{j,k}}{N_{2019}}$$

For example, $\Delta_{UKIP,retweets}$ corresponds to the difference in the retweet rate for the UK Independence Party between 2020 and 2019.

In each case, we estimate an OLS regression predicting the difference in party-level engagement rates. The key independent variable a binary populism measure from the PopuList Mudde (2004) influential "ideational" definition. The dataset focuses on populist parties, so we assume that parties without a score are non-populist.

We control include controls for left-right ideology, whether there was an election in 2019 and 2020, the percentage of parliamentary seats each party held in 2020, and whether each party was party of the governing cabinet in 2020.[1] Each model also includes country-level fixed effects. The total number of countries is 28, although the coverage varies across each dataset.

The table below shows the estimated effect of populism across all six engagement types for each measure of populism. The estimates represent the expected difference in engagement between populist and non-populist parties.

[1]The only changes in seats and cabinet positions recorded during this period are for parties located in Lithuania, Romania, Slovakia, and Croatia. Since there is only change in a handful of cases we decided not to include change in seats percentage or cabinet membership in the final models.

We see positive, statistically significant effects for all engagement types with the exception of retweets. The size of the effects appears to be larger on Facebook than Twitter.

	Dependent variable:					
	Likes (FB)	Likes (TW)	Shares	Replies	Comments	Retweets
	(1)	(2)	(3)	(4)	(5)	(6)
Populist	168.672***	22.259***	64.364***	3.627**	45.407***	−9.249
	(35.937)	(8.276)	(23.884)	(1.578)	(11.110)	(23.232)
Left-Right Ideology	1.940	−2.047	−0.607	−0.458*	−1.020	0.794
	(5.936)	(1.310)	(3.945)	(0.250)	(1.835)	(3.676)
Election (2019)	27.823	−9.551	23.261	−0.064	20.919	4.441
	(56.077)	(11.590)	(37.270)	(2.209)	(17.337)	(32.534)
Election (2020)	1.378	10.630	18.568	1.839	8.620	−155.905*
	(82.147)	(32.578)	(54.597)	(6.210)	(25.397)	(91.450)
Seats (%)	2.863**	−0.167	−1.018	−0.082	0.800*	1.175
	(1.441)	(0.302)	(0.958)	(0.058)	(0.445)	(0.848)
Cabinet member	−47.933	0.678	−36.767	2.876*	−7.167	8.830
	(36.199)	(7.705)	(24.058)	(1.469)	(11.191)	(21.628)
Constant	−121.250	14.682	22.134	1.133	−20.080	−21.296
	(97.218)	(18.935)	(64.613)	(3.610)	(30.056)	(53.153)
Observations	338	230	338	230	338	230
R^2	0.186	0.290	0.096	0.278	0.187	0.124
Adjusted R^2	0.098	0.175	−0.002	0.161	0.099	−0.018
Residual Std. Error	246.992 (df = 304)	43.519 (df = 197)	164.156 (df = 304)	8.296 (df = 197)	76.360 (df = 304)	122.163 (df = 197)
F Statistic	2.103*** (df = 33; 304)	2.513*** (df = 32; 197)	0.977 (df = 33; 304)	2.370*** (df = 32; 197)	2.119*** (df = 33; 304)	0.874 (df = 32; 197)
Note:						*p<0.1; **p<0.05; ***p<0.01

TABLE A2

4 Differences in tweets by location

Data and preprocessing steps

The goal of this analysis is to assess whether tweets written by users with valid locations differ from those written by users whom we were unable to locate. Additionally, we also assess whether the content of tweets differs according to whether they mention a populist politician or party or a mainstream politician or party. To do this, we sample tweets from our corpus and analyze the texts using topic modeling.

We begin by removing mentions and URLs from tweets and filtering out any tweets with fewer than 10 words. For each country, we then take a sample balanced by location and whether a populist is mentioned, selecting 500 tweets in each quadrant. This allows us to rule out the possibility that any observed differences are a function of frequency. We also stratify by user to avoid oversampling from users who tweet at a particularly high rate, allowing up to five tweets per user in our final sample. All non-English tweets are translated into English using the Google Translate API. This approach has been shown to be highly accurate and a qualitative analysis indicates that the translations are interpretable. Our final sample consists of 9,861 tweets, 50.7% of which have a valid location.[2].

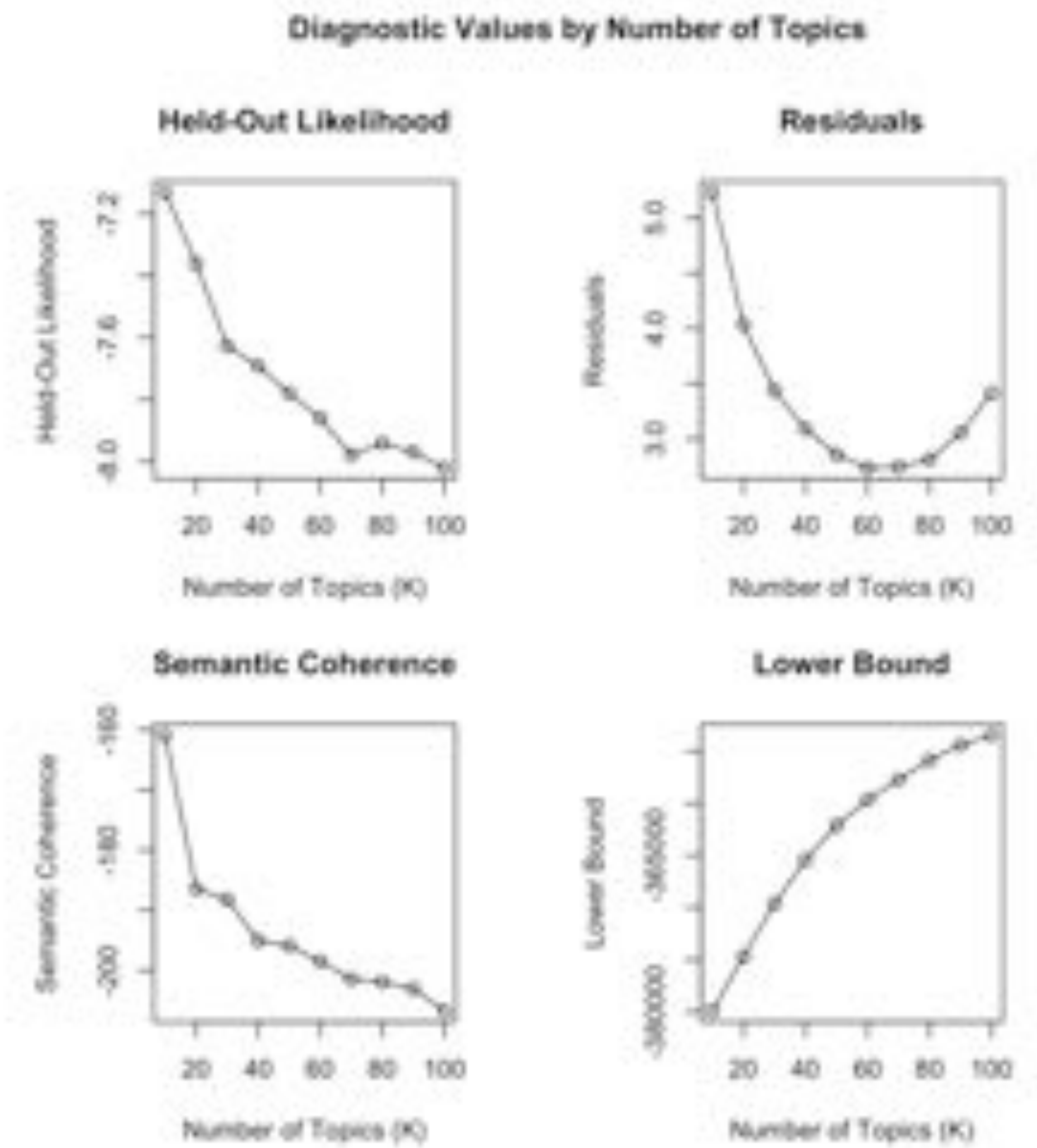
Once the final sample has been selected and tweets from Germany, France, Italy, and the Netherlands have been translated into English, we then conduct some additional text preprocessing (Martin and Jurafsky, 2009). We remove numbers and punctuation, as well as rare, low-frequency words (those occurring in fewer than 5 tweets), and very frequent words known as "stop words". Words that occur in fewer than three countries are also removed to allow us to focus on the common language used across countries. These mostly consist of names of people and places, although some are retained. Additionally, we remove documents with less than ten words, since these documents do not contain much information (we repeat this step since document length has changed after prepossessing. After pre-processing, we are left with a sample of 4492 documents. The sample is reasonably balanced across the two dimensions of interest: 51.2% have a valid location and 47.5% mention a populist politician or political party.

Estimating a structural topic model

We train a structural topic model using the translated texts and associated metadata. Topic modeling is an inductive approach to summarizing large corpora of text to identify underlying themes. The structural topic model allows for the inclusion of additional covariates (Roberts et al., 2014, 2019),

[2]There were only 361 tweets that had valid locations and mentioned non-populists available in the Netherlands.

enabling us to consider how the prevalence of each topic varies according to attributes of interest. In this case, we add four covariates: country fixed-effects, dummy variables denoting whether the author provided valid location information and whether the tweet mentions a populist politician or leader, and a spline variable to capture temporal trends. We use a spline due to expect non-linearity in the prevalence of different topics over time and to capture how these trends may vary across different countries.



Notes: The plot shows four different diagnostics for each value of K.

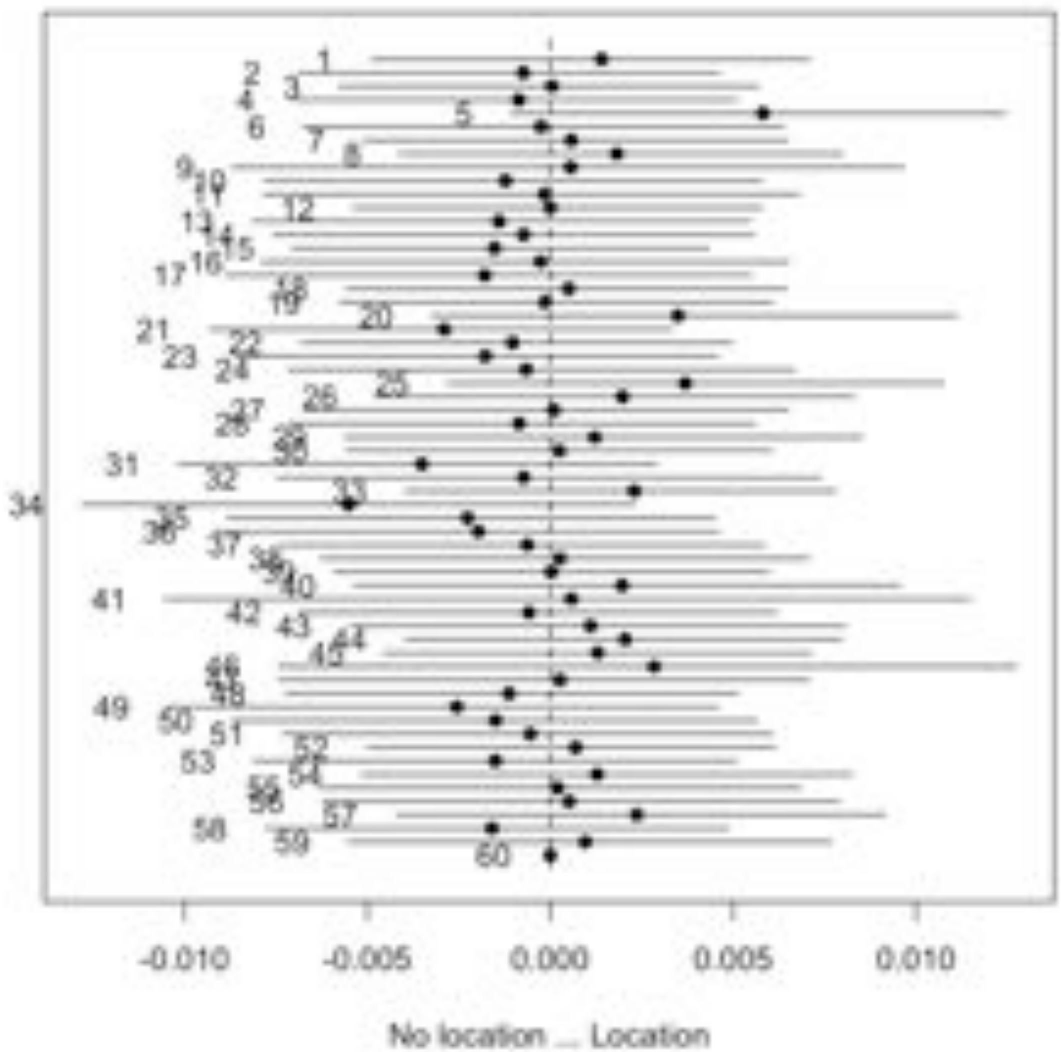
FIGURE A3. SEARCH K RESULTS

Topic models require users to set a parameter k, which defines the expected number of topics in the corpus. There is no way to determine this $apriori$, although larger, more varied corpora generally require a higher value of k. We estimated models with a range of plausible values of k, from 10 to 100 in increments of 10, and used diagnostic statistics to assess the results. The diagnostics suggest that models with values between N and K best fit the data. In this case, the residual is most informative, showing that residuals are minimized around $k = 60$. See Roberts et al. (2014) for further information on these diagnostics.

In this case, we are not interested in directly interpreting the results of the topic model (i.e. reading examples and summarizing the corpus) but analyzing the overall patterns to determine whether the content varies according to location.

Results

Once a model is estimated, we can run a linear regression to assess the extent to which the prevalence of each topic varies according to a covariate of interest. In this case, Figure 1 shows estimates and 95% confidence intervals for the location variable. This demonstrates that the content of the tweets does not systematically vary according to whether a user provides a valid location on their profile. Additionally, we estimated models with $k = 40$ and $k = N80$ and observed similar results, with no evidence of any statistically significant associations between topic prevalence and location, indicating that this finding is robust to differences in topic model specification.



Notes: The plot shows estimated coefficients and 95% confidence intervals for the associated between the prevalence of all 60 topics and whether or not tweets have valid location data. Each coefficient is estimated using OLS, net of country, time, and whether a populist is mentioned in each tweet.

FIGURE A4. TOPIC PREVALENCE ESTIMATES BY LOCATION

We found some evidence that the content varied according to whether a populist was mentioned, the country the politician belonged to, and the particular date that tweets were written. This indicates that the null effects for location are not simply a function of a lack of statistical power.

	Model 1	Model 2	Model 3	Model 4
Geolocated	−0.073		−0.073	−0.074
	(0.049)		(0.049)	(0.049)
Populist mention		−0.005	−0.005	−0.007
		(0.001)	(0.001)	(0.002)
Geolocated*Populist				0.003
				(0.002)
Num.Obs.	419 046	419 046	419 046	419 046
R2	0.301	0.301	0.301	0.301
R2 Adj.	0.173	0.173	0.173	0.173
Country FE	✓	✓	✓	✓
Day FE	✓	✓	✓	✓
User FE	✓	✓	✓	✓

Linear probability models estimating probability each tweet uses a COVID-19 related keyword. The model includes fixed effects for country, day, and user. Standard errors are clusted by author.

4.1 Keyword analysis

To further assess the extent to which tweets vary with respect to COVID-19, we use the entire corpus of mentions to estimate a regression. We use three terms as keywords, creating a dummy variable to indicate whether tweets used the terms "covid," "corona," or "virus." These words are all common to the five major languages considered (Dutch, English, French, German, and Italian). Overall, we find that approximately 3.3% of tweets mentioning populists or other major parties and politicians used one or more of these keywords during the period from January 1st to June 30th 2020. The table below shows estimates from a linear probability model with fixed effects for country, day, and user. The coefficient for geolocation suggests that users with valid information may be less likely to mention COVID-19 but it is not statistically significant in any of the specifications. The coefficient for whether the tweet mentions a populist party or leader is statistically significant in all three specifications, but the point estimate suggests a very small difference: these tweets are approximately half a percentage point *less* likely to mention COVID-19.

5 French Electoral Analysis: Robustness Checks

Outcome variable: RN Vote Share 2020	(1)	(2)	(3)
Exposure to Superspreader Events	0.014		
(Time-Invariant)	(0.015)		
Exposure to Superspreader Events		0.020**	
(Early-Weighted)		(0.001)	
Exposure to Superspreader Events			0.009**
(Late-Weighted)			(0.004)
Trend in RN Vote Share	0.890***	0.890***	0.890***
	(0.162)	(0.162)	(0.162)
NUTS-3 FE	✓	✓	✓
Alternative Demographic & Socioeconomic Controls	✓	✓	✓
Observations	9,307	9,307	9,307
R^2	0.377	0.378	0.377
Mean Outcome Variable	0.005	0.005	0.005

Notes: This table replicates Table 6 with an alternative battery of control variables, all of which are measured at the municipality level as of 2019 unless specified otherwise: trends in the RN's vote share, measured as the average difference in this share between each set of elections since 2001; the number of registered voters; the share of the population that is at least 60 years old; the share of workers employed in the industrial sector; the share of manual workers between 15 and 64 years old; and the share of the population that lived in a different municipality, NUTS-3 region, or metropolitan region in 2018. All data are from INSEE (2022).

**Significant at the 5 percent level.

*Significant at the 10 percent level.

TABLE A3. COVID-19 Exposure and Populist Support in French Municipal Elections: Alternative Controls

Outcome Variable: RN Vote Share 2020	(1)	(2)	(3)
Panel A. Treatments: Tweets Engaging with RN			
Relative Mentions of RN Leader	0.008		
	(0.008)		
Relative Mentions of RN Party		0.010*	
		(0.005)	
Relative Mentions of RN Leader or Party			0.006**
			(0.002)
Front National Vote Share 2014	0.493***	0.569***	0.489***
	(0.049)	(0.049)	(0.048)
Panel B. Treatments: Unique Twitter Users Engaging with RN			
Relative Mentions of RN Leader	0.006		
	(0.005)		
Relative Mentions of RN Party		0.012**	
		(0.006)	
Relative Mentions of RN Leader or Party			0.007***
			(0.003)
Front National Vote Share 2014	0.495***	0.567***	0.489***
	(0.074)	(0.104)	(0.059)
NUTS-3 FE	✓	✓	✓
Demographic & Socioeconomic Controls	✓	✓	✓
Observations	459	280	526
Mean Outcome Variable	0.024	0.031	0.026

Notes: This table presents OLS estimates of the association between Twitter engagement with the *Rassemblement National* (RN) and this party's vote share in the first round of 2020 French municipal elections. The outcome variable is the RN candidates' aggregate vote share in a given municipality. In Panel A, the treatment variables are the number of tweets published between 1 January 2020 and 15 March 2020 (the date of the elections) in each municipality that mention the RN leader (column 1), the RN party (column 2), and either of the two (column 3) normalized by the number of tweets in the same period and location that mentioned nonpopulist leaders or parties. In Panel B, the treatments are identical except that they measure numbers of unique Twitter users rather than tweets. Controls are the same as in Table 6. Huber-White standard errors, in parentheses, are clustered at the NUTS-3 level.
**Significant at the 5 percent level.
***Significant at the 1 percent level.

TABLE A4. Populist Support and Twitter Mentions in French Municipal Elections: Alternative Measures

6 LISS Panel Survey on Consequences of COVID

6.1 COVID-19 Exposure and Populist Voting Intention

The full questions from the LISS panel survey on "Consequences of COVID for the quality of society" (CentERdata, 2020) that we employ in Section 5.4 are:

- "If *Tweede Kamer* (House of Representatives) elections were to be held right now, would you vote?" Answer scale: 17 categories, where 1 = 50PLUS (pensioners' interests party); 2 = CDA (Christian democratic party); 3 = ChristenUnie (Christian union party); 4 = D66 (liberal-democratic party); 5 = DENK (pro-diversity party); 6 = Forum voor Democratie (pro-direct democracy party); 7 = GroenLinks (Green-left party); 8 = Partij voor de Dieren (Party for the animals); 9 = PvdA (Labor party); 10 = PVV (Party for Freedom); 11 = SGP (Christian reformed party); 12 = SP (Socialist Party); 13 = VVD (Liberal party); 14. = Other party, namely ...; 15 = Blank vote; 16 = I don't know yet (excluded from analysis); 17 = I don't want to say. In Table 9, *Populist Voting Intention* is equal to 1 if respondents select option 6 or 10 and to 0 otherwise.

- "Has anybody close to you been severely ill or died as a result of COVID-19?...yes, someone in my household." Answer scale: 0-1 binary, where 0 = No; 1 = Yes.

- "Has anybody close to you been severely ill or died as a result of COVID-19?...yes, a family member (someone outside my household)." Answer scale: 0-1 binary, 0 = No; 1 = Yes. In Table 9, *Family or Household Affected by COVID-19* equals 1 if respondents select option 1 for this or the question question and 0 otherwise.

In addition, we control for several demographic variables, which we convert into categorical form:

- Profile code for gender: two values corresponding to categories "male"; "female."

- Profile code for level of education: five values corresponding to categories "Elementary education"; "VMBO (prevocational secondary education)"; "HAVO/VWO (senior general secondary education/preuniversity education) + MBO (senior secondary vocational education)"; "HBO (higher professional education)"; "University." Each category is converted into a separate dummy variable in our analysis.

- Age of the household member (preloaded variable): ordinal scale.

- Primary occupation (preloaded variable): 14 values corresponding to categories "Paid employment," "Works or assists in family business," "Autonomous professional, freelancer, or self-employed," "Job seeker following job loss," "First-time job seeker," "Exempted from job seeking following job loss," "Attends school or is studying," "Takes care of the housekeeping," "Is pensioner ([voluntary] early retirement, old age pension scheme)," "Has (partial) work disability," "Performs unpaid work while retaining unemployment benefit," "Performs voluntary work," "Does something else," and "Is too young to have an occupation." Each category is converted into a separate dummy variable.

- Position within the household (preloaded variable): nine values corresponding to categories "Household head," "Wedded partner," "Unwedded partner," "Parent (in law)," "Child living at home," "Housemate," "Family member or boarder," and "Unknown (missing)." Each category is converted into a separate dummy variable.

6.2 Causal Mechanisms

In Section 6.1's analysis of causal mechanisms, we analyze responses to a large number of additional questions, which we group into six categories: *confidence in institutions*, *economic situation*, *social isolation*, *anxiety*, *opposition to government response*, and *out-group hostility*.

Confidence in institutions

- "Can you indicate, on a scale from 0 to 10, how much confidence you personally have in each of the following institutions?" Options: "Dutch government, Dutch parliament, the legal system, the police, the media, healthcare, science. Answer scale: 0-10 ordinal, where 0 = no confidence at all; 10 = full confidence; 11 = I don't know (excluded from analysis). Included in all survey waves.

Economic situation

- "Please indicate, on a scale from 0 to 10, whether the financial situation of your household is better or worse than six months ago (i.e., before COVID)." Answer scale: 0-10 ordinal, where 0 = much better; 5 = no change; 10 = much worse; 11 = I don't know (excluded from analysis).

- "How would you describe the financial situation of your household at this moment?" Answer scale: 1-5 categorical, where 1 = we are accumulating debts; 2 = we are somewhat eating into savings; 3 = we are just managing to make ends meet; 4 = we have a little bit of money to spare; 5 = we have a lot of money to spare.

- "On a scale from 1 to 10, please indicate how satisfied you are with: The Dutch economy." Answer scale: 1-10 ordinal, where 1 = very dissatisfied; 10 = very satisfied; 11 = don't know (excluded from analysis).

- "Compared to six months ago (before COVID), has anything changed in your work situation?…yes, I am working fewer hours now." Answer scale: binary, where 0 = No; 1 = Yes.
- " Do you think that there is any chance that you might lose your job in the coming 12 months (not because you are retiring)?" Answer scale: 0-100 percentage, where 0 = I am sure that I will not lose my job; 100 = I am sure that I will lose my job.

Social isolation

- "To what extent do the following statements apply to you, based on how you are feeling at present?…I know a lot of people that I can fully rely on." Answer scale: 1-3 categorical, where 1 = yes; 2 = more or less; 3 = no.
- "To what extent do the following statements apply to you, based on how you are feeling at present?" Options: "I know a lot of people that I can fully rely on"; "there are enough people to whom I feel closely"; "I miss having people around me"; "I often feel deserted." Answer scale: 1-3 categorical, where 1 = yes; 2 = more or less; 3 = no.
- "How different is this compared to six months ago (before COVID)? Has it increased, remained the same, or decreased?" Options: "Tensions in your core family"; "Connectedness with the neighborhood." Answer scale: 1-3 categorical, where 1 = increased; 2 = the same; 3 = decreased; 4 = don't know.
- "Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people? Please indicate a score of 0 to 10." Answer scale: 0-10 ordinal, where 0 = You can't be too careful; 10 = Most people can be trusted.

Anxiety

- "This past month…I felt very anxious." Answer scale: 1-6 categorical, 1 = never; 2 = seldom; 3 = sometimes; 4 = often; 5 = mostly; 6 = continuously.
- "Do you feel more cheerful or more dejected than [before COVID]?" Answer scale: 1-5 categorical, where 1 = much more cheerful; 2 = a bit more cheerful; 3 = the same; 4 = a bit dejected; 5 = much more dejected; 6 = I don't know (excluded from analysis).
- "How worried are you about the consequences of the COVID-19 pandemic for…" Options: "your own health or the health of a loved one"; "your own job or income or the job or income of a loved one." Answer scale: 1-5 categorical, where 1 = extremely; 2 = very; 3 = not very; 4 = a little; 5 = very little; 6 = I don't know (excluded from analysis).

- “Generally speaking, do you think that things in the Netherlands are heading in the right direction or the wrong direction?” Answer scale: 1-4 categorical, where 1 = Definitely in the wrong direction; 2 = Slightly more in the wrong direction than the right direction; 3 = Slightly more in the right direction than the wrong direction; 4 = Definitely in the right direction; 5 = I don’t know (excluded from analysis).

Opposition to government response (July 2020 wave only)

- “The government introduced/has introduced a variety of measures to prevent the spread of COVID-19, such as observing a distance of one and a half meters, not receiving many visitors, avoiding public transportation as much as possible, working from home as much as possible, and not organizing any large gatherings of people. To what extent do you agree or disagree with the following statements? I think that people should follow these kinds of measures...” Options: “even if they personally disagree with them;” “even if they do not understand why”; “even if it is to their own disadvantage.” Answer scale: 1-5 categorical, where 1 = completely disagree; 2. disagree; 3 = neither agree nor disagree; 4 = agree; 5 = completely agree; 6 = I don’t know (excluded from analysis).

- “Please indicate how you feel about the way the Dutch government is handling the situation.” Answer scale: 1-7 categorical, where 1 = The government is not taking enough measures to protect people with vulnerable health; 4 = The government is doing a good job in this regard; 7 = The government is taking too many measures to protect people with vulnerable health; 8 = I don’t know (excluded from analysis).

- “Please indicate how you feel about the way the Dutch government is handling the situation.” Answer scale: 1-7 categorical, where 1 = The government is not taking enough measures to protect people with vulnerable health; 4 = The government is doing a good job in this regard.; 7 = The government is taking too many measures to protect people with vulnerable health; 8 = I don’t know (excluded from analysis).

- “Please indicate how you feel about the way the Dutch government is handling the situation.” Answer scale: 1-7 categorical, where 1 = The government needs to take more responsibility to prevent the virus from spreading further; 4 = The government is doing a good job in this regard.; 7 = The government needs to leave more to citizens’ own responsibility to prevent the virus from spreading further; 8 = I don’t know (excluded from analysis).

Out-group hostility (July 2020 wave only)

- "In every country, there is friction between different social groups sometimes. In your opinion, how serious is the friction between the following groups in the Netherlands?...People with migration backgrounds and people without migration backgrounds." Answer scale: 1-10 ordinal, where 1 = No friction at all; 10 = Severe friction; 11 = I don't know (excluded from analysis).

- "The next question is about Europe. Do you agree or disagree with the following statement? The Netherlands should provide financial support to other European countries whose economies have been hit hard by the COVID-19 pandemic." Answer scale: 1-5 categorical, where 1 = completely disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = completely agree; 6 = I don't know (excluded from analysis).

- "Please indicate, on a scale from 1 (not entitled) to 10 (completely entitled), to what extent the following groups are, in your opinion, entitled to financial support." Options: "People who fled to the Netherlands in the past five years"; "People who do not speak Dutch well." Answer scale = 1-10 ordinal, where 1 = not entitled; 10 = completely entitled; 11 = I don't know (excluded from analysis).