Right-Wing Populism and the COVID-19 Shock: Evidence from Early Superspreader Events*

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Abstract

Can public health shocks boost right-wing populism? We investigate how the onset of the COVID-19 pandemic impacted support for populists in Western Europe, an unresolved debate on which surprisingly little systematic evidence exists. Building on theories of populist mobilization in societal crises, we hypothesize a positive aggregate effect driven by declining confidence in public institutions, intensifying hostility toward outgroups, and opposition to government restrictions. Exploiting variation in local COVID-19 incidence stemming from the idiosyncratic timing of early superspreader events, we find a rise in online engagement with populists in regions with higher infection rates. We document a similar increase in populist support in the 2020 French municipal elections and in representative British and Dutch survey data. These varied sources corroborate our three posited mechanisms while casting doubt on possible alternative economic, social, and psychological channels. The findings broaden our understanding of the types of societal shocks that foster extreme politics.

Keywords: populism, public health, political behavior, COVID-19, social media, political economy

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Introduction

Understanding the drivers of right-wing populism has emerged over the past decade as one of the most pressing tasks confronting scholars of advanced democracies. While much attention has been devoted to secular economic and cultural trends, such as rising international trade (Colantone and Stanig, 2018; Rodrik, 2021), skill-biased technological change (Im et al., 2019; Gallego, Kurer, and Schöll, 2022), and the erosion of liberal and progressive values (Norris and Inglehart, 2019), recent years have seen burgeoning interest in the impact of more fast-moving and exogenous societal shocks, including financial crises (Algan et al., 2017; Funke, Schularick, and Trebesch, 2016), refugee inflows (Dinas et al., 2019; Dustmann, Vasiljeva, and Piil Damm, 2019), terrorist attacks (Sabet, Liebald, and Friebel, 2025; Vlandas and Halikiopoulou, 2025), and abrupt policy shifts (Fetzer, 2019; Ahlquist, Copelovitch, and Walter, 2020). There remains strikingly little consensus, however, about whether the largest and most disruptive such shock of recent decades — the spread of coronavirus disease (COVID-19) — helped or hindered populists. According to one view, the COVID-19 pandemic undermined populist appeals by highlighting the dangers of policy mismanagement and unifying societies around a common threat (Foa et al., 2022) — claims consistent with evidence of voters "rallying around the flag" (Baekgaard et al., 2020; Yam et al., 2020) and engaging in a "flight to safety" (Bisbee and Honig, 2022). An alternative perspective maintains that COVID-19 made little difference to support for populists, who responded pragmatically to public health risks while struggling to capitalize on frustration with mainstream parties (Kaltwasser and Taggart, 2022; Wondreys and Mudde, 2022; Zulianello and Guasti, 2023).

These conclusions are hard to reconcile with cross-national electoral trends during the COVID-19 era, most notably in Europe, where populist parties — especially those on the ideological right — registered notable gains in legislative elections (Silver, 2022). They also sit uneasily with an earlier body of research emphasizing the pivotal role of societal crises in launching and strengthening populist movements by undermining confidence in the political status quo and creating opportunities to foment social divisions and distance elites from ordinary citizens (Laclau, 1977; Moffitt, 2015; Stavrakakis et al., 2018). Building on this literature, we argue that major public health shocks such as the COVID-19 pandemic — transnational crises that expose shortcomings in political institutions while necessitating deeper state intervention — are unlikely to constitute an exception. This dynamic is particularly plausible in the era of mass social media, which permit fringe and extreme views to be directly and rapidly disseminated to large audiences. Our central claim is that the onset of the pandemic spurred an aggregate increase in support for populists by eroding confidence in public institutions, intensifying hostility toward outgroups, and provoking opposition to government restrictions.

To test this hypothesis, we undertake a granular yet wide-ranging analysis that seeks to move beyond the existing literature's typical focus on individual countries and on "correlations rather than... causal effects" (Guriev and Papaioannou, 2022, 814) — key reasons, we believe, for its mixed results. We pursue an instrumental variables strategy that exploits the idiosyncratic location-specific timing of superspreader events (SSEs) — social gatherings with unusually high rates of secondary infection, such as birthday parties, public performances, and workplace meetings — in early 2020. During this period, SSEs were a key mechanism of COVID-19 transmission and occurred in an unpredictable fashion, in large part because they were often planned before the pandemic and confined to small groups of family members, friends, or colleagues who did not anticipate elevated transmission. Building on Avetian et al. (2022), we argue that in a given location, the timing of early SSEs in nearby areas is plausibly exogenous to other factors influencing support for populism and hence unlikely to affect political preferences other than through COVID-19 trends. Focusing on the initial phase of the pandemic, we thus instrument a location's rate of COVID-19 incidence with its proximity to recent SSEs within a specified radius, weighting this distance by a temporal function derived from a widely used epidemiological model of infectious disease dynamics.

We implement our instrumental variables approach in a variety of empirical contexts, concentrating on five major Western European countries — France, Germany, Italy, the Netherlands, and the United Kingdom — with long-standing populist traditions and multiple SSEs in the first six months of 2020.[1] We begin by examining public engagement with populist parties and party leaders on social media, a rich, high-frequency source of data on how today's citizens acquire information on, communicate with, and express support for political actors (Vaccari, 2017; Theocharis et al., 2023). Analyzing a daily panel of geolocated Twitter posts, we document a statistically and substantively meaningful rise in multiple forms of interaction with populist politicians in NUTS-3 regions with higher COVID-19 rates. In our preferred two-stage least squares (2SLS) specification, a 1% increase in new COVID-19 cases (per 10,000 inhabitants) is associated with 0.1% more mentions, 0.8% more retweets, and 0.6% more likes of populists per day. In contrast, mentions of mainstream politicians decline by 0.6%, implying a 0.7% rise in the ratio of populist to mainstream mentions. Our estimates remain similar across a host of robustness checks, from the addition of Twitter user fixed effects to the use of varying distance and time cutoffs for including SSEs in our instrument.

In the second part of our investigation, we turn to COVID-19's impact on electoral support for populists. We focus on the first round of the 2020 French municipal elections, the only national vote to take place in our five countries of interest during the first half of 2020. We implement our instrumental variables strategy within a difference-in-differences framework that compares changes in the vote share of the *Rassemblement National* (RN) — a prominent populist party formerly known as the *Front National* — between the 2014 and 2020 elections across municipalities with varying COVID-19 burdens. In a context of growing concern about the disease yet relatively few infections — the 2020 elections were held in mid-March — we find that even small outbreaks yielded substantial electoral gains for the RN: a 1% rise in a municipality's pre-election COVID-19 incidence raised the party's vote share by more than one-tenth. This figure lies at the upper end of estimated increases in populist vote shares resulting from socioeconomic shocks.[2]

Next, we study the evolution of populist voting preferences with nationally representative survey

[1] Replication materials and code can be found at Lall, Davidson, and Hagemeister (2026).

[2] For example, Algan et al. (2017) find that a 1% rise in unemployment following the global financial crisis lifted the NUTS-2-level vote share of European antiestablishment parties by 2-4 percentage points; Fetzer (2019) that British austerity measures beginning in 2010 boosted support for the UK Independence Party (UKIP) by 3.5-11.9 percentage points in local elections; and Sabet, Liebald, and Friebel (2025) that terrorist attacks in Germany since 2010 have increased municipality-level votes for the *Alternative für Deutschland* by 4.5 percentage points in state elections.

data from the British Election Study (BES) and the Longitudinal Internet Studies for the Social Sciences (LISS) Panel in the Netherlands. We use the BES to analyze changes in the intention to vote for the *UK Independence Party* (UKIP) and *Reform UK* — the United Kingdom's right-wing populist parties — following the emergence of COVID-19 among individuals with varying local and personal exposure to the disease. We find that residents of local authorities subject to larger COVID-19 shocks — as instrumented by time-weighted proximity to early SSEs — became more likely to vote for one of the two parties, and that this shift occurred among individuals both with and without first-hand experience of the disease. The LISS Panel also tracks individual exposure to COVID-19 but only covers electoral preferences in one wave, restricting us to a cross-sectional analysis. The results, while correlational in nature, are consistent with a COVID-induced boost in support for the *Forum voor Democratie* (FvD) and the *Partij voor de Vrijheid* (PVV), the two Dutch populist parties.

Finally, we triangulate between these varied data sources to explore the mechanisms behind the positive association between COVID-19 exposure and populist support. The BES and LISS Panel provide consistent support for our three posited mechanisms — institutional mistrust, outgroup hostility, and opposition to government containment measures — while casting doubt on possible alternative channels, such as financial hardship and social isolation. The social media data corroborate our third hypothesized mechanism, showing that European regions with more restrictive lockdowns saw higher growth in Twitter engagement with populists. In addition, these data suggest that our findings are not simply explained by differences in attention to COVID-19 among politicians: populists neither discussed the pandemic more frequently on Twitter nor used the platform more actively than their mainstream counterparts in early 2020.

The findings expand our understanding of the types of societal shocks that foster extreme politics. While personal illness and disability have been found to predict support for populist parties in Europe (Kavanagh, Menon, and Heinze, 2021), little is known about the consequences of mass public health events — a more exogenous source of variation in health vulnerability — for such preferences. Our estimates suggest that COVID-19's impact on populist support was comparable in magnitude to that of previous large-scale societal shocks and underpinned by both similar mechanisms (reduced institutional confidence, heightened nativism and xenophobia) and distinct ones (antipathy to government intervention). In doing so, they complement research on the pandemic's effect on "status-quo outcomes," such as support for incumbent parties, trust in institutions, and satisfaction with democracy, which has also yielded mixed findings. Whereas early descriptive studies reported improvements in these outcomes (Baekgaard et al., 2020; Yam et al., 2020), there is an emerging consensus that pandemic-era attitudes toward the status quo were contingent upon preexisting partisan attachments and patterns of political polarization (Barberia, Plümper, and Whitten, 2021; Gadarian, Goodman, and Pepinsky, 2022; Goldstein and Wiedemann, 2022). While not ruling out the possibility of pro-establishment effects in specific geographical and temporal contexts, our results reinforce and add nuance to this conclusion: in Western European countries with established populist movements, the COVID-19 shock strengthened political forces actively *opposed* to the status quo.

Right-Wing Populism, Societal Crisis, and the COVID-19 Pandemic

As an anti-establishment ideology characterized by an emphasis on popular sovereignty and a Manichean distinction between the "corrupt elite" and the "pure people" (Mudde, 2004), populism has always been intimately related to societal crisis. Stavrakakis et al. (2018, 7) note that "most analyses of populist phenomena claim that they emerge within a crisis context," while Laclau (1977, 175) observes that "the emergence of populism is historically linked to a crisis of the dominant ideological discourse, which in turn is part of a more general social crisis." In particular, three features of crises are considered critical in arousing populist sentiment of a right-wing variety — all of which, we argue, are likely to be present in public health shocks with characteristics comparable to those of the COVID-19 pandemic.

First, crises erode confidence in government and political elites, opening up space for right-wing populists to stake an alternative, purportedly superior claim to represent the public will (Moffitt, 2015; Stavrakakis et al., 2018; Algan et al., 2017). Eichengreen, Saka, and Aksoy (2024) show that epidemics stretching back to 1970 have persistently undermined trust in political institutions and leaders by revealing shortcomings in state capacity. During the COVID-19 pandemic, a similar process played out across many advanced democracies — particularly those in Western Europe, an early epicenter of the outbreak, where populists lambasted incumbents for "responding too late, too slow, or too weakly" (Wondreys and Mudde, 2022, 89). As a *BMJ* review of the European response to COVID-19 summarizes, "All country governments lost trust of their populations during the epidemic due to a mix of communication and transparency failures, and increased questioning of government legitimacy and technical capacity by the public" (Hanson et al., 2021, 1).[3] Similar effects on political trust have been identified in other parts of the world, from the United States (Aassve et al., 2024) to China (Liu, Bao, and Wu, 2023). Experimental evidence indicates that diminished confidence in government spilled over into dissatisfaction with democracy more generally, albeit not into support for nondemocratic alternatives (Becher et al., 2024).

Second, crises can exacerbate cultural conflict and negative attitudes toward outgroups, such as immigrants, refugees, and asylum seekers — prime targets for populists. Unlike ineffective government performance, these frictions tend to enhance the appeal not of nonincumbents in general but of parties espousing nativist and "exclusionary" values characteristic of European right-wing populism (Mudde and Kaltwasser, 2013; Moffitt, 2015). Major public health shocks are rarely confined to a single country, allowing populists to attribute responsibility and blame to segments of society with foreign ties or associations. This opportunity was not missed during the COVID-19 pandemic, which originated in China and spread across advanced democracies through international travel and migration (Lall, 2023). Indeed, populist parties throughout Europe were quick to link the outbreak to open borders and freedom of movement, often vilifying migrants and tourists believed to have imported the disease (Wondreys and Mudde, 2022; Zulianello and Guasti, 2023). In many countries, blame was extended to immigrants and ethnic and religious minorities more broadly, leading to a spike in xenophobic and discriminatory attitudes as well as racially motivated hate crimes (Freitag and Hofstetter, 2022;

[3] Also see https://yougov.co.uk/international/articles/29429-perception-government-handling-covid-19.

Dipoppa, Grossman, and Zonszein, 2023).

Third, crises can provoke governments into taking emergency measures that expand their authority and influence over society, rendering them vulnerable to populist accusations of overreach (Brubaker, 2021). They may thus find themselves in the awkward position of appearing to be both "not doing enough" to address salient societal problems and "doing too much" when calamity strikes. COVID-19's dangerous symptoms and high level of contagiousness prompted health authorities to interfere in public life in unprecedented ways, including by restricting physical movement, closing communal spaces, and mandating masks and vaccines. These interventions provided ample fodder for populists — many of whom had earlier disparaged the COVID-19 policy response as too weak — to condemn politicians for flouting democratic principles, undermining civil liberties, and jeopardizing livelihoods (Wondreys and Mudde, 2022; Zulianello and Guasti, 2023). In pursuing this critique, they embraced a more market-oriented, libertarian strain of populism traditionally more common in the United States than in Europe (Norris and Inglehart, 2019). Mixed with growing mistrust of public institutions and experts, this critique fueled the spread of conspiracy theories such as the notion that governments manufactured COVID-19 as a bioweapon or a tool for population control (Eberl, Huber, and Greussing, 2021; Stecula and Pickup, 2021).

Finally, it is important to consider how changes in communication patterns during crises shape opportunities for populist mobilization. With movement and in-person interaction limited by containment measures, the COVID-19 pandemic was characterized by a pronounced rise in the use of online news sources and social networks in advanced democracies (Dixon, 2023). The rollout of broadband internet has strengthened support for populist parties across Europe (Guriev, Melnikov, and Zhuravskaya, 2021), in large part because social media facilitate information sharing about government performance and reward simple, emotional, and pejorative communication styles (Engesser, Fawzi, and Larsson, 2017). Not only do populists receive more public engagement on social media platforms than other types of politicians (Cassell, 2021; Larsson, 2022), but such interaction has been found to rise during economic downturns and when internet and social media penetration is high (Davidson and Enos, 2025) — conditions prevalent during the pandemic.

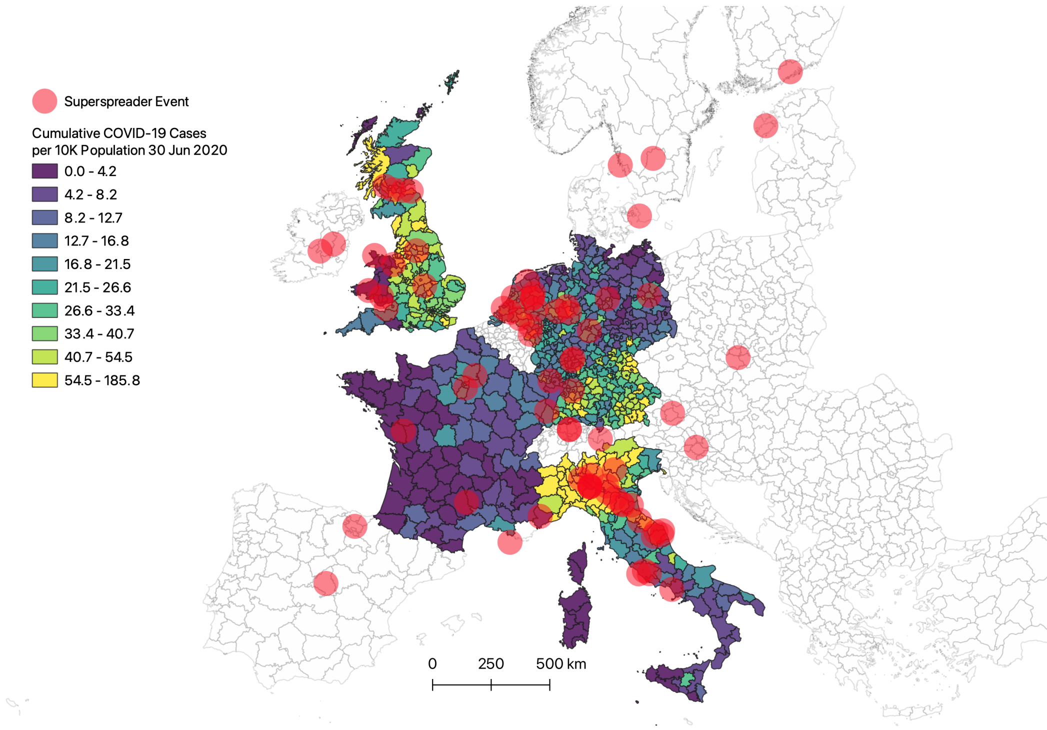
In sum, insights from scholarship on the nexus of societal crisis and right-wing populism offer grounds for expecting the onset of the COVID-19 pandemic to influence attitudes toward public institutions, political elites, and outgroups in ways that benefit — rather than hinder — populists across Western Europe. In the subsequent sections, we set out and implement an empirical strategy for more systematically assessing this proposition.

Identification Strategy: Exploiting Exposure to Early SSEs

In attempting to determine COVID-19's impact on right-wing populism, we might begin by analyzing how support for populists evolved across locations with varying incidence of the disease, controlling for potentially confounding geographical and temporal characteristics. While addressing some obvious sources of endogeneity, this approach could nevertheless produce a biased estimate. For instance, local disease rates could themselves be affected by levels of populist support if politicians influenced public perceptions of COVID-19 health risks or containment policies.

Our principal strategy for addressing this endogeneity challenge is to develop an instrument for local COVID-19 incidence based on the erratic timing of SSEs in the initial stages of the pandemic. The starting point for our approach is the observation that early COVID-19 transmission was highly "overdispersed," that is, the vast majority of infections stemmed from just 10-20% of contagious individuals (Endo et al., 2020; Miller et al., 2020). SSEs, many of which were organized before the pandemic, were the primary mechanism of overdispersion, typically taking place in crowded indoor spaces with poor ventilation and hygiene (Lewis, 2021). Common examples include birthday parties, office meetings, religious ceremonies, musical performances, and nursing home visits. Contrary to popular perception, few SSEs were mass gatherings; it is not a large absolute number of infections but a high ratio of secondary cases to contagious individuals that defines such events. This proportion was difficult even for participants to foresee: most social events involving contagious individuals did *not* spread

FIGURE 1. COVID-19 Incidence and Superspreader Events in Europe, Early 2020



Notes: Distribution of SSEs across Europe and of COVID-19 incidence across 792 NUTS-3 regions of five countries (FR, DE, IT, NL, UK) between 1 February and 30 June 2020.

COVID-19 extensively, with SSEs usually identified only retrospectively via contact tracing, epidemiological modeling, and genomic sequencing (Althouse et al., 2020). As a result, the early months of 2020 were characterized by idiosyncratic disease clusters and hotspots with little discernible connection to factors influencing local support for populism. Indeed, the sizable public health literature on COVID-19 has yet to identify consistent predictors of SSE timing and location, with many studies treating these variables as unpredictable (Zenk et al., 2020; Namilae et al., 2022) or quasi-random (Avetian et al., 2022; González-Val and Marcén, 2022).

We identify SSEs using the SARS-CoV-2 Superspreading Events Database (Swinkels et al., 2021), an open-source, expert-validated compendium that updates and extends Leclerc et al.'s (2020) influential list with the aid of public health records, epidemiological studies, and verified media reports. While not guaranteed to be exhaustive — some SSEs may not have been detected by public health authorities, scientists, or news outlets — it is the most comprehensive and well-substantiated source of information on early SSEs of which we are aware.[4]

Figure 1 maps all European SSEs during the first six months of 2020 as per the SARS-CoV-2 Superspreading Events Database. These 80 events, which took place in diverse settings ranging from ski resorts and navy ships to slaughterhouses and churches, are projected onto a Eurostat GISCO shapefile of NUTS-3 regions, the smallest geographical unit for which cross-national COVID-19 data are available.[5] The 792 regions constituting our five countries of interest are shaded by cumulative COVID-19 cases per 10,000 inhabitants between 1 February and 30 June 2020 with data from the COVID-19 European Regional Tracker (Naqvi, 2021). Two features of the figure are worth noting. First, consistent with overdispersed transmission, regions that host or are near SSEs tend to exhibit higher cumulative COVID-19 rates. This pattern is also illustrated in panel A of Figure 2: regions whose mean distance to SSEs is below the sample median recorded more population-adjusted COVID-19 cases over most of the period, with a major spike occurring shortly after the initial spate of SSEs in late February and early March. Second, SSEs are not distributed according to any clear pattern, such as greater concentration in major cities, metropolitan zones, border areas, or coastal regions.

Table 1 presents more systematic evidence that the geographical distribution of early SSEs is orthogonal to that of populist support prior to the pandemic. Comparing European NUTS-3 regions with and without SSEs, there is little difference — substantively or statistically — in the mean vote share of right-wing populist parties in legislative elections in 2019 or the previous five years.[6] The same is true of the mean annual change in this share between 2014 and 2019. The two sets of regions also have similar pre-pandemic mean values of several known predictors of populist support (Guriev and Papaioannou, 2022): population density and urbanization, the gender ratio, the proportion of young

[4]We have seen no evidence of systematic underreporting and later show that reported SSEs strongly predict nearby COVID-19 cases. Note that even in the (unlikely) event that reporting were correlated with pre-pandemic populist support, this would not threaten our identification strategy, which exploits within-region variation over time.

[5]The events are listed in Table A1 of Online Appendix A, which includes details of their location and setting. The latter's heterogeneous nature reduces the likelihood that SSEs disproportionately involved individuals with particular political orientations; indeed, none of the gatherings were overtly political in nature.

[6]Data come from the European NUTS-Level Election Database (Schraff, Vergioglou, and Demirci, 2022).

TABLE 1. Balance Table: Regions with and without Early Superspreader Events

	NUTS Level	Regions without SSEs		Regions with SSEs		T-Test: Diff. in Means		
		Mean	St. Dev.	Mean	St. Dev.	t	p	p^{*}_{1000}
Populist vote share (%), 2019	3	25.42	15.44	25.01	12.64	-0.22	0.82	0.87
Mean populist vote share (%), 2014-19	3	23.25	13.39	21.03	9.82	1.55	0.13	0.16
Δ Populist vote share (%), 2014-19	3	4.94	14.63	8.40	15.36	-1.57	0.12	0.12
Population per km^2, 2019	3	390.74	1,036.61	586.16	1,064.23	-1.32	0.19	0.11
Share of urban households (%), 2019	2	38.84	17.66	38.15	12.18	0.34	0.74	0.81
Women per 100 men, 2019	3	103.05	4.04	103.06	3.00	-0.027	0.98	0.98
Share of people aged < 20 (%), 2019	3	20.70	4.62	20.99	3.21	-0.83	0.41	0.41
Share of people aged 65+ (%), 2019	3	20.38	4.62	20.56	3.21	-0.42	0.67	0.72
Median male age, 2019	3	42.42	4.83	42.50	3.15	-0.18	0.86	0.91
Males aged < 25 w/o tertiary ed. (%), 2019	2	46.10	25.54	42.59	24.29	1.31	0.19	0.18
Share of foreign citizens (%), 2019	2	8.05	7.69	9.13	5.22	-1.21	0.23	0.20
Net migration per capita, 2014-19	3	0.003	0.006	0.004	0.003	-1.46	0.15	0.17
GDP per capita growth (%), 2014-2019	3	17.11	15.48	17.17	19.11	-0.02	0.98	0.90
Industrial employment (%), 2019	3	18.44	8.86	17.80	10.15	0.45	0.66	0.70
Manufacturing employment (%), 2019	3	16.63	8.61	16.60	10.15	0.02	0.98	0.97
Mean China shock instrument, 1988-2007	2	1.57	1.65	1.89	1.63	-0.95	0.35	0.32

Notes: Comparison of European regions with and without early SSEs (1 January — 30 June 2020) on measures and predictors of populist support before the COVID-19 pandemic. The last three columns report the results of a two-sample *t*-test — regular and bootstrapped with 1,000 samples — of the difference in means between the two sets of regions.

and elderly people, immigration, economic growth, the size of the industrial sector, and exposure to international trade.[7] As shown in Table A3 of Online Appendix C, these various measures remain balanced even when we employ a more stringent definition of "early" SSEs, namely, those that occurred during the first two months of 2020.

In light of these considerations, we construct an instrument for region i's COVID-19 incidence that captures its proximity to recent and nearby SSEs weighted by the time elapsed since their occurrence:

$$\mathrm{Z}_{it} = \begin{cases} \sum_{k_{-i}=1}^{K_{-i}} \lambda_t (1 - \frac{\Phi_{ik_{-i}}}{\phi_i}) & \text{if } \Phi_{ik_{-i}} < \phi_i, \mathrm{T}_{tk_{-i}} \leq \tau_{k_{-i}} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where $\Phi_{ik_{-i}}$ is the distance between region i and external SSE k_{-i}; T_{tk} is the number of days since k_{-i} on day t; ϕ_i is some maximum radius around i; $\tau_{k_{-i}}$ is some maximum number of days since k_{-i};

[7]All variables are based on Eurostat statistics, with the exception of trade exposure, which we measure using a variant of the "China shock" instrument developed by Colantone and Stanig (2018).

and λ_t is a set of temporal weights. We parameterize λ_t using the Susceptible-Infected-Recovered (SIR) model, the workhorse epidemiological tool for analyzing the spread of infectious diseases. In this model, the number of infections in a given population evolves according to the formula:

$$\frac{\delta I_t}{\delta t} = \frac{\beta^{\text{SIR}} S_t I_t}{N} - \gamma^{\text{SIR}} I_t \tag{2}$$

where I_t and S_t are the number of infected and susceptible individuals on day t, respectively; N is the population size; β^{SIR} is the infection rate, i.e., the average number of susceptible individuals who become infected per t; and γ^{SIR} is the recovery rate, i.e., the average number of infected individuals who recover per t.[8] In sum, the instrument aggregates region i's inverse distances from all external SSEs $k_{-i}, \dots, K_{-i}$ occurring within a radius of ϕkm during the previous τ days and weights this sum according to a temporal function based on the SIR infection distribution. Thus, higher instrument values indicate greater exposure to SSEs.

In general terms, our identifying assumption can be stated as follows: conditional on time and region fixed effects and any covariates in our instrumental variables specification, the occurrence of additional COVID-19 cases in region i during period t due to recent SSEs in proximate regions is exogenous to other factors influencing local support for populists. Consequently, time-weighted distance to these events at t only affects populist support in i through the spread of COVID-19 (the exclusion restriction). Strictly speaking, therefore, identification does not require the location of SSEs to be as-if random: since the instrument leverages the timing of SSE-induced COVID-19 cases in a given location — whose fixed characteristics we hold constant — we can arrive at a causal estimate even if SSEs happened to be concentrated in or near populist strongholds. To the extent that SSE location *is* unrelated to determinants of populist support, as suggested earlier, this further reduces the likelihood of unobserved spatial heterogeneity and thus strengthens inferential credibility.

[8] We discuss the SIR model in greater detail in Online Appendix C. As it does not shed light on how far infections will spread on any given day, we take an inductive approach to specifying $\Phi_{ik_{-i}}$ and $\tau_{k_{-i}}$, testing a range of plausible values and selecting those that maximize the instrument's predictive power in our main specification. The instrument is thus informed by a combination of theory and context-specific evidence about the dynamics of COVID-19 diffusion, which we see as an advantage.

Nor does our approach rest on strong assumptions about the types of individuals who participate in gatherings with superspreader potential: we exclude from our analyses all regions that host SSEs during the sample period. A potential threat to the exclusion restriction is that SSE-induced infections may be more likely to spread to regions with characteristics related to support for populism (for instance, low levels of rule compliance). As suggested above, however, our strategy controls for these attributes by exploiting within-region variation over time.[9] Moreover, Table A4 in Online Appendix C shows that regions with SSEs are statistically indistinguishable from neighboring territories with respect to the measures and predictors of pre-pandemic populist support considered earlier.

Another possibility is that populist politicians attempt to mobilize support by criticizing incumbent parties for the outbreak of nearby SSEs, creating a direct pathway from the instrument to the outcome. To our knowledge, there are no publicized examples of such efforts. SSEs rarely became topics of public debate during the pandemic's initial months — most likely due to their typically small size and delayed identification — and the few exceptions (such as the February 2020 outbreak in the Austrian ski resort of Ischgl) were blamed on participants and vendors rather than politicians or the government.[10] The COVID-19 outbreaks that stemmed from such events, in contrast, tended to receive intense media scrutiny and to be widely perceived as evidence of ineffective pandemic management. For these various reasons, we believe that the exclusion restriction stands on solid ground in our empirical context.

[9]Our identification strategy would only be jeopardized if regions close to SSEs coincidentally developed populist traits around the time of such events, which does not seem plausible.

[10]https://www.theguardian.com/world/2020/sep/05/everyone-was-drenched-in-the-virus-was-this-austrian-ski-resort-a-covid-19-ground-zero.

Populist Engagement on Social Media: Evidence from Twitter

Data

Our first approach to gauging public support for right-wing populists focuses on trends in social media engagement with these actors. Beyond their widespread usage, social media platforms have the advantage of remaining "always-on" as the COVID-19 pandemic unfolded (Salganik, 2017), allowing us to observe behavior at high temporal resolution. In our main analysis, we examine daily interactions with populist parties and leaders on Twitter — the most popular platform that disclosed data on individual users in early 2020 — accessed via the Twitter API for Academic Research. Twitter exchanges with political actors can predict users' ideological leanings (Guess et al., 2019) as well as parties' electoral performance (Tumasjan et al., 2011; DiGrazia et al., 2013; Wang, Sundar, and Ram, 2024).[11] A limitation of any Twitter-based sample is that it is unlikely to be representative of the broader population: Twitter users tend to be younger, better educated, and more liberal than non-users (Mellon and Prosser, 2017). While these differences do not favor our hypothesis, we stress that our results may not be generalizable to entire Western European electorates and should thus be interpreted alongside evidence from our subsequent analyses, which are based on nationally representative samples.

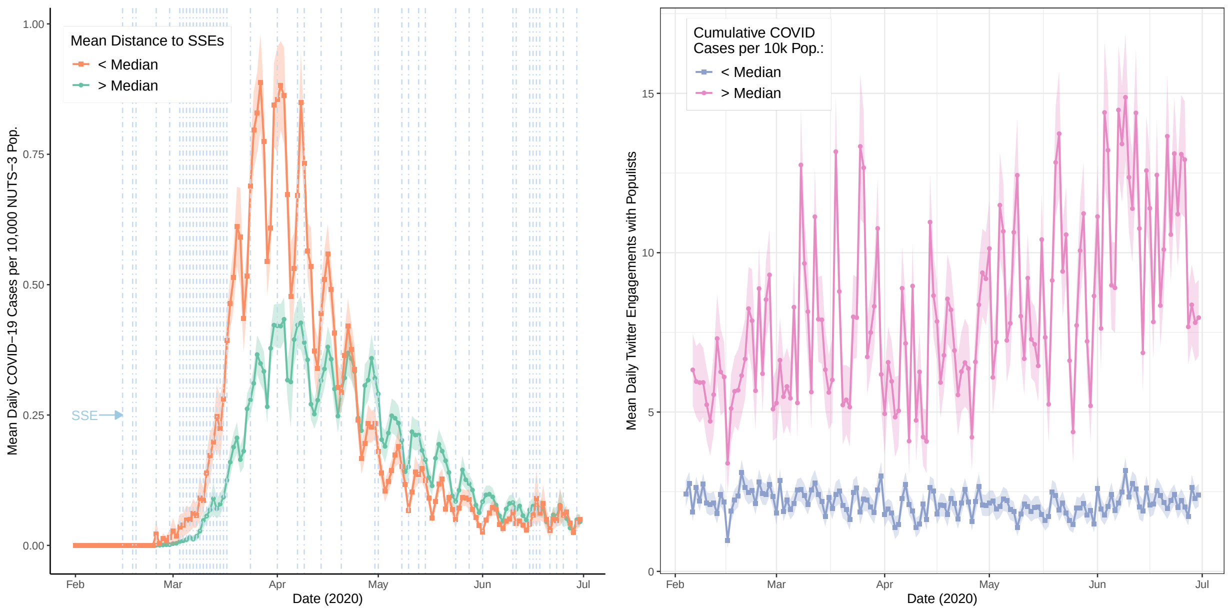
For each day between 1 February and 30 June 2020, we record all Twitter mentions (27,098), non-quote retweets (666,603), and likes (1,048,111) of domestic populist parties and leaders per NUTS-3 region of our five countries of interest.[12] Mentions are a noisier indicator of populist support than retweets and likes, as they may reflect criticism rather than endorsement. Nonetheless, mentions of politicians have been found to reliably predict their electoral performance (DiGrazia et al., 2013). In our sample, moreover, mentions are positively correlated with both retweets ($r = 0.37$, $p < 0.001$) and

[11]We later provide evidence of a connection between populists' level of Twitter engagement and electoral performance in the French context.

[12]Essentially all regions (98%) exhibit some form of engagement with populists and are thus included in our sample. Our classification of right-wing populist parties follows the PopuList dataset (Rooduijn et al., 2023). For a supplementary analysis discussed below, we also gather mentions of mainstream politicians. Table A6 in Online Appendix D provides a list of all parties and associated Twitter profiles in our sample.

FIGURE 2. Trends in Daily COVID-19 and Populist Twitter Engagement, Early 2020

Panel A: COVID-19 Incidence — Panel B: Populist Twitter Interactions



Notes: NUTS-3-day-level trends in COVID-19 incidence (panel A) and Twitter mentions, retweets, and likes of right-wing populists (panel B) in five European countries (DE, FR, IT, NL, UK) between 1 February and 30 June 2020.

likes ($r = 0.36$, $p < 0.001$).

We follow the standard approach of using self-reported profile locations to geocode Twitter accounts, assigning coordinates with the aid of the Google Geolocation API.[13] A potential concern about this strategy is that users who provide location information — approximately three-quarters of those who mention a populist party or leader — may differ in inferentially relevant ways from those who do not. In the absence of additional personal information, we compare the content of tweets by geolocatable and non-geolocatable users with a structural topic model. As detailed in Online Appendix B, there is no statistical difference between the two sets of tweets in the frequency with which common topics are discussed or in the likelihood of mentioning COVID-19 or populist politicians.

We merge our three measures of populist Twitter engagement with NUTS-3-level data on daily COVID-19 incidence from the COVID-19 European Regional Tracker. The first infection is recorded

[13] Figure A4 in Online Appendix D displays the distribution of users who mention populists across NUTS-3 regions.

on 3 February 2020 but the median number of cases per NUTS-3 region remains 0 until 11 March, ensuring a reasonable "pretreatment" period for most units. Consistent with a positive relationship between COVID-19 incidence and Twitter interactions with populists, Panel B of Figure 2 shows that regions above the sample median of cumulative cases per 10,000 inhabitants in mid-2020 exhibited higher growth in combined populist mentions, retweets, and likes over the previous five months.

Finally, the dataset includes a daily index of lockdown stringency from the Oxford COVID-19 Government Response Tracker (Hale et al., 2021), which is constructed at the country level (where most restrictions were implemented). Since national lockdown measures could be affected by COVID-19 incidence in region i (creating a risk of posttreatment bias), we report our main results both including and excluding this index. The final sample is a NUTS-3-day-level panel of 124,948 observations spanning 828 regions of five European countries over 151 days between 1 February and 30 June 2020.

Specification

We implement our instrumental variables strategy using a 2SLS estimator, the first stage of which can be written as:

$$\text{COVID}_{it} = \varphi_0 + \varphi_1 \text{Z}_{it} + \varphi_2 \text{Lockdown}_{c(i)t} + \mu_i + \delta_t + \nu_{it} \quad (3)$$

where $COVID_{it}$ is the logarithm of new COVID-19 cases per 10,000 inhabitants of region i on day t; $Lockdown_{c(i)t}$ is the level of lockdown stringency in i's country (c) on t; δ_t denote day fixed effects, which capture the general (region-invariant) dynamics of COVID-19 diffusion and Twitter activity; and μ_i denote NUTS-3 fixed effects, which account for stable (time-invariant) regional characteristics, including preexisting levels of populist support and exposure to online political rhetoric.

In constructing the instrument, Z_{it}, we experiment with maximum distances between region i and SSEs (ϕ in Equation 1) ranging from 200-800km in 100km increments and with maximum time lags since SSEs (τ) ranging from 20-60 days in 10-day increments. These ranges are consistent with known patterns of COVID-19 diffusion and allow for the (realistic) possibility that i's incidence is compounded by exposure to multiple SSEs occurring in close geographical and temporal proximity.[14] As summarized in Figure A5 of Online Appendix D, while most of the 35 resulting combinations strongly predict $COVID_{it}$, the highest F-statistic (89.33) occurs when ϕ = 600km and τ = 40 days, values we accordingly select for our second-stage specification. Following previous studies of COVID-19 transmission dynamics (Chen et al., 2020; AlQadi and Bani-Yaghoub, 2022), we draw temporal weights (λ_t) from an SIR distribution with an infection rate (β^{SIR} in Equation 2) of 0.5 and a recovery rate (γ^{SIR}) of 0.13.

The second stage takes the form:

$$Y_{it} = \beta_0 + \beta_1 \widehat{\text{COVID}}_{it} + \beta_2 \text{Lockdown}_{c(i)t} + \mu_i + \delta_t + \epsilon_{it} \tag{4}$$

where the outcome variable, Y_{it}, is the logarithm of Twitter mentions, likes, or retweets of populist parties and leaders in i on t. For comparison, we also estimate a (potentially biased) OLS version of Equation 4 in which predicted values of $COVID_{it}$ are replaced by observed values. In both specifications, heteroskedasticity-robust standard errors are clustered by NUTS-3 region.

Results

Panel B of Table 2 presents the key second-stage estimates without (columns 1, 3, 5) and with (columns 2, 4, 6) the lockdown stringency control. In accordance with a COVID-induced boost in populist Twitter engagement, the estimated coefficient on the instrumented treatment variable (β_1 in Equation 4) is large, positive, and statistically significant for all three outcomes. Holding lockdown stringency constant, a 1% increase in daily COVID-19 cases per 10,000 NUTS-3 inhabitants is associated with approximately 0.14% additional mentions, 0.85% additional retweets, and 0.60% additional likes of populist parties and leaders. Omitting the lockdown control raises these estimates by around one-

[14] COVID-19 has been found to spread more than 800km in the wake of early SSEs — a well-documented example being the religious gathering in Mulhouse, France, in February 2020 — though such cases are rare. Below distances of 200km and lags of 20 days, there are too few SSEs to accurately predict local COVID-19 rates.

TABLE 2. Relationship between COVID-19 Exposure and Populist Twitter Engagement

Outcome:	Log Populist Mentions		Log Populist Retweets		Log Populist Likes	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS Estimates						
Log Daily COVID Cases per 10,000 Population	0.030*** (0.009)	0.025*** (0.009)	0.105*** (0.023)	0.052*** (0.019)	0.072*** (0.020)	0.022 (0.017)
Panel B: 2SLS Estimates (Instrument = SSE Exposure)						
Log Daily COVID Cases per 10,000 Pop. (Instrumented)	0.162** (0.070)	0.136* (0.073)	1.193*** (0.234)	0.847*** (0.215)	0.929*** (0.214)	0.603*** (0.201)
First-Stage F-Statistic	99.273	89.334	99.273	89.334	99.273	89.334
Day FE	✓	✓	✓	✓	✓	✓
NUTS-3 FE	✓	✓	✓	✓	✓	✓
Lockdown Stringency		✓		✓		✓
Mean Outcome Variable	0.09	0.09	0.84	0.84	0.98	0.98
N	119,393	119,393	119,393	119,393	119,393	119,393

Notes: NUTS-3-day-level OLS estimates (panel A) and 2SLS estimates (panel B) with robust standard errors, clustered by NUTS-3 region, in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

third, on average.

Similarly, panel A shows that the corresponding OLS estimates are positive and significant or near-significant for all engagement types. However, they are substantially smaller than their 2SLS counterparts, capturing only a fraction of the effect identified in the instrumental variables specification. Omitted variable bias in the OLS analysis is likely to explain much of this discrepancy: there may be unobserved confounders that are either negatively correlated with COVID-19 incidence and positively correlated with populist Twitter engagement or vice versa. In addition, the gap could reflect some degree of measurement error in COVID-19 rates as well as differences between "complier" observations where incidence spiked because of spatial and temporal proximity to SSEs (the focus of the 2SLS estimation) and "always-taker" observations where incidence would have risen regardless of this distance (which solely enter the OLS estimation).

Extensions and Robustness Checks

We now explore our findings in greater depth, estimating a host of alternative specifications to corroborate a causal interpretation and test additional implications. Unless otherwise indicated, the results are presented in Online Appendix D.

Within-User Analysis First, we shift the level of analysis from NUTS-3 regions to Twitter users, helping us to account for potentially confounding individual-level characteristics that covary with local COVID-19 exposure (such as social media usage). We estimate a within-individual specification on the set of Twitter users who engaged with populist parties or leaders at least twice during the sample period, which entails converting the dataset into three user-day-level panels — one for each type of Twitter engagement — and substituting user fixed effects for NUTS-3 fixed effects in Equations 3 and 4.[15] The treatment coefficients, reported in Table 3, remain positive and highly significant, implying that users issued 0.04% more mentions, 0.10-0.13% more retweets, and 0.04-0.06% more likes with each 1% increase in daily COVID-19 cases per 10,000 residents of their NUTS-3 region.

Comparison with Mainstream Parties Since the findings could reflect a general rise in political engagement during the pandemic, we check whether they hold for major mainstream parties in the five countries in our sample. Table 4 shows that instrumented COVID-19 rates have a strong negative association with mentions of mainstream parties and leaders, which decline by 0.60% with each 1% increment in daily cases per 10,000 NUTS-3 inhabitants (column 1).[16] As indicated in column 2, this translates into a 0.74% decline in the ratio of mainstream to populist mentions. In line with our theoretical discussion, these results do not merely reflect a backlash against parties in power: the treatment is also associated with a decline in relative mentions of both incumbent (column 3) and nonincum-

[15] Robust standard errors are clustered by user.

[16] We were unable to extend this analysis to the other two outcomes due to the very large quantity of retweets and likes received by mainstream politicians, which exceeded Twitter API for Academic Research rate limits.

TABLE 3. Within-User Extension of Instrumental Variables Analysis

Outcome:	Log Populist Mentions		Log Populist Retweets		Log Populist Likes	
	(1)	(2)	(3)	(4)	(5)	(6)
Log Daily COVID Cases per 10,000 Pop. (Instrumented)	0.041*** (0.009)	0.035*** (0.010)	0.134*** (0.008)	0.101*** (0.008)	0.056*** (0.004)	0.036*** (0.004)
Day FE	✓	✓	✓	✓	✓	✓
User FE	✓	✓	✓	✓	✓	✓
Lockdown Stringency		✓		✓		✓
First-Stage F-Statistic	886.376	740.541	2,505.599	1,978.100	6,121.931	4,516.058
Mean Outcome Variable	0.02	0.02	0.04	0.04	0.03	0.03
N	1,239,371	1,239,371	7,031,691	7,031,691	19683982	19683982

Notes: Individual-day-level 2SLS estimates from a modified version of Equation 4 in which Twitter users are the unit of analysis; robust standard errors, clustered by user, are in parentheses. The sample comprises users who engaged with populists multiple times between 1 February and 30 June 2020: 8,869 "mentioners," 47,851 "retweeters," and 134,105 "likers." $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

bent (column 4) mainstream politicians.[17] Hence, our results *are* specific to populist politicians, who enjoyed material gains in their share of Twitter political discourse in early 2020.

Country Heterogeneity Table A7 indicates that the estimated treatment effects vary little in strength across countries: when we multiply the treatment (and instrument) by country indicators, the coefficients on the resulting interaction terms are positive and significant or close to significant for 14 of the 15 country-outcome combinations. Table A8, meanwhile, indicates that the results are robust to the inclusion of interactive country × day fixed effects, which capture potentially confounding trends and shocks affecting multiple regions within the same country.

Spatial Correlation We use two strategies to address the possibility of spatial dependence between NUTS-3 regions. First, we rerun the analysis using Colella et al.'s (2019) arbitrary correlation regression estimator, which corrects 2SLS standard errors for geographical clustering. The results, plotted

[17] This is measured as the log difference between mainstream and populist mentions. Variation in incumbency status across party families is less than ideal in our countries of interest, with only France and the United Kingdom containing major mainstream parties that did not hold power in early 2020.

TABLE 4. Populist versus Mainstream (Incumbent and Nonincumbent) Twitter Mentions

	Outcome: Mentions of Mainstream Politicians			
	Log Total	Relative to Populists (Δ Log)		
Mainstream Parties:	All	All	Incumb.	Nonincumb.
	(1)	(2)	(3)	(4)
Log COVID Cases per 10,000 Pop. (Instrumented)	-0.602***	-0.738***	-0.785***	-0.224**
	(0.140)	(0.160)	(0.158)	(0.105)
Day FE	✓	✓	✓	✓
NUTS-3 FE	✓	✓	✓	✓
Lockdown Stringency	✓	✓	✓	✓
First-Stage F-Statistic	89.33	89.33	89.33	89.33
Mean Outcome Variable	0.30	-0.21	-0.15	-0.03
N	119,393	119,393	119,393	119,393

Notes: NUTS-3-day-level 2SLS estimates with robust standard errors, clustered by NUTS-3 region, in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

in Figure A6, are substantively similar across a variety of distance cutoffs for defining spatial clusters. Second, we estimate a spatial 2SLS (S-2SLS) version of our specification in which a spatially lagged outcome variable — generated using a spatial weight matrix of power functional form — is included as an additional exogenous regressor (Betz, Cook, and Hollenbach, 2020). Table A9 confirms that the results are again robust.

Dynamic Treatment Effects Next, we check for the presence of potentially confounding "pretrends" in populist engagement through an event study analysis, which requires converting the treatment into a binary indicator for whether a NUTS-3 region records any new COVID-19 cases on a given day. We employ Liu, Wang, and Xu's (2022) fixed effects counterfactual estimator, which allows for treatment reversals (i.e., days with new cases followed by days with none) in addition to correcting potential biases arising from effect heterogeneity. The results, which appear in Figure A7, are consistent with an absence of pretrends: the coefficients on each binary treatment only become consistently positive and significant during the treatment period.

Varying Instrument Parameters Finally, we demonstrate robustness to variation in key parameters of the instrument. First, we modify the maximum radius (ϕ) and time lag (τ) within which SSEs may occur using the 35 combinations of these parameters from our exploratory first-stage tests (Figure A8). Second, we alter the temporal weights attached to the instrument (λ_t), reparameterizing the SIR model with an infection rate (β^{SIR}) ranging from 0.3-0.8 in increments of 0.1 and a recovery rate (γ^{SIR}) of either 0.1 or 0.2 (Figure A9). Third, as an alternative approach, we replace the SIR curve with three simpler functions: (1) a normal distribution; (2) a linear incline; and (3) a linear decline (Figure A9). Fourth, taking a more agnostic stance toward parametric form, we incorporate almost 500 variants of the instrument — all combinations of the alternative ϕ, τ, β^{SIR}, and γ^{SIR} values considered in this section — into a single lasso model (Table A10).

Voting Behavior: Electoral and Survey Evidence

Was increased social media engagement with right-wing populists in the early stages of the pandemic accompanied by higher levels of electoral support for them? This section examines COVID-19's consequences for voting behavior, focusing first on the 2020 French municipal elections and then on representative survey data from the United Kingdom and the Netherlands.

Populist Performance in the 2020 French Municipal Elections

Data and Empirical Strategy The 2020 French municipal elections were held on 15 March (first round) and 28 June (second round) amid rising public concern about the spread of COVID-19. Whether and how this trend impacted support for France's dominant populist party — the RN — has yet to be directly examined, with existing scholarship pointing in different directions. Leromain and Vannoorenberghe (2022) find that COVID-19 disproportionately suppressed first-round turnout in municipalities (*communes*) that lean toward the RN. Bisbee and Honig (2022) present evidence that non-centrist parties suffered larger losses between the first and second rounds, though the RN is excluded from the analysis. On the other hand, Froio (2022) emphasizes that the RN won more cities with over 1,000 inhabitants than in the previous (2014) set of elections and that favorable public attitudes toward its leader, Marine Le Pen, rose around the time of the first round.

Adopting a similar design to Leromain and Vannoorenberghe, we analyze whether local COVID-19 incidence predicts changes in the RN's vote share between the 2014 and 2020 municipal elections. We follow this study in focusing on the first round of each contest, in which all party lists are included, and on municipalities with more than 1,000 inhabitants, in which councilors are elected by proportional representation. Municipalities with smaller populations employ a different electoral system involving non-proportional block voting and panachage, rendering direct vote share comparisons difficult. An additional advantage of examining the first round is that it took place relatively early in the pandemic, when SSE location and timing were most plausibly exogenous and lockdown measures had yet to be widely adopted in France.[18]

The outcome variable, measured with data from France's Ministry of the Interior, is the RN's vote share in a given municipality and set of elections.[19] Figure 3 displays this variable's geographical distribution in the 2020 elections. Suggestively, many municipalities with high RN vote shares are located near pre-election SSEs in France and neighboring countries, most notably in the southeastern Provence region and the central northern Île-de-France region.

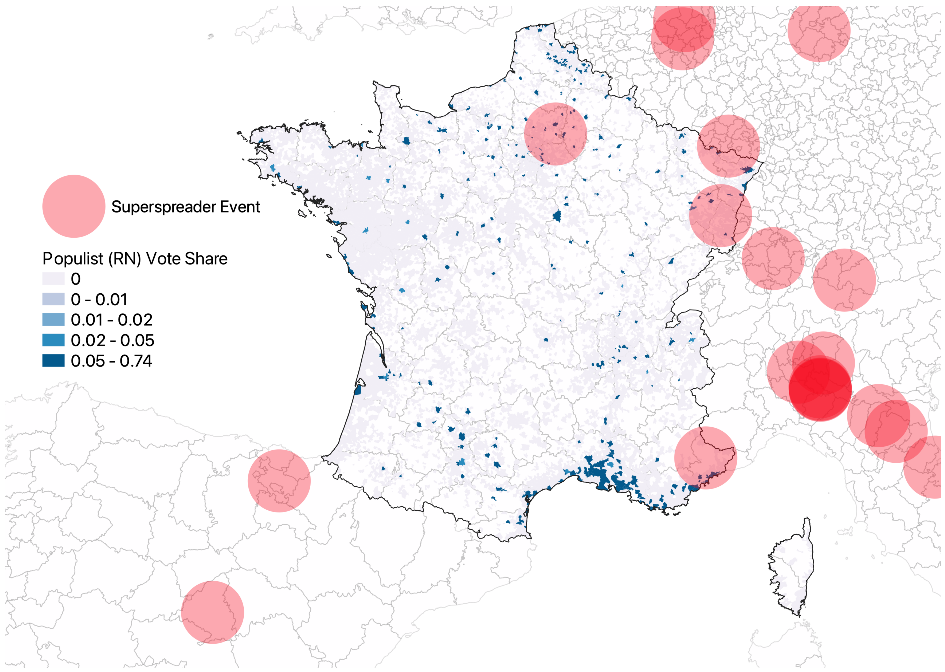
The treatment variable is more complicated to measure because daily COVID-19 statistics are not available below the NUTS-3 (*département*) level in France. We employ two empirical strategies to address this limitation. First, we estimate a 2SLS specification in which the endogenous regressor is the logarithm of cumulative COVID-19 cases per 10,000 inhabitants of municipality m's NUTS-3 region on the date of election e, weighted by m's share of the regional population ($COVID^{FR}_{me}$).[20] We instrument this variable with a modified version of Equation 1 that aggregates m's time-weighted

[18] The first official lockdown restrictions were introduced a few days after the elections, though some local authorities in COVID-19 clusters prohibited public gatherings in early March (Leromain and Vannoorenberghe, 2022, 3).

[19] `https://www.data.gouv.fr/fr/datasets/elections-municipales-2020-resultats`.

[20] As the temporal unit of analysis is now an election rather than a day, we switch to a cumulative measure of COVID-19 incidence.

FIGURE 3. Superspreader Events and Populist Voting in France, March 2020



Notes: This map displays approximately 10,000 municipalities with more than 1,000 inhabitants as of the first round of the 2020 French municipal elections (15 March). Only SSEs before this date are shown.

proximity to nearby SSEs between 1 January and 15 March 2020 (Z_{me}^{FR}).[21] The first stage can thus be expressed as:

$$\text{COVID}_{me}^{FR} = \varphi_0 + \varphi_1 Z_{me}^{FR} + \varphi_X \mathbf{X}_{m,e-1} + \mu_m + \delta_e + \nu_{me} \tag{5}$$

where μ_m and δ_e denote municipality and election fixed effects, respectively; and $\mathbf{X}_{m,e-1}$ is a vector of lagged municipality-year-level controls, including the male-female ratio; population density (in km^2); the share of inhabitants aged 15-24 years; the share of inhabitants aged at least 75 years; the share of unemployed inhabitants; the share of employment in industry; the share of recent overseas migrants in the population; the share of inhabitants over 14 years old with no elementary school diploma; and total RN voters.[22] Similarly to before, we estimate this specification using 21 variants of the instrument with ϕ ranging from 200-800km and τ from 20-40 days (given the 43-day upper bound). While all

[21]Given freedom of movement within the European Union, we do not exclude SSEs outside French borders.

[22]Data are from France's national statistics bureau: `https://www.insee.fr/fr/statistiques/5359146`. All controls are well balanced between municipalities with and without SSEs before 15 March 2020 (see Table A12, Online Appendix E).

F-statistics comfortably exceed 10, they peak when ϕ = 200km and τ = 30-40 days. The second stage is given by:

$$v_{me}^{FR} = \beta_0 + \beta_1 \widehat{\text{COVID}}_{me}^{FR} + \beta_{\text{X}} \mathbf{X}_{m,e-1} + \mu_m + \delta_e + \epsilon_{me} \tag{6}$$

where v_{me}^{FR} is the RN's vote share in municipality m in election e. In both stages, robust standard errors are clustered by municipality.

Our second empirical strategy is to regress the outcome variable directly on the instrument, maintaining the fixed effects and controls in the 2SLS specification. This approach, which avoids the need to impute municipality-level COVID-19 rates, can be justified by the high concentration of early infections around a handful of SSEs in northern and eastern France (Paireau et al., 2022). As a result of this pattern, the local average treatment effects identified by our two strategies should be reasonably comparable to the average treatment effect on the full population of municipalities affected by COVID-19 before 15 March 2020.[23]

Results Table 5 presents the results of both strategies. Panel A reports second-stage 2SLS estimates from Equation 6 for the five instrument variants with the highest first-stage F-statistics. In every column, the coefficient on instrumented COVID-19 incidence is positive, large, and statistically significant at the 5% level. Averaging across models, a 1% rise in population-adjusted COVID-19 cases comes with an increase in the RN's vote share of around 14 percentage points. The large magnitude of this effect — the RN's vote share has a mean of 1% and a standard deviation of 4% — stems in part from the low incidence of COVID-19 before 15 March 2020, when the majority of French NUTS-3 regions recording fewer than 50 cumulative cases.[24]

Panel B shows that all five instrument variants also strongly predict RN performance itself. On average, a 100km reduction in a municipality's time-weighted distance to a given pre-election SSE lifts the RN's vote share by around 0.2 percentage points. This translates into appreciable differences in

[23] Moreover, they are based on a similar sample to estimates of COVID-19's impact on first-round turnout, which use proximity to infection clusters as a proxy for exposure to the disease (Noury et al., 2021; Leromain and Vannoorenberghe, 2022).

[24] The RN's vote share in the 2020 elections ranged between 0% and 74%.

TABLE 5. Local COVID-19 Exposure and Populist Support in French Municipal Elections

Outcome: RN Vote Share (mean= 0.01)	(1)	(2)	(3)	(4)	(5)
Panel A: 2SLS Estimates (Instrument = SSE Exposure)					
Log Cumulative COVID Cases	13.827**	13.827**	13.525**	14.200***	14.200***
per 10,000 Pop. (Instrumented)	(5.638)	(5.638)	(5.694)	(5.478)	(5.478)
First-Stage F-Statistic	377.417	377.417	354.218	333.351	333.351
Panel B: OLS Estimates (Treatment = Instrument)					
SSE Exposure Instrument	0.00003**	0.00003**	0.00003**	0.00001***	0.00001***
	(0.00001)	(0.00001)	(0.00001)	(0.000003)	(0.000003)
Instrument Maximum Radius (ϕ)	200	200	200	400	400
Instrument Maximum Lag (τ)	30	40	20	30	40
Municipality FE	✓	✓	✓	✓	✓
Election (2014/2020) FE	✓	✓	✓	✓	✓
Municipality-Level Controls	✓	✓	✓	✓	✓
N	19,209	19,209	19,209	19,209	19,209

Notes: Municipality-election-level 2SLS (panel A) and OLS (panel B) estimates with robust standard errors, clustered by municipality, in parentheses. Controls (all lagged): male-female ratio, population density, share of young people, share of elderly people, share of people with no schooling, share of industrial workers, share of unemployed people, manual share of employment, share of recent overseas migrants, total RN voters, size of housing stock. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

predicted RN support between municipalities close to and far from multiple SSEs. For example, the RN's predicted 2020 vote share in the northern municipality of Chauny is almost 2 percentage points higher than that in the southern municipality of Carcassonne due to SSE proximity, a notable share of the overall 7-percentage-point difference.[25]

Additional Specifications Online Appendix E exhibits similar estimates for both specifications with the remaining combinations of ϕ and τ from the first stage (Figures A10 and A12). We also document robustness to almost every alternative temporal function (λ_t) tested in the Twitter engagement analysis (Figures A11 and A13). Third, we conduct a placebo test that compares the RN's vote share in the 2008 and 2014 municipal elections, treating the latter year as the start of the pandemic. All treatment coefficients shrink substantially and lose significance (Table A13). Finally, we show that the RN's

[25]The RN's predicted vote share is 21% in Chauny and 14% in Carcassonne. The actual shares were 23% and 17%, respectively.

performance in the 2020 elections is positively associated with Twitter likes, retweets, and mentions of the party in the run-up to the contest (Table A14), revealing a connection between social media activity and voting behavior that adds to the substantive significance of our first analysis.

Local COVID-19 Exposure and Populist Voting Preferences

To examine whether the link between local COVID-19 exposure and populist voting preferences extends to the individual level, we make use of national survey data from the pandemic's early stages. The only such data that identify individuals by region in our countries of interest come from the BES, a longitudinal probability sample survey administered to roughly 30,000 British adults in each wave. We analyze responses to a voting intention question — "How likely is it that you would ever vote for each of the following parties?" — across four survey waves between November 2019 and May 2021 (Waves 18 to 21), the last two of which were conducted during the pandemic. We merge these responses with COVID-19 statistics at the local authority level (353 units) — the level at which BES respondents are identified — from the UK Health Security Agency (2022).

Extending our instrumental variables strategy, we estimate a 2SLS specification that exploits within-individual variation before and after the pandemic's onset. The second stage is described by:

$$v_{ilw}^{UK} = \beta_0 + \beta_1 \widehat{\text{COVID}}_{lw}^{UK} + \beta_{\text{X}} \mathbf{X}_{ilw} + \eta_i + \alpha_l + \delta_w + \epsilon_{ilw} \tag{7}$$

where v_{ilw}^{UK} is an indicator for whether respondent i in local authority l is "likely" to vote for UKIP or Reform UK in survey wave w;[26] COVID_{lw}^{UK} is the logarithm of cumulative COVID-19 cases per capita in l as of w, as instrumented by time-weighted distance to SSEs within a maximum radius (ϕ) of 700km and time lag (τ) of 30 days (the combination yielding the highest first-stage F-statistic); $\mathbf{X}_{iw}$ is a vector of respondent-wave-level controls, namely, left-right ideological position (0-10 integer scale), age, and indicator variables for education level, employment status, gross income, social class,

[26] This is coded as a score of at least 5 on a 0-10 scale where 0 is "very unlikely" and 10 is "very likely."

TABLE 6. COVID-19 Exposure and Populist Voting Preferences in the United Kingdom

Outcome: Populist Vote Likely	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Local Exposure to COVID-19, 2SLS Estimates (Instrument = SSE Exposure)								
Log Cumul. COVID Cases per 10,000 Pop. (Instrumented)	0.116*** (0.024)	0.134*** (0.029)					0.117*** (0.030)	0.135*** (0.037)
First-Stage F-Statistic	1,029.11	565.89					688.76	372.11
Panel B: Individual Exposure to COVID-19, OLS Estimates								
Infected with COVID			0.035*** (0.008)	0.035* (0.021)				
Close to Someone Infected with COVID					0.015* (0.008)	0.030** (0.015)		
Respondent-Level Controls	✓	✓	✓	✓	✓	✓	✓	✓
Wave FE	✓	✓	✓	✓	✓	✓	✓	✓
Respondent FE		✓		✓		✓		✓
Local Authority FE	✓	✓	✓	✓	✓	✓	✓	✓
Exposed Respondents Included	✓	✓	✓	✓	✓	✓		
Mean Outcome Variable	0.10	0.11	0.19	0.20	0.20	0.20	0.09	0.09
N	47,192	40,308	17,816	7,940	20,152	9,886	41,172	33,926

Notes: Respondent-wave-level 2SLS (panel A) and OLS (panel B) estimates with robust standard errors, clustered by respondent, in parentheses. Controls: left-right ideology, age, ethnicity, education level, gross income, employment status, social class, homeownership, household size. In columns 7 and 8, respondents who have been infected or close to someone infected with COVID-19 are excluded from the sample. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

homeownership, and household size; and η_i, α_l, and δ_w denote respondent, local authority, and survey wave fixed effects, respectively. Robust standard errors are clustered by respondent.

Panel A of Table 6 reports the results, first excluding (column 1) and then including (column 2) respondent fixed effects. In both columns, the coefficient on instrumented COVID-19 incidence is positive and highly significant ($p < 0.001$). Conditional on all fixed effects, respondents become 0.13 percentage points more likely to vote for UKIP or Reform UK with each 1% increase in cumulative COVID-19 cases per 10,000 inhabitants of their local authority. This effect is far from negligible, considering that cumulative COVID-19 cases rose by as much as 42% between Waves 20 and 21 (June 2020 and May 2021). For example, the model predicts that the COVID-19 spike in the Welsh local authority of Ceredigion during this period boosted the proportion of residents likely to vote for a populist party by almost 6 percentage points.

Individual COVID-19 Exposure and Populist Support

Does local COVID-19 incidence influence populist voting intentions through first-hand exposure to the disease, heightened awareness of its threat, or both? To shed light on this question, we analyze responses from two surveys in our countries of interest that include questions on both individual exposure and voting intentions. The first is the BES (Waves 20 and 21), which asks respondents whether (1) they have been infected with COVID-19 and (2) anyone close to them (such as a parent, child, or partner) has been infected.[27] In Table A15, Online Appendix F, we show that local and individual exposure to COVID-19 go hand-in-hand in the British context: there is a strong positive association between the logarithm of cumulative COVID-19 cases per 10,000 inhabitants of respondent i's local authority in a given wave and the likelihood that i or someone close to i has contracted the disease.

As we might expect, therefore, replacing $\widehat{COVID}_{lw}^{UK}$ in Equation 7 with the two measures of individual exposure to the disease and substituting OLS for 2SLS again yields positive and significant treatment coefficients. Panel B of Table 6 indicates that, on average, individuals who contracted COVID-19 between June 2020 and May 2021 became 3.5 percentage points more likely to vote for UKIP or Reform UK (column 4), while individuals who were close to someone infected during this period became 2.9 percentage points more likely (column 6).[28] Excluding respondent fixed effects does not materially alter these results (columns 3 and 5).

To isolate the explanatory role of local but non-personal exposure to COVID-19, we reestimate Equation 7 excluding respondents who were either infected or close to someone infected during the sample period. Whether respondent fixed effects are excluded (column 7 in Table 6) or included (column 8), the coefficient on instrumented COVID-19 incidence remains positive, highly significant,

[27] Affirmative responses were given by 15% and 4% of respondents who answered these questions, respectively.

[28] Interestingly, these results vary neither with the severity of COVID-19 symptoms nor with age, a key predictor of vulnerability to the disease's most severe effects (see Table A16, Online Appendix F). This suggests that the key distinction is *whether* rather than *how much* individuals are exposed to COVID-19, with even relatively mild experiences sufficient to strengthen populist sentiment.

and similar to that based on the full sample. This suggests that the positive association between local exposure and populist voting preferences is driven by an increase in *both* personal and non-personal exposure to COVID-19.

The second survey is the LISS Panel study of the "consequences of COVID for the quality of society," which was administered to a random sample of almost 2,000 adults across the Netherlands in three waves between July 2020 and July 2021. While including similar items to the BES, this survey does not disclose respondents' region and only includes a voting intention question in its first wave, preventing us from leveraging our SSE instrument or within-respondent variation over time. We thus adopt a simpler correlational approach, estimating two linear probability models predicting whether respondents would vote for the FvD or the PVV if legislative elections were held tomorrow. In the first model, the treatment is an indicator for whether respondents have previously contracted COVID-19; in the second, it is an indicator for whether a member of their family or household has been severely ill or died due to the disease. We control for the five main socioeconomic characteristics measured by the study: age and indicators for gender, education level, occupation, and household position. As shown in Table A17 of Online Appendix G, both treatment coefficients are positive and highly significant.

Mechanisms

Why did the onset of the COVID-19 pandemic boost public engagement with and support for right-wing populists? Drawing on the survey and social media data analyzed previously, this section assesses our three hypothesized causal mechanisms as well as a host of possible alternative channels.

Dutch Survey Evidence

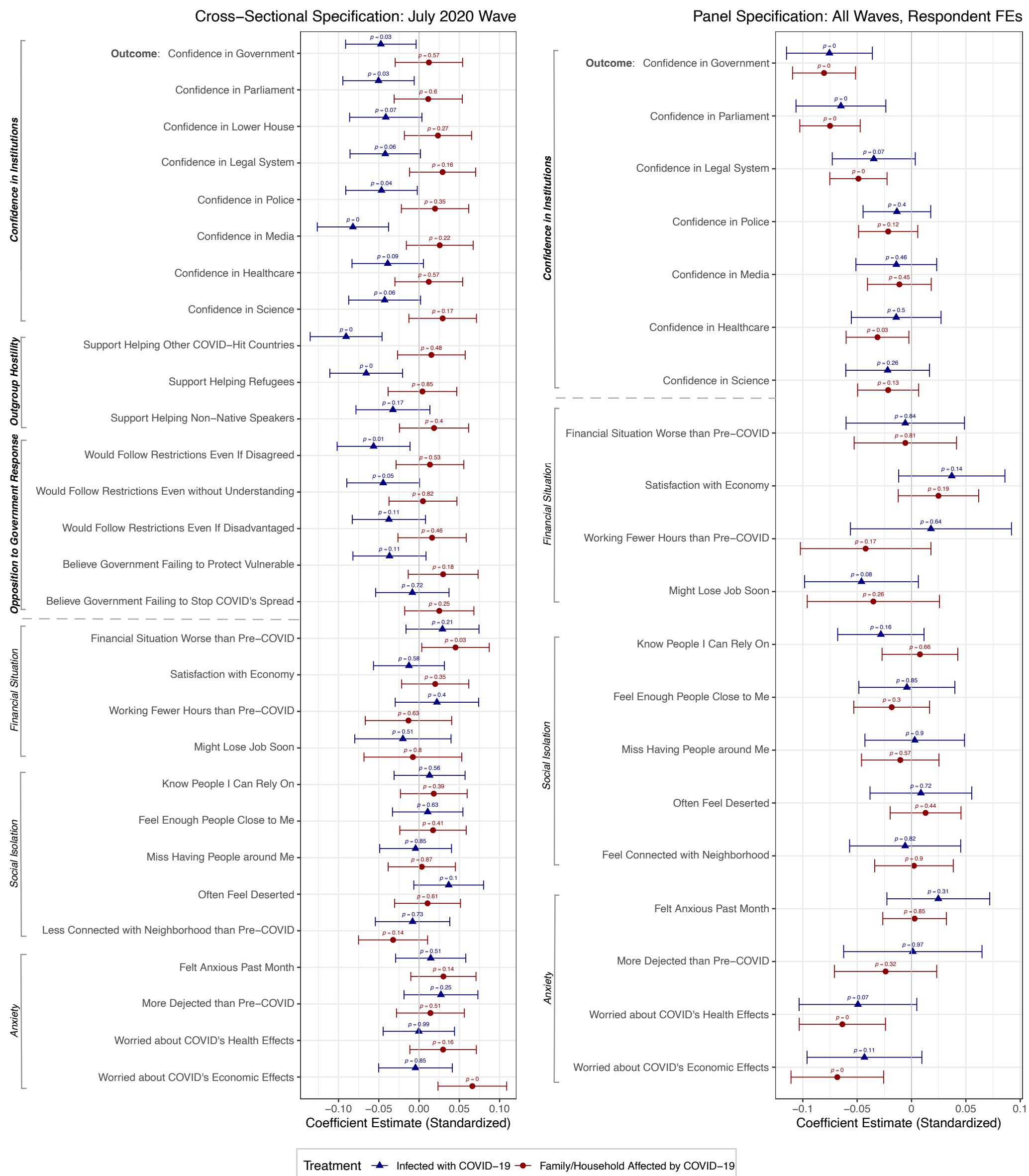
We start by revisiting the LISS Panel questionnaire on the pandemic's societal consequences. Along with exposure to COVID-19 and populist voting intentions, the survey captures a variety of attitudes, beliefs, and characteristics that could plausibly drive the positive relationship between these two variables. Specifically, it sheds light on six potential mechanisms, which we summarize as *confidence in institutions*, *outgroup hostility*, *opposition to government response*, *financial situation*, *social isolation*, and *anxiety*. The first three channels were emphasized in our theoretical discussion: we expect COVID-19 exposure to foster populist sentiment by denting confidence in public institutions, deepening negative attitudes toward outgroups, and inciting opposition to government controls. The last three mechanisms capture the possibility that COVID-induced financial pressures, isolation from social networks, and feelings of general anxiety fueled the populist surge (Lall and Vilalta, 2025).

The first wave of the survey, conducted in July 2020, contains questions on all six mechanisms; the second and third waves, conducted in October 2020 and July 2021, respectively, do not cover the *outgroup hostility* and *opposition to government response* channels. We estimate two sets of standardized models, both of which regress responses to mechanism-related questions on the two measures of personal COVID-19 exposure from the previous section (entered separately).[29] The first set of models is restricted to the July 2020 wave and includes the same respondent-level controls as Table A17. The second set encompasses all three waves, adds respondent fixed effects, and clusters robust standard errors by respondent, thereby exploiting variation within individuals over time.

Standardized coefficients from the two sets of models are displayed in stacked pairs in Figure 4. In the first-wave models (left column), the *confidence in institutions*, *outgroup hostility*, and *opposition to government response* mechanisms all receive support. Infection with COVID-19 is negatively and significantly associated with confidence in government, parliament, the lower house, the police, and the media as well as with support for assisting refugees and other pandemic-hit countries. It has a similar, albeit slightly weaker, relationship with the belief that people should follow COVID-19 restrictions even if they disagree with, are disadvantaged by, or do not understand these measures and that the government is failing to protect people with vulnerable health. In contrast, the coefficient on the family/household exposure treatment is generally small and nonsignificant, suggesting that the three mechanisms are operating primarily through personal infection. The results for the *financial*

[29]These items originally have an ordinal scale that mostly ranges from 0-10, 1-3, or 1-7.

FIGURE 4. Exploring Mechanisms: Analysis of Dutch Survey Responses, July 2020-2021



Notes: Standardized respondent-level OLS estimates with 95% confidence intervals based on robust standard errors (clustered by respondent in the right column). Cross-sectional controls: age, gender, level of education, occupation, household position.

situation, *social isolation*, and *anxiety* mechanisms are similarly weak, with most coefficients on both treatment variables statistically indistinguishable from 0.

The panel models (right column), which do not test the *opposition to government response* and *outgroup hostility* mechanisms, again provide broad support for the *confidence in institutions* pathway. Unlike in the first-wave models, however, the coefficient on *both* treatment variables is negative and significant at the 5% level in several models. That is, individuals with family or household as well as personal exposure to COVID-19 between July 2020 and July 2021 experienced a loss of confidence in public institutions. Once again, the treatment coefficients mostly fail to reach significance when a proxy for *financial situation*, *social isolation*, or *anxiety* is the outcome variable. The only exceptions are the models in which family/household exposure is the treatment and COVID-related health or economic anxiety is the outcome, in which the estimates are negative — the opposite of what the *anxiety* mechanism implies.

British Survey Evidence

In addition to personal COVID-19 exposure and voting intentions, Wave 20 (June 2020) of the BES includes questions on all six previously tested mechanisms. Extending the approach taken in Figure 4, we regress responses to these questions on indicators for (1) personal infection with COVID-19 and (2) the infection of someone close. We include local authority fixed effects and the same battery of respondent-level controls as Table 6's models. Robust standard errors are clustered by local authority.

The results, displayed in standardized form in Table 7, are consistent with those in Figure 4. There is robust support for the *confidence in institutions* (columns 1-2), *opposition to government response* (columns 3-5), and *outgroup hostility* (columns 6-8) mechanisms, with almost every treatment coefficient pointing in the predicted direction and reaching or approaching statistical significance. The two models whose outcome is an indicator for *financial situation*, on the other hand, yield null results (columns 9-10). The *anxiety* mechanism receives mixed backing: three of the six treatment coefficients exhibit the expected sign and attain significance (columns 11-13), but only the infection of someone close is strongly associated with the most direct measure, namely, an overall anxiety scale (column 11). Lastly, both treatments are negatively associated with proxies for the absence of social connections (columns 14-16), providing evidence against the *social isolation* mechanism.

TABLE 7. Exploring Mechanisms: Analysis of British Survey Responses, June 2020

Mechanism:	*Confidence in Institutions*		*Opposition to Government Response*			*Outgroup Hostility*		
Outcome:	Trust in MPs (1)	Trust in Westminster (2)	Opinion of Lockdown Handling (3)	Opinion of Test Handling (4)	Approval of Lockdown (5)	Immigration Improves Culture (6)	Favor More Immigration (7)	Favor More Asylum (8)
Infected with COVID	-0.093***	-0.040	-0.044*	-0.080***	-0.107*	-0.054**	-0.057**	-0.103*
	(0.027)	(0.028)	(0.027)	(0.027)	(0.059)	(0.027)	(0.027)	(0.053)
Close to Someone Infected with COVID	-0.048**	-0.043*	-0.076***	-0.111***	-0.031	0.021	0.047**	-0.024
	(0.023)	(0.023)	(0.023)	(0.023)	(0.045)	(0.022)	(0.022)	(0.044)
Individual-Level Controls	✓	✓	✓	✓	✓	✓	✓	✓
Local Authority FE	✓	✓	✓	✓	✓	✓	✓	✓
N	10,600	10,548	10,888	10,728	2,690	10,448	10,084	2,480
Mechanism:	*Financial Situation*		*Anxiety*			*Social Isolation*		
Outcome:	Finances Better (9)	Economy Better (10)	Overall Anxiety (11)	Life Satisfaction (12)	Life Is Worthwhile (13)	No Support Network (14)	No Professional Network (15)	No Skilled Network (16)
Infected with COVID	0.007	-0.024	0.034	-0.099*	-0.030	-0.070	-0.091*	-0.096*
	(0.027)	(0.029)	(0.055)	(0.055)	(0.055)	(0.058)	(0.054)	(0.055)
Close to Someone Infected with COVID	-0.008	-0.028	0.146***	-0.089*	-0.033	-0.161***	-0.219***	-0.139***
	(0.022)	(0.024)	(0.047)	(0.047)	(0.047)	(0.046)	(0.045)	(0.045)
Individual-Level Controls	✓	✓	✓	✓	✓	✓	✓	✓
Local Authority FE	✓	✓	✓	✓	✓	✓	✓	✓
N	10,813	10,603	2,711	2,717	2,692	2,654	2,700	2,699

Notes: Standardized respondent-level OLS estimates with robust standard errors, clustered by local authority, in parentheses. Controls: left-right ideology, age, ethnicity, education level, gross income, employment status, social class, homeownership, household size. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Lockdown Stringency and Twitter Engagement

A third source of evidence on the *opposition to government response* mechanism is the relationship between lockdown policies and Twitter engagement with populist politicians. If rising populist sentiment in early 2020 was fueled in part by a backlash against such restrictions, we might expect lockdown stringency to be positively associated with Twitter mentions, retweets, and likes of populist parties and leaders. Table A18 in Online Appendix D offers support for this implication, presenting estimates from a modified version of Equation 4 in which $Lockdown_{c(i)t}$ is the endogenous regressor. This index is strongly predicted by the SSE exposure instrument in the first stage, and its second-stage values have a positive and highly significant relationship with all three measures of populist engagement. On average, a 10% increase in lockdown stringency — roughly the difference between Germany and Italy's mean index scores over the first half of 2020 — is associated with 0.06% more mentions, 0.33% more retweets, and 0.33% more likes of populists per day.

The "Supply" of Online Populist Discourse

A final possibility worth considering is that growing support for populists reflected an expansion in their "supply" of messaging and rhetoric in response to COVID-19. To investigate this pathway, we test whether populists were more likely to discuss the pandemic on Twitter during the first half of 2020. Drawing on a daily panel of all tweets published by populist and mainstream parties and leaders in the five countries in our sample, we estimate a linear probability model predicting whether a given post mentions COVID-19, conditional on whether the author is a populist. We control for the logarithm of new and cumulative COVID-19 cases per country, an indicator for whether the author's account represents a party or a politician, and country and day fixed effects, clustering robust standard errors by account. As shown in Table A19 of Online Appendix H, the likelihood of tweeting about the pandemic does not vary between populist and mainstream politicians. Nor did populists publish a higher volume of tweets about the pandemic or in general: when we replace the previous outcome with the logarithm of (1) tweets that mention COVID-19 and (2) all tweets (regardless of topic), the coefficient on the populist author indicator remains small and far from significant.

Discussion

The rise of right-wing populism and the spread of COVID-19 are two of the most salient political developments to sweep advanced democracies in recent decades. While each phenomenon is the subject of a large and expanding literature, the pandemic's implications for the fortunes of populist movements remain surprisingly unclear. Resolving this question is crucial for understanding the determinants of populist support, the political implications of public health shocks, and the post-pandemic electoral landscape.

We have made the case for theorizing the COVID-19 pandemic not as a sui generis epidemiological calamity but as a salient instance of societal crisis in the age of mass social media — a situation that creates fertile ground for populists to attract support by highlighting the limitations of public institutions, challenging the authority of elites, and inflaming ingroup-outgroup tensions. Our empirical examination focused on the early months of the pandemic, when the unpredictable location-specific timing of SSEs provides a source of plausibly exogenous variation in local COVID-19 incidence. Applying our instrumental variables strategy to a diverse range of sources — including high-frequency social media interactions, municipal electoral data, and individual-level surveys — we consistently found that the outbreak of COVID-19 led to a sharp uptick in support for populists in Western Europe. Further analysis of these sources suggested that the populist surge was driven by an erosion of confidence in political institutions, a hardening of attitudes toward outgroups, and disapproval of COVID-19 containment measures.

In addition to highlighting major public health shocks as a catalyst for swings to the extreme right, the findings enrich our understanding of *how* societal crises spur and shape patterns of populist mobilization. Complementing research emphasizing the agency of populist parties and leaders in framing crises to their advantage (Moffitt, 2015; Stavrakakis et al., 2018), we provide evidence that the *demand* side of the political equation can also play a crucial catalytic role. Indeed, while populist narratives about COVID-19 — which sometimes lacked clarity and coherence (Kaltwasser and Taggart, 2022; Wondreys and Mudde, 2022; Hinterleitner, Kammermeier, and Moffitt, 2024) — reached broad audiences, areas more exposed to the disease saw markedly larger shifts in political attitudes and behaviors. This may explain why, as noted earlier, some accounts of the pandemic emphasize the relative ineffectiveness of top-down populist messaging and campaigning. More generally, the localized nature of COVID-19's effects sheds fresh light on the "geography of discontent" associated with the rise of populism in Western Europe, which has been conceptualized primarily in economic terms (e.g., Carreras, Irepoglu Carreras, and Bowler, 2019; Bolet, 2021; Broz, Frieden, and Weymouth, 2021).

Understanding COVID-19's longer-term political ramifications is an important task for future research. Later phases of the pandemic were characterized by new dimensions of policy conflict and growing ideological heterogeneity among populist parties (Wondreys and Mudde, 2022; Zulianello and Guasti, 2023), though the latter have continued to make electoral inroads across the countries studied: Giorgia Meloni of the *Fratelli d'Italia* was elected prime minister of Italy in 2022; the RN emerged as the largest opposition party in the French National Assembly in the same year; the PVV became the largest of *all* parties in the Dutch lower house in 2023; Reform UK won its first parliamentary seats in the United Kingdom's 2024 general election and has since led national opinion polls; and the *Alternative für Deutschland* doubled its vote share in the 2025 German federal election. While many factors have undoubtedly contributed to these gains, our results suggest that the pandemic may have delivered a significant impetus.

The extent to which our findings apply to smaller disease outbreaks or different types of public health shocks — such as natural disasters, humanitarian emergencies, and bioterrorist incidents — is also an open question. While COVID-19 is unusual in its scale and scope, there is no theoretical reason why such shocks could not (to varying degrees) activate similar demand-side mechanisms of populist mobilization. As noted earlier, for instance, exposure to epidemics has been found to inflict lasting damage on confidence in political institutions. Investigating the consequences of a wider range of public health shocks for populism as well as other forms of extreme politics is another promising avenue for further work.

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Online Appendices for:

Right-Wing Populism and the COVID-19 Shock: Evidence from Early Superspreader Events

May 12, 2026

Contents

A List of Superspreader Events

TABLE A1. European Superspreader Events, February-June 2020

#	Country	Date (dd/mm)	Region	Setting	Detail	Indoor / Outdoor
1	Austria	03/03	Ischgl	Bar		Indoor
2	Austria	06/03	Losenstein	Choir	Practice	Indoor
3	Czech Republic	15/05	Karviná	Mine: coal	Darkov mine	Indoor
4	Estonia	04/03	Saaremaa	Sports: audience	Champagne festival, volleyball championship	Indoor
5	Finland	05/03	Sipoo	Party		Indoor
6	Finland	05/03	Levi	Bar	Ski resort	Indoor
7	Finland	05/03	Southern Finland	Party		Indoor
8	Finland	10/03	Vuokatti	Bar	Ski resort	Indoor
9	France	15/02	Crépy-en-Valois	School		Indoor
10	France	18/02	Mulhouse	Religious		Indoor
11	France	05/03	Alpes-Martimes	Nursing home		Indoor
12	France	12/03	Wihr-au-Val	Choir	Practice	Indoor
13	France	01/04	Mediterranean	Ship: Military	Navy ship	Indoor
14	France	09/04	Sévérac-d'Aveyron	Nursing home	Ehpad Gloriande	Indoor
15	France	13/05	Villeneuve-le-Roi	Construction site	Asbestos removal at Lycée Georges-Brassens	Indoor / Outdoor
16	France	11/06	Pouzauges	Food	Fleury Michon	Indoor
17	Germany	15/02	Gangelt	Party	Carnival celebration	Indoor
18	Germany	29/02	Berlin	Bar	3 Events at night club Kater Blau	Indoor
19	Germany	09/03	Berlin	Choir	Berlin Cathedral Choir	Indoor
20	Germany	15/03	Wolfsburg	Nursing home	Wilhelmstadt-Gymnasium	Indoor
21	Germany	15/03	Münster	Medical	Pediatric dialysis unit of the University Hospital of Münster	Indoor
22	Germany	20/04	Birkenfeld	Meat plant	Cattle slaughterhouse	Indoor
23	Germany	10/05	Frankfurt	Religious	Baptist church prayer	Indoor
24	Germany	10/05	Frankfurt	Religious	Baptist church prayer	Indoor
25	Germany	15/05	Dissen	Meat plant	Cattle slaughterhouse	Indoor
26	Germany	10/06	Gütersloh	Meat plant	Toennies meat plant	Indoor
27	Ireland	20/04	Roscrea	Meat plant	Roscrea Meat Plant	Indoor
28	Ireland	01/05	Edenderry	Meat plant	Rosderra Irish Meats plant	Indoor
29	Italy	15/02	Castiglione D'Adda	Hospital	One person infects 13 others in various locations	Indoor / Outdoor
30	Italy	19/02	Milan	Sports: audience	Soccer game attendance	Indoor / Outdoor
31	Italy	07/03	Bologna	Factory		Indoor
32	Italy	08/03	Montecopiolo	Party		Indoor
33	Italy	10/03	Lombardy	Nursing home	Care Homes	Indoor
34	Italy	11/03	Codogno	Hospital	Hospital care	Indoor
35	Italy	12/03	Obereggen	Hotel	Ski hotel	Indoor
36	Italy	13/03	Codogno	Household		Indoor
37	Italy	14/03	Codogno	Party	Local pub	Indoor
38	Italy	15/03	Cingoli	Nursing home		Indoor

39	Italy	24/03	Corridonia	Nursing home		Indoor
40	Italy	24/03	Recanati	Nursing home		Indoor
41	Italy	07/04	Dosolo	Meat plant		Indoor
42	Italy	07/04	Ravenna	Agriculture		Indoor / Outdoor
43	Italy	14/04	Castelraimondo	Nursing home		Indoor
44	Italy	08/05	Rodigo	Agriculture		Indoor / Outdoor
45	Italy	28/05	Bologna	Household		Indoor
46	Italy	16/06	Rocca di Papa	Nursing home		Indoor
47	Italy	23/06	Rome	Hospital		Indoor
48	Italy	25/06	Mondragone	Household		Indoor
49	Italy	25/06	Rovereto	Factory		Indoor
50	Italy	29/06	Fiumicino	Restaurant	Indoor	
51	Netherlands	05/03	Kessel	Concert	Fundraising music performance in small community	Indoor
52	Netherlands	08/03	Amsterdam	Choir	Recital	Indoor
53	Netherlands	09/03	Heerde	Choir	Practice	Indoor
54	Netherlands	10/03	Heerde	Nursing home		Indoor
55	Netherlands	01/04	Hasselt	Nursing home		Indoor
56	Netherlands	30/04	Dordrecht	Nursing home	Verpleeghuis Parkhuis	Indoor
57	Netherlands	01/05	Groenlo	Meat plant		Indoor
58	Netherlands	01/05	Sneek	Asylum seekers center		Indoor
59	Netherlands	16/06	Boxtel	Meat plant		Indoor
60	Netherlands	17/06	Maassluis	Nursing home		Indoor
61	Slovenia	04/03	Maribor	Sports: participation	Squash hall, locker room, or hallway	Indoor
62	Spain	25/02	Vitoria-Gasteiz	Funeral	Funeral	Indoor / Outdoor
63	Spain	08/03	Madrid	Demonstration	Political rally, indoor socializing in cafes and restaurants	Indoor / Outdoor
64	Sweden	15/05	Skellefteå	School: pre-school	Kågeskolan in Skellefteå	Indoor
65	Sweden	15/05	Jönköping	Hospital	Ryhov County Hospital	Indoor
66	Sweden	24/05	Vrångö	Choir	Members of 3 different churches	Indoor
67	Sweden	15/06	Malmö	Hospital	Neurology department of Sköne University Hospital	Indoor
68	Switzerland	10/03	Zurich	Office	11 infected of 13-person team doing office work	Indoor
69	Switzerland	21/06	Zurich	Bar	Nightclub	Indoor
70	UK	15/03	Dumbarton	Nursing home		Indoor
71	UK	15/03	Luton	Nursing home		Indoor
72	UK	16/03	North Lanarkshire	Nursing home		Indoor
73	UK	17/03	East Lothian	Nursing home		Indoor
74	UK	15/05	Weston-Super-Mare	Hospital	Weston General Hospital	Indoor
75	UK	01/06	Desborough	Nursing home		Indoor
76	UK	10/06	Edinburgh	Nursing home	Milford House Care Home	Indoor
77	UK	15/06	Merthyr Tydfil	Meat plant	Kepak meat plant	Indoor
78	UK	15/06	Wrexham	Meat plant	Rowan foods meat plant	Indoor
79	UK	15/06	Cleckheaton	Meat plant	Asda-owned Kober meat plant	Indoor
80	UK	18/06	Llangefni on Anglesey	Meat plant	2 Sisters Food Group meat plant	Indoor

Source: SARS-CoV-2 Superspreading Events Database (Swinkels et al., 2021).

B Are Geolocatable Tweets Different?

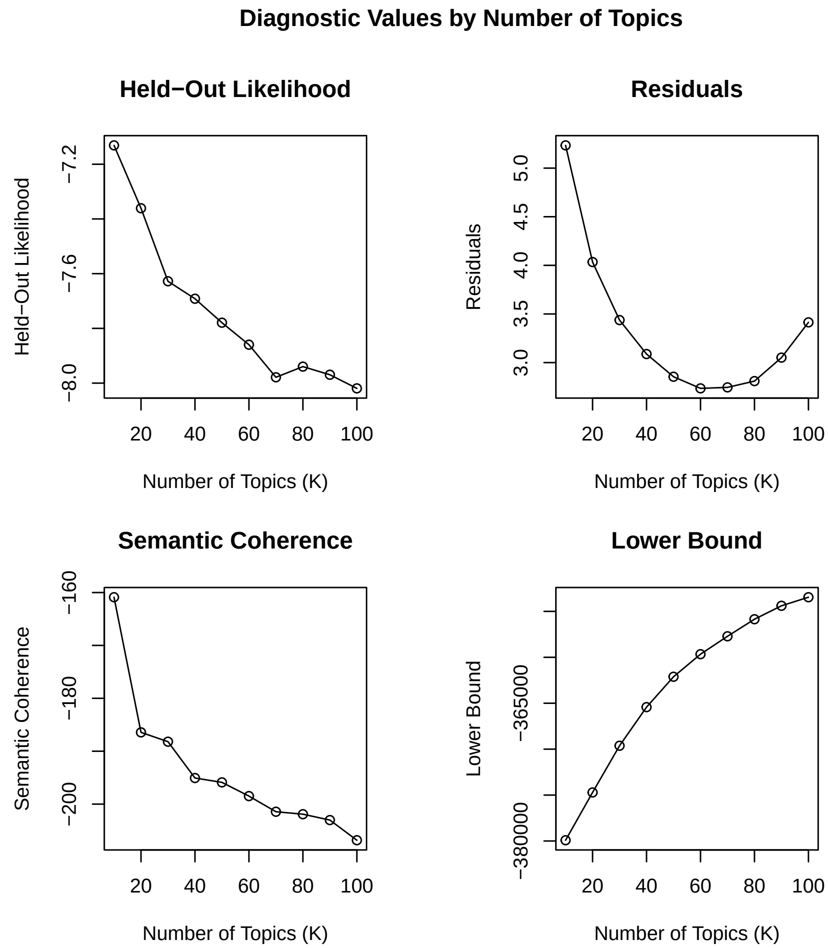
In this appendix, we investigate whether there are systematic differences between tweets by users with and without location data. Our approach involves randomly sampling tweets from our corpus — all tweets mentioning populist politicians published in France, Germany, Italy, the Netherlands, and the United Kingdom between 1 January and 30 June 2020 — and analyzing their textual content using structural topic modeling, a machine learning-based classification technique.

Sample Selection We begin by removing mentions and web addresses (URLs) from all tweets, before filtering out those with fewer than 10 words (whose substantive content is typically limited). For each of our five countries, we then draw a random sample of tweets stratified by (1) whether their author provides a valid location and (2) whether they mention a right-wing populist. We sample 500 tweets in each quadrant, ensuring that our comparison is not affected by the frequency of each type of tweet. To avoid oversampling from individuals who tweet at a high frequency, we set a maximum of five tweets per user. Non-English tweets are translated into English using the Google Translate API. We are left with a corpus of 9,861 tweets, 50.7% of which have a valid location.

To prepare the stratified sample for topic modeling, we conduct several preprocessing steps. We remove numbers, punctuation, low-frequency words (those appearing in fewer than five tweets), and "stop words" that make little difference to the meaning of a sentence (e.g., "and," "the," "or"). We also omit words used in fewer than three countries (mostly names of people and places), helping us to focus on common transnational language. As text length is altered by the previous steps, we again exclude tweets with fewer than 10 words, which provide little information to the topic model. The final sample consists of 4,492 tweets that are reasonably balanced across the two dimensions of interest: 51.2% include a valid location and 47.5% mention a populist party or leader.

Topic Model Training Next, we train a structural topic model on the sample and associated metadata. Topic modeling is an inductive, unsupervised method for identifying substantive themes in large

FIGURE A1. Diagnostics for Assessing Structural Topic Model Fit



Notes: This figure, generated by the `stm` package in R (Roberts, Stewart, and Tingley, 2019), plots four diagnostic statistics for assessing the fit of our structural topic model with varying numbers of topics (K).

text corpora (Roberts et al., 2014). A structural approach permits the inclusion of additional covariates, enabling us to assess how the frequency of each topic varies with textual attributes of interest. We specify four sets of covariates: (1) country fixed effects; (2) an indicator for whether a tweet's author provides a valid location; (3) an indicator for whether a tweet mentions a populist party or leader; and (4) a spline to capture temporal trends (topic frequency may vary in a non-linear fashion over time and across countries).

A key parameter in topic models is the user-specified number of topics in the corpus (K). There is no way to determine K a priori, though larger and more varied corpora generally require higher values. We estimate models with a range of plausible K values — 10 to 100 in increments of 10 — and assess the resulting model fit using four diagnostic statistics recommended by Roberts, Stewart, and Tingley (2019): (1) held-out likelihood, the model's success in predicting words within tweets; (2) model residuals; (3) semantic coherence, a measure of how frequently "likely" words in topic k co-occur; and (4) an approximation to the lower bound of the marginal likelihood, the model's internal measure of fit. As illustrated in Figure A1, these diagnostics suggest that a K value between 40 and 80 provides the best fit to the data. We thus initially set K to 80 after experimenting with alternative values within the 40-80 range.

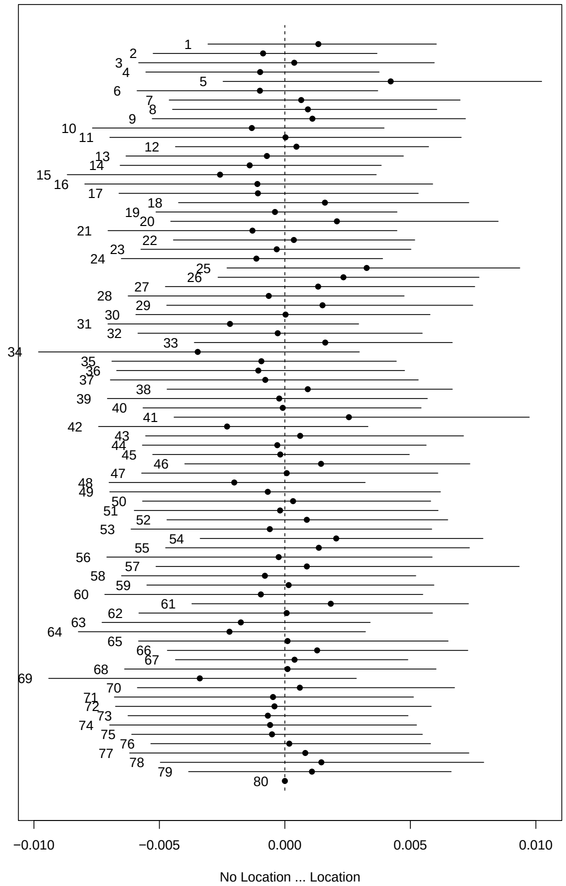
Results Having trained the topic model, we examine how topic frequency varies with covariates of interest. We estimate a linear regression in which the outcome variable is an indicator for the proportion of topic k in a given tweet and the treatment variable is an indicator for whether this tweet is accompanied by valid location data. We maintain all controls in the topic model. Standard errors are clustered by NUTS-3 region.

Figure A2 displays the estimated coefficient on the geolocatability indicator for each topic with 95% confidence intervals. None of the 80 coefficients reach statistical significance at this level, implying that there is no meaningful difference in tweet content between users with and without valid location data. The results are similar when we set K to 40, 50, 60, and 70.

Keyword Analysis

Given our interest in COVID-19's impact on social media engagement with right-wing populists, we additionally assess whether geolocatable tweets are more likely to discuss the pandemic or populist politicians. Using our entire corpus of tweets that mention political parties or leaders — 419,046 tweets — we estimate two sets of linear probability models with user, country, and day fixed effects: (1) a set whose outcome variable is an indicator for whether a tweet contains the terms `covid`, `corona`, or `virus`, words common to all five major languages in the sample (Dutch, English, French, German, and Italian); and (2) a set whose outcome variable is an indicator for whether a tweet mentions a

FIGURE A2. Relationship between Topic Occurrence and User Geolocatability



Notes: This figure, generated by the `stm` package in R (Roberts, Stewart, and Tingley, 2019), plots tweet-level OLS estimates from 80 (K) separate models with 95% confidence intervals based on standard errors clustered by country. The outcome variable is the proportion of topic k in a given tweet. The treatment variable is an indicator for whether the tweet's author provides a valid location. All models control for country fixed effects, a temporal spline, and whether a right-wing populist is mentioned.

populist party or leader. The treatment is an indicator for whether a tweet has a valid location. In total, 3.3% of tweets in the sample mention a COVID-19 keyword and 33.4% mention a populist party or leader. Standard errors are clustered by user and country.

Table A2 shows the results, first without (columns 1 and 3) and then with (columns 2 and 4) country fixed effects. The coefficient on geolocatability is small, negative, and far from statistical significance in every model. When all fixed effects are included, geolocatable users are just 0.07 percentage points less likely to mention COVID-19 and 0.06 percentage points less likely to mention a populist party

TABLE A2. Relationship between User Geolocatability and Tweet Content

Outcome:	COVID-19 Mention		Populist Mention	
	(1)	(2)	(3)	(4)
User Geolocation	-0.050	-0.073	-0.111	-0.055
	(0.044)	(0.064)	(0.135)	(0.075)
N	419,046	419,046	419,046	419,046
Mean Outcome Variable	0.034	0.034	0.334	0.334
R-Squared	0.301	0.301	0.744	0.744
User FE	✓	✓	✓	✓
Day FE	✓	✓	✓	✓
Country FE		✓		✓

Notes: Tweet-level OLS estimates with robust standard errors clustered by Twitter user and country. The sample is a corpus of 419,046 tweets mentioning a political party or leader published in five European countries (FR, DE, IT, NL, UK) between 1 January and 30 June 2020.

or leader. In sum, the analysis offers little evidence that Twitter users with and without valid location information differ in their propensity to discuss COVID-19 or engage with populists.

C Instrumental Variables Strategy

Susceptible-Infected-Recovered (SIR) Model

This appendix provides a more detailed description of our strategy for predicting the trajectory of COVID-19 cases following SSEs, which is based on the workhorse Susceptible-Infected-Recovered (SIR) model in epidemiology. The standard SIR model without births and deaths divides the population (N) in a given period (t) into three "compartments": infected individuals (I_t), susceptible individuals (S_t), and recovered individuals (R_t). The size of each group evolves according to the following set of differential equations:

$$\frac{\delta S_t}{\delta t}(t) = -\beta^{\text{SIR}}\frac{S_t I_t}{N} \tag{A1}$$

$$\frac{\delta I_t}{\delta t}(t) = \beta^{\text{SIR}}\frac{S_t I_t}{N} - \gamma^{\text{SIR}} I_t \tag{A2}$$

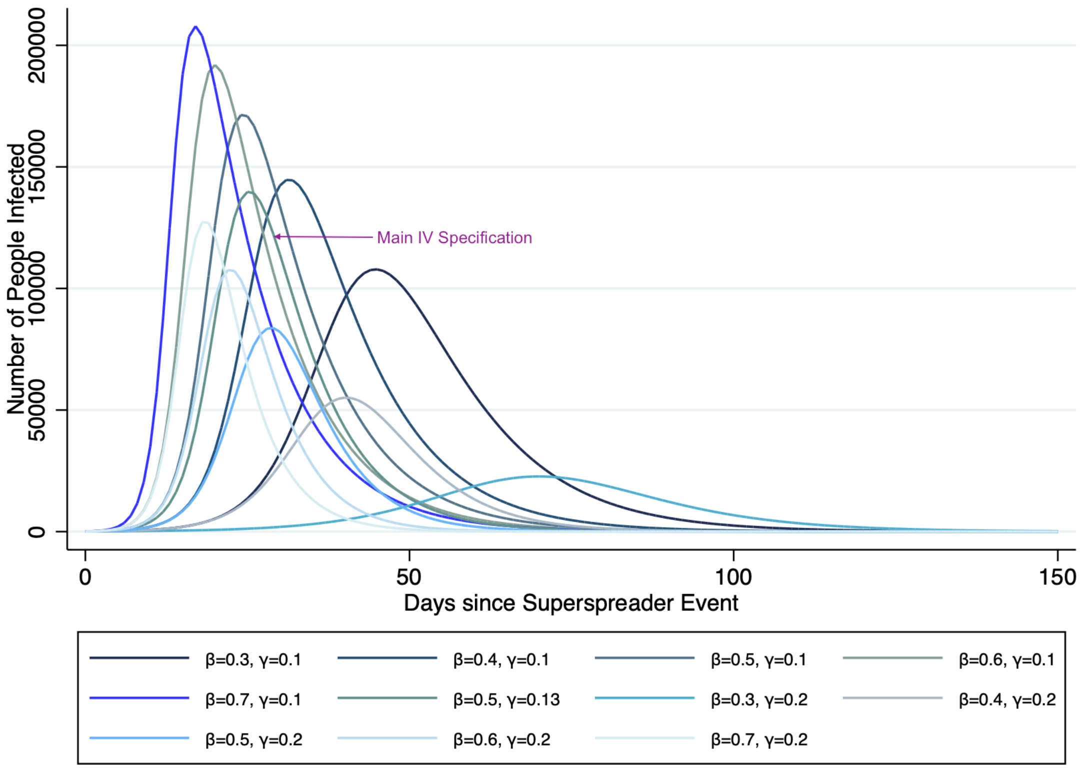
$$\frac{\delta R_t}{\delta t}(t) = \gamma^{\text{SIR}} I_t \tag{A3}$$

where β^{SIR} is the infection rate; and γ^{SIR} is the recovery rate. Note that the basic reproduction number (R_0), a widely reported statistic during the COVID-19 pandemic, is the ratio of β^{SIR} to γ^{SIR}. In other words, it measures the expected number of people infected by a contagious person (secondary infections).

For the purposes of modeling COVID-19 infections over time, Equation A2 is most relevant. As noted in the main text, existing studies of COVID-19 transmission dynamics suggest that β^{SIR} is typically 0.5 and that the average recovery period (i.e., $1/\gamma^{\text{SIR}}$) is approximately seven days, which implies a γ^{SIR} value of 0.13. We follow these parameter choices in our main instrumental variables specifications.

Figure A3 illustrates the shape of the SIR infection curve with varying values of β^{SIR} and γ^{SIR} between 0 and 150 days following an SSE. All inhabitants are included in the susceptible population, S_t (an average of 358,863 per NUTS-3 region). As indicated in the legend, β^{SIR} ranges from 0.3 to 0.7

FIGURE A3. SIR Curves with Varying Infection and Recovery Rates



Notes: SIR curves of the expected number of COVID-19 infections in a population of approximately 350,000 people (the average population of European NUTS-3 regions in 2020) between 0 and 150 days after an SSE. In the legend, β^{SIR} and γ^{SIR} are the infection rate and the recovery rate per day, respectively. The general formula for the curves is given by Equation A2.

in increments of 0.1, while γ^{SIR} is 0.1, 0.13, or 0.2. Higher γ^{SIR} values lower the peak of the SIR curve, resulting in a smaller number of infected people at any given point in the post-SSE period. Higher β^{SIR} values shift the distribution to the left, which entails that infections peak more rapidly after the SSE.

To construct the temporal weights in our instrument (λ_t in Equation 1), we generate an SIR infection distribution for each SSE within the specified maximum radius (ϕ) and time lag (τ), setting t to 0 on the date of occurrence. The distribution used for our main instrumental variables specification — where $\beta^{\text{SIR}} = 0.5$ and $\gamma^{\text{SIR}} = 0.13$ — is indicated in Figure A3.

Additional Balance Tables

TABLE A3. Balance Table: Regions With and Without Superspreader Events before March 2020

	NUTS Level	Regions without SSEs before March 2020		Regions with SSEs before March 2020		*T*-Test: Difference in Means		
		Mean	St. Dev.	Mean	St. Dev.	t	p	p^*_{1000}
Populist vote share (%), 2019	3	25.35	15.31	32.53	15.22	-1.24	0.26	0.45
Mean populist vote share (%), 2014-19	3	23.11	13.23	28.40	14.43	-0.97	0.37	0.45
Δ Populist vote share (%), 2014-19	3	5.08	14.64	9.03	20.04	-0.52	0.62	0.63
Population per km^2, 2019	3	398.17	1,039.77	529.96	700.91	-0.49	0.64	0.54
Share of urban households (%), 2019	2	38.70	16.94	39.22	7.00	-0.17	0.87	0.94
Women per 100 men, 2019	3	103.05	4.01	103.56	1.54	-0.86	0.42	0.38
Share of people aged < 20 (%), 2019	3	20.72	4.62	19.56	3.21	0.10	0.36	0.68
Share of people aged 65+ (%), 2019	3	20.38	4.57	21.61	2.39	-1.35	0.22	0.30
Median male age, 2019	3	42.42	4.78	44.46	2.77	-1.93	0.10	0.29
Males aged < 25 w/o tertiary ed. (%), 2019	2	45.55	25.42	43.04	22.58	0.38	0.71	0.68
Share of foreign citizens (%), 2019	2	8.22	7.34	9.67	3.90	-0.87	0.42	0.42
Net migration per capita, 2014-19	3	0.003	0.006	0.004	0.003	-1.15	0.29	0.46
GDP per capita growth (%), 2014-2019	3	17.13	15.67	14.29	7.53	0.99	0.36	0.40
Industrial employment (%), 2019	3	18.39	8.93	21.15	7.04	-1.03	0.34	0.28
Manufacturing employment (%), 2019	3	16.61	8.69	19.96	7.00	-1.26	0.25	0.20
Mean China shock instrument, 1988-2007	2	1.64	1.65	0.94	0.56	1.69	0.30	0.48

Notes: Comparison of European regions with and without SSEs before 1 March 2020 on measures and predictors of populist support before the COVID-19 pandemic. The last three columns report the results of a two-sample *t*-test — regular and bootstrapped with 1,000 samples — of the difference in means between the two sets of regions.

TABLE A4. Balance Table: Regions With and Close to Early Superspreader Events

	NUTS Level	Regions Near SSEs		Regions with SSEs		*T*-Test: Diff. in Means		
		Mean	St. Dev.	Mean	St. Dev.	t	p	p^*_{1000}
Populist vote share (%), 2019	3	26.70	13.23	25.01	12.64	0.85	0.40	0.42
Mean populist vote share (%), 2014-19	3	23.38	10.66	21.03	9.82	1.51	0.14	0.16
Δ Populist vote share (%), 2014-19	3	7.14	15.96	8.40	15.36	-0.52	0.60	0.57
Population per km^2, 2019	3	522.50	1,691.23	586.16	1,064.23	-0.35	0.73	0.78
Share of urban households (%), 2019	2	37.15	13.97	38.15	12.18	-0.45	0.65	0.64
Women per 100 men, 2019	3	102.76	3.19	103.06	3.00	-0.72	0.47	0.49
Share of people aged<20 (%), 2019	3	21.03	3.32	20.99	3.21	-1.20	0.23	0.21
Share of people aged 65+ (%), 2019	3	21.14	3.32	20.56	3.21	1.30	0.20	0.18
Median male age, 2019	3	43.29	3.54	42.50	3.15	1.77	0.08	0.08
Males aged < 25 w/o tertiary ed. (%), 2019	2	44.99	24.85	42.59	24.29	0.80	0.42	0.45
Share of foreign citizens (%), 2019	2	8.43	5.28	9.13	5.22	-0.79	0.43	0.43
Net migration per capita, 2014-19	3	0.004	0.004	0.004	0.003	1.06	0.29	0.24
GDP per capita growth (%), 2014-2019	3	15.82	14.04	17.17	19.11	-0.49	0.63	0.55
Industrial employment (%), 2019	3	17.62	7.95	17.80	10.15	-0.12	0.90	0.87
Manufacturing employment (%), 2019	3	16.19	7.72	16.60	10.15	-0.28	0.78	0.74
Mean China shock instrument, 1988-2007	2	1.94	1.98	1.89	1.63	0.12	0.90	0.92

Notes: Comparison of European regions with SSEs (1 February — 30 June 2020) and directly adjacent regions on measures and predictors of populist support before the COVID-19 pandemic. The last three columns report the results of a two-sample *t*-test — regular and bootstrapped with 1,000 samples — of the difference in means between the two sets of regions.

D Social Media Analysis: Further Information and Robustness

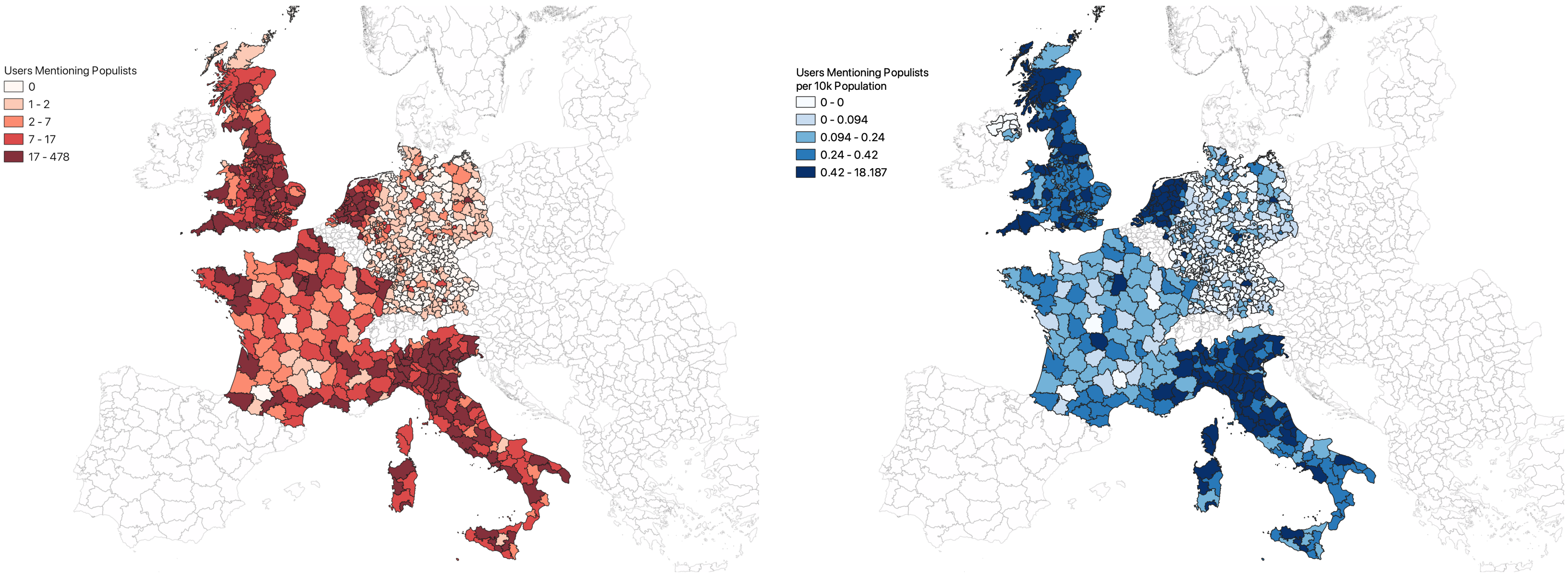
TABLE A5. Summary Statistics: Social Media Analysis

	(1) Mean	(2) Std. Dev.	(3) Min.	(4) Max.	(5) N
Panel A: Twitter Engagement Measures					
Log Mentions of Populists	0.10	0.33	0.00	4.30	124,948
Log Retweets of Populists	0.86	1.16	0.00	6.92	124,948
Log Likes of Populists	1.00	1.30	0.00	8.30	124,948
Log Mentions of Mainstream Politicians	0.33	0.71	0.00	6.31	129,276
Mainstream Mentions Relative to Populists (Log Δ)	-0.20	0.70	-5.28	4.11	124,948
Incumbent Mainstream Mentions Relative to Populists (Log Δ)	-0.14	0.62	-4.72	4.11	124,948
Nonincumbent Mainstream Mentions Relative to Populists (Log Δ)	-0.02	0.48	-5.04	4.11	124,948
Panel B: COVID-19 Variables					
Lockdown Stringency	56.31	27.20	0.00	93.52	124,948
Log COVID-19 Cases per 10,000 Population	0.13	0.23	0.00	2.91	124,948
Superspreader Exposure Instrument	14.09	17.52	0.00	142.99	119,393

Notes: This table provides summary statistics for the main variables in our analysis of COVID-19's impact on Twitter engagement with right-wing populists at the NUTS-3-day-level.

FIGURE A4. Geographical Distribution of Twitter Users Mentioning Populists

Panel A: Total Users　　　　Panel B: Users per 10k Population



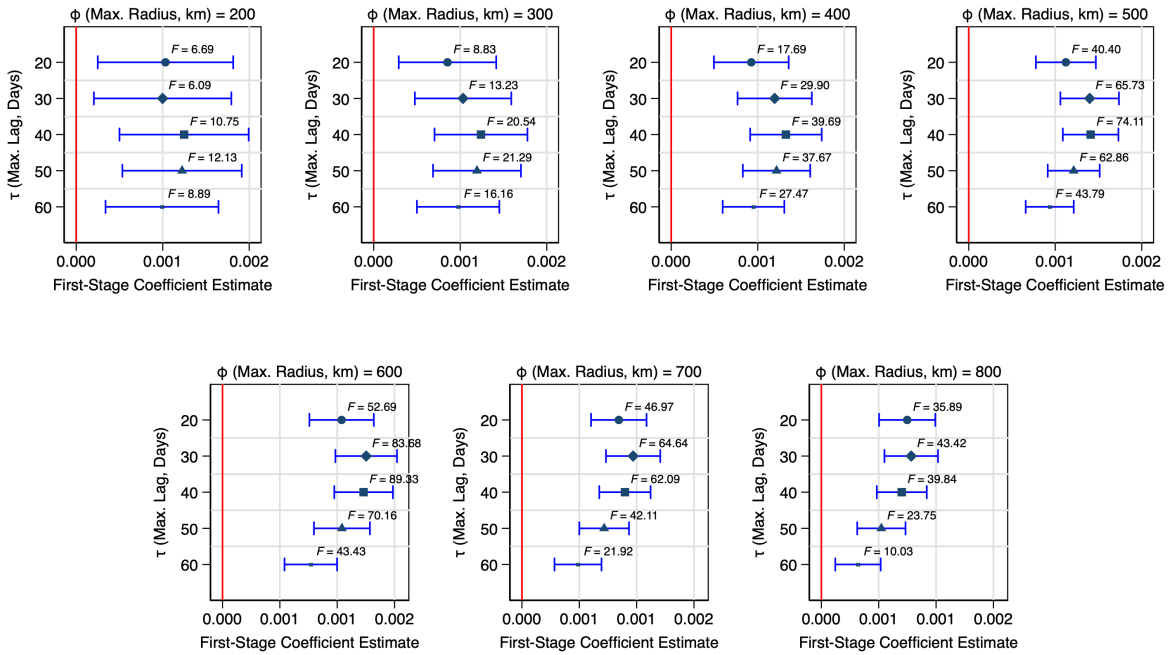
Notes: The sample comprises 8,190 Twitter users across 792 NUTS-3 regions of five European countries (FR, DE, IT, NL, UK) who mentioned a right-wing populist party or leader at least once between 1 February and 30 June 2020.

TABLE A6. Twitter Accounts of Parties and Party Leaders

Twitter Handle (@)	Party Name	Account Type	Country	Party Family
tino_chrupalla	Alternative für Deutschland (AfD)	Leader	DE	RWP
joerg_meuthen	Alternative für Deutschland (AfD)	Leader	DE	RWP
Alice_Weidel	Alternative für Deutschland (AfD)	Leader	DE	RWP
AfD	Alternative für Deutschland (AfD)	Party	DE	RWP
MLP_officiel	Rassemblement National (RN)	Leader	FR	RWP
RNational_off	Rassemblement National (RN)	Party	FR	RWP
Nigel_Farage	Reform UK	Leader	UK	RWP
TiceRichard	Reform UK	Leader	UK	RWP
reformParty_GB	Reform UK	Party	UK	RWP
UKIP	UK Independence Party (UKIP)	Party	UK	RWP
giorgiameloni	Fratelli d'Italia (FdI)	Leader	IT	RWP
berlusconi	Forza Italia (FI)	Leader	IT	RWP
matteosalvinimi	Lega Nord (LN)	Leader	IT	RWP
FratellidItalia	Fratelli d'Italia (FdI)	Party	IT	RWP
forza_italia	Forza Italia (FI)	Party	IT	RWP
LegaSalvini	Lega Nord (LN)	Party	IT	RWP
geertwilderspvv	Partij voor de Vrijheid (PVV)	Leader	NL	RWP
thierrybaudet	Forum voor Democratie (FvD)	Leader	NL	RWP
fvdemocratie	Forum voor Democratie (FvD)	Party	NL	RWP
Markus_Soeder	Christlich-Soziale Union in Bayern (CSU)	Leader	DE	Main.
EskenSaskia	Sozialdemokratische Partei Deutschlands (SPD)	Leader	DE	Main.
NowaboFM	Sozialdemokratische Partei Deutschlands (SPD)	Leader	DE	Main.
cdu	Christlich Demokratische Union Deutschlands (CDU)	Party	DE	Main.
CSU	Christlich-Soziale Union in Bayern (CSU)	Party	DE	Main.
spdde	Sozialdemokratische Partei Deutschlands (SPD)	Party	DE	Main.
EmmanuelMacron	La République En Marche (EM)	Leader	FR	Main.
chjacob77	Les Républicains (LR)	Leader	FR	Main.
faureolivier	Parti Socialiste (PS)	Leader	FR	Main.
enmarchefr	La République En Marche (EM)	Party	FR	Main.
lesRepublicains	Les Républicains (LR)	Party	FR	Main.
partisocialiste	Parti Socialiste (PS)	Party	FR	Main.
BorisJohnson	Conservative Party	Leader	UK	Main.
Keir_Starmer	Labour Party	Leader	UK	Main.
jeremycorbyn	Labour Party	Leader	UK	Main.
EdwardJDavey	Liberal Democrats	Leader	UK	Main.
Conservatives	Conservative Party	Party	UK	Main.
LabourParty	Labour Party	Party	UK	Main.
LibDems	Liberal Democrats	Party	UK	Main.
nzingaretti	Partito Democratico (PD)	Leader	IT	Main.
pdnetwork	Partito Democratico (PD)	Party	IT	Main.
markrutte	Volkspartij voor Vrijheid en Democratie (VVD)	Leader	NL	Main.
VVD	Volkspartij voor Vrijheid en Democratie (VVD)	Party	NL	Main.

Notes: This table lists the Twitter accounts of all right-wing populist (RWP) and mainstream parties and party leaders in France (FR), Germany (DE), United Kingdom (UK), the Netherlands (NL), and Italy (IT) during the first six months of 2020.

FIGURE A5. First-Stage Results with Varying Instrument Parameters



Notes: NUTS-3-day-level first-stage 2SLS estimates from 35 variants of Equation 3, with 95% confidence intervals based on robust standard errors clustered by NUTS-3 region. Two key parameters of the instrument, defined in Equation 1, vary across models: (1) ϕ, the maximum radius around a NUTS-3 region's centroid within which SSEs may occur; and (2) τ, the maximum time lag since SSEs. Kleibergen-Paap Wald rk F-statistics are reported above the estimated coefficients.

TABLE A7. Exploring Country Heterogeneity

Outcome:	Log Populist Mentions (1)	Log Populist Retweets (2)	Log Populist Likes (3)
COVID-19 Cases per 10,000 Pop. ×	0.212	1.825**	2.419**
Germany (Instrumented)	(0.175)	(0.848)	(1.166)
COVID-19 Cases per 10,000 Pop. ×	0.783**	5.316***	7.790***
UK (Instrumented)	(0.361)	(1.887)	(2.672)
COVID-19 Cases per 10,000 Pop. ×	1.408	11.666**	12.929**
France (Instrumented)	(0.977)	(5.144)	(6.424)
COVID-19 Cases per 10,000 Pop. ×	0.424***	2.212***	2.429***
Italy (Instrumented)	(0.151)	(0.684)	(0.912)
COVID-19 Cases per 10,000 Pop. ×	0.684	6.152**	11.640***
Netherlands (Instrumented)	(0.864)	(2.962)	(4.354)
Lockdown Stringency	✓	✓	✓
NUTS-3 FE	✓	✓	✓
Day FE	✓	✓	✓
Mean Outcome Variable	0.094	0.842	0.977
N	119,393	119,393	119,393

Notes: NUTS-3-day-level 2SLS estimates from a modified version of Equation 4 that includes interactions between the treatment and country indicators; robust standard errors, clustered by NUTS-3 region, are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

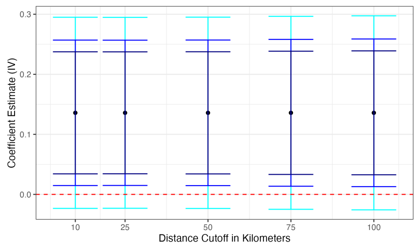
TABLE A8. Robustness to Country × Day Fixed Effects

Outcome:	Log Populist Mentions (1)	Log Populist Retweets (2)	Log Populist Likes (3)
Log Daily COVID Cases per	0.211	2.047***	1.754***
10,000 Pop. (Instrumented)	(0.135)	(0.521)	(0.458)
Country × Day FE	✓	✓	✓
First-Stage F-Statistic	105.22	105.22	105.22
Mean Outcome Var.	0.09	0.84	0.98
N	119,393	119,393	119,393

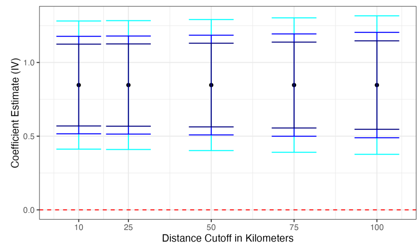
Notes: NUTS-3-day-level 2SLS estimates from a modified version of Equation 4 that includes interactive country × day fixed effects; robust standard errors, clustered by NUTS-3 region, are in parentheses. The instrument is time-weighted proximity to early SSEs within a maximum radius of 600km and time lag of 60 days. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

FIGURE A6. Robustness to Spatial Correlation Adjustment

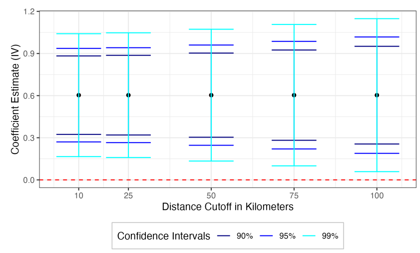
Panel A: Log Populist Mentions



Panel B: Log Populist Retweets



Panel C: Log Populist Likes



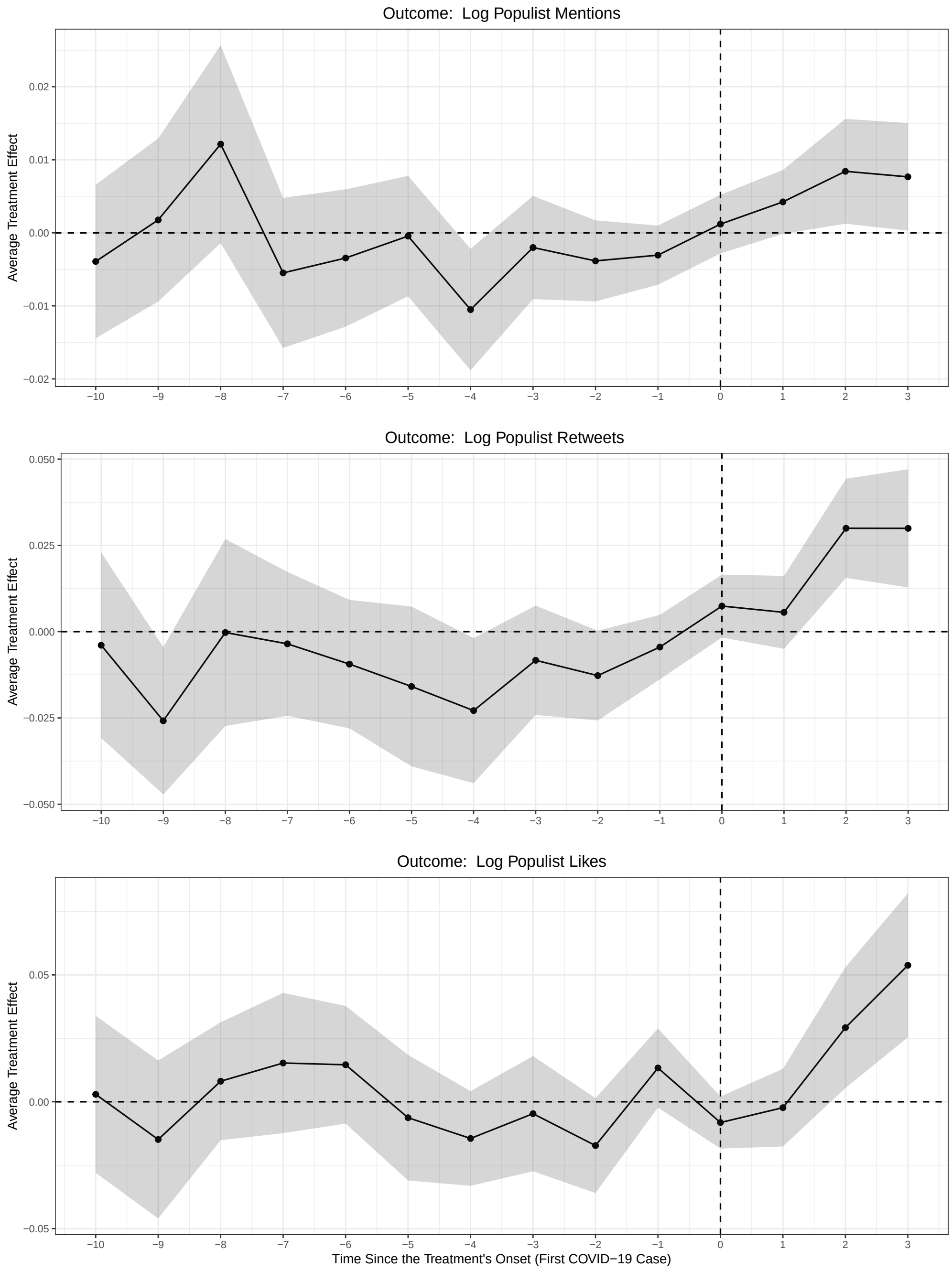
Notes: NUTS-3-day-level 2SLS estimates from Equation 4 with confidence intervals (of varying width) based on standard errors clustered by NUTS-3 region and corrected for spatial dependence using Colella et al.'s (2019) arbitrary correlation regression estimator.

TABLE A9. Robustness to Spatial Two-Stage Least Squares Estimator

Outcome:	Log Populist Mentions (1)	Log Populist Retweets (2)	Log Populist Likes (3)
Log Daily COVID Cases per 10,000 Pop. (Instrumented)	0.228***	0.213*	0.197*
	(0.060)	(0.126)	(0.107)
Lockdown Stringency	✓	✓	✓
NUTS-3 FE	✓	✓	✓
Day FE	✓	✓	✓
First-Stage F-Statistic	19.13	17.39	18.33
Mean Outcome Var.	0.09	0.84	0.97
Observations	110,858	110,851	110,851

Notes: NUTS-3-day-level spatial 2SLS (S-2SLS) estimates from a modified version of our instrumental variables specification that includes a spatial lag of the outcome variable — generated using a spatial weight matrix of power functional form — as a second endogenous regressor (see Betz, Cook, and Hollenbach, 2020). As additional instruments, we specify lags of this variable (1-10 days) plus a spatial lag of the SSE exposure instrument. Robust standard errors, clustered by NUTS-3 region, are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

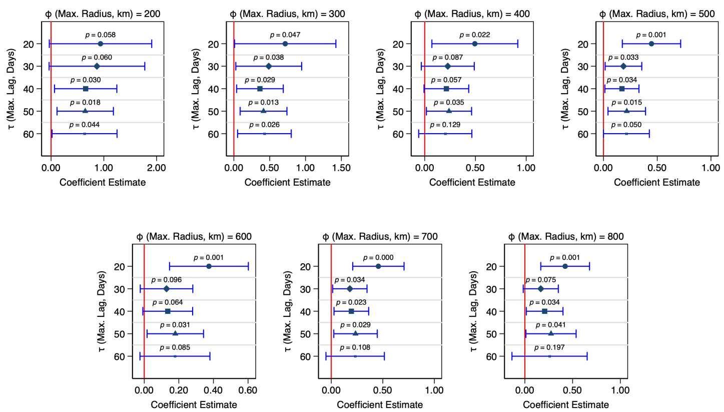
FIGURE A7. Event Study Analysis with Binary COVID-19 Treatment



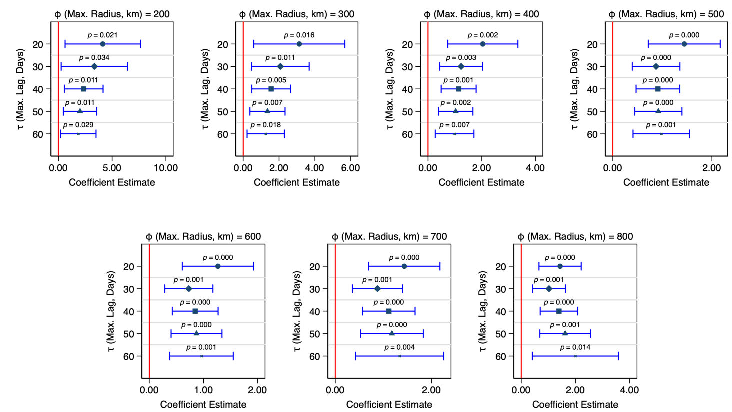
Notes: NUTS-3-day-level event study estimates computed using Liu, Wang, and Xu's (2022) two-way fixed effects counterfactual method; shaded 95% confidence intervals are based on nonparametric bootstrapped standard errors clustered by NUTS-3 region (bootstrap runs = 50). The treatment variable is an indicator for whether a NUTS-3 region records any new COVID-19 cases on a given day. All models control for NUTS-3 fixed effects, day fixed effects, and a country-level index of lockdown stringency.

FIGURE A8. Robustness to Varying Instrument Parameters

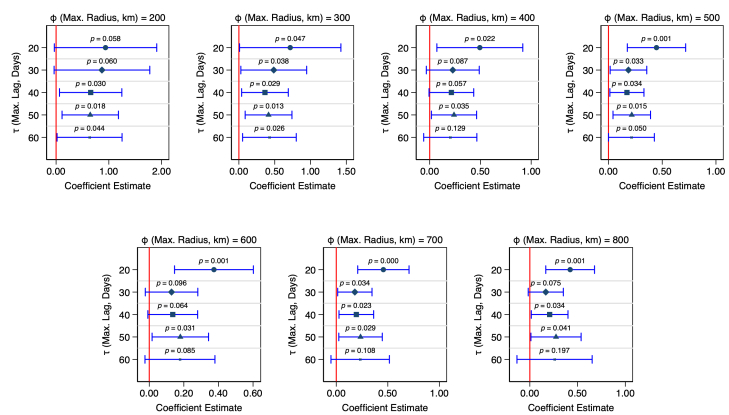
Panel A: Log Populist Mentions



Panel B: Log Populist Retweets

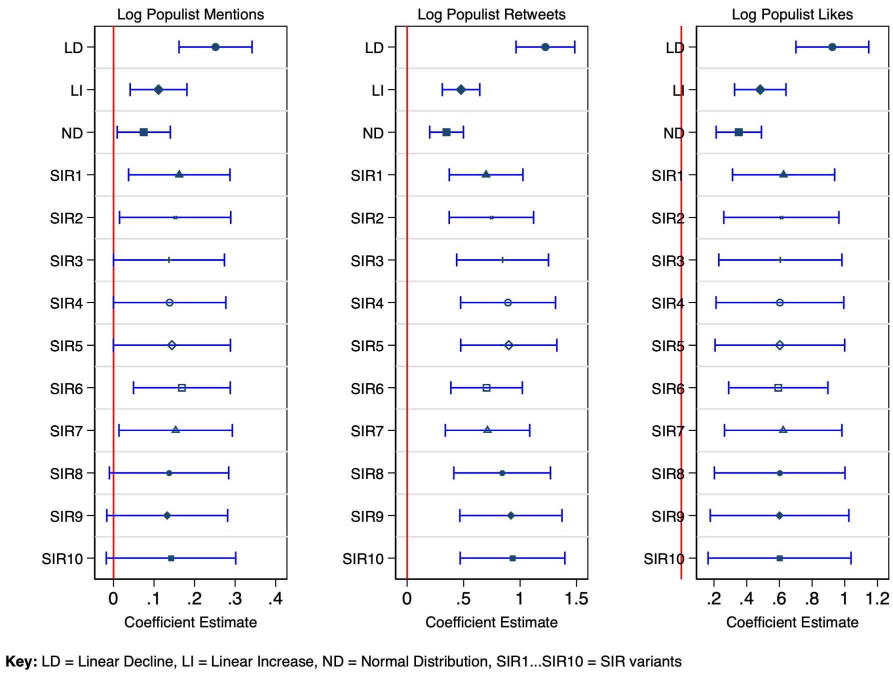


Panel C: Log Populist Likes



Notes: NUTS-3-day-level 2SLS estimates from Equation 4 with 95% confidence intervals based on standard errors clustered by NUTS-3 region. Two parameters of the SSE exposure instrument (defined in Equation 1) vary across models: (1) ϕ, the maximum radius around a NUTS-3 region within which SSEs may occur; and (2) τ, the maximum time lag since SSEs.

FIGURE A9. Robustness to Alternative Temporal Functions



Notes: NUTS-3-day-level 2SLS estimates from Equation 4 with 95% confidence intervals based on robust standard errors clustered by NUTS-3 region. As per the legend, the distribution of temporal weights attached to the SSE exposure instrument (λ in Equation 1) varies across models.

TABLE A10. Lasso Model with All Instrument Variations

Outcome:	Log Populist Mentions (1)	Log Populist Retweets (2)	Log Populist Likes (3)
Log Daily COVID Cases	0.099***	0.397***	0.361***
	(0.033)	(0.075)	(0.066)
Lockdown Stringency	✓	✓	✓
NUTS-3 FE	✓	✓	✓
Day FE	✓	✓	✓
First-Stage F-Statistic	15.374	15.374	15.374
Mean Outcome Variable	0.09	0.84	0.98
N	119,393	119,393	119,393

Notes: NUTS-3-day-level 2SLS estimates from Equation 4 with robust standard errors, clustered by NUTS-3 region, in parentheses. The instruments are selected via the lasso method from 443 variants of Equation 1 with varying values of ϕ (between 100km and 800km), τ (between 20 days and 60 days), β^{SIR} (between 0.3 and 0.8), and γ^{SIR} (0.1, 0.13, or 0.2). $^{***}p$ < 0.01, $^{**}p$ < 0.05, $^{*}p$ < 0.1.

E French Electoral Analysis

TABLE A11. Summary Statistics: French Electoral Analysis

	N	Mean	St. Dev.	Min.	Max.
Panel A: Outcome and Treatment Variables					
RN Vote Share	19,480	0.01	0.04	0.00	0.74
Log COVID-19 Cases per 10,000	19,209	0.0000	0.0003	0.00	0.02
RN Vote Share	19,480	0.01	0.04	0.00	0.74
Log COVID-19 Cases per 10,000	19,209	0.0000	0.0003	0.00	0.02
SSE Exposure Instrument (p=200,t=30)	19,210	12.48	26.41	0.00	186.99
SSE Exposure Instrument (p=200,t=40)	19,210	12.48	26.41	0.00	186.99
SSE Exposure Instrument (p=200,t=20)	19,210	9.67	20.16	0.00	144.64
SSE Exposure Instrument (p=400,t=30)	19,210	59.45	87.04	0.00	360.42
SSE Exposure Instrument (p=400,t=40)	19,210	59.45	87.04	0.00	360.42
Panel B: Control Variables					
Male-Female Ratio	19,209	0.49	0.02	0.40	0.75
Population Density	19,209	474.88	1,326.53	4.76	27,419.92
Young Population Share	19,209	0.10	0.02	0.04	0.40
Elderly Population Share	19,209	0.10	0.04	0.01	0.32
Employed Population Share	19,209	0.44	0.08	0.13	0.74
No Schooling Population Share	19,209	0.77	0.04	0.36	0.92
Industry Employment Share	19,209	0.15	0.13	0.00	0.80
Manual Workers Share	19,209	0.24	0.09	0.01	0.56
Migrant Population Share	19,209	0.002	0.004	0.00	0.07
RN Voters	19,480	70.99	506.72	0	17,910
Housing Stock (# Residences)	19,209	1,895.13	3,198.39	204.97	113,775.50

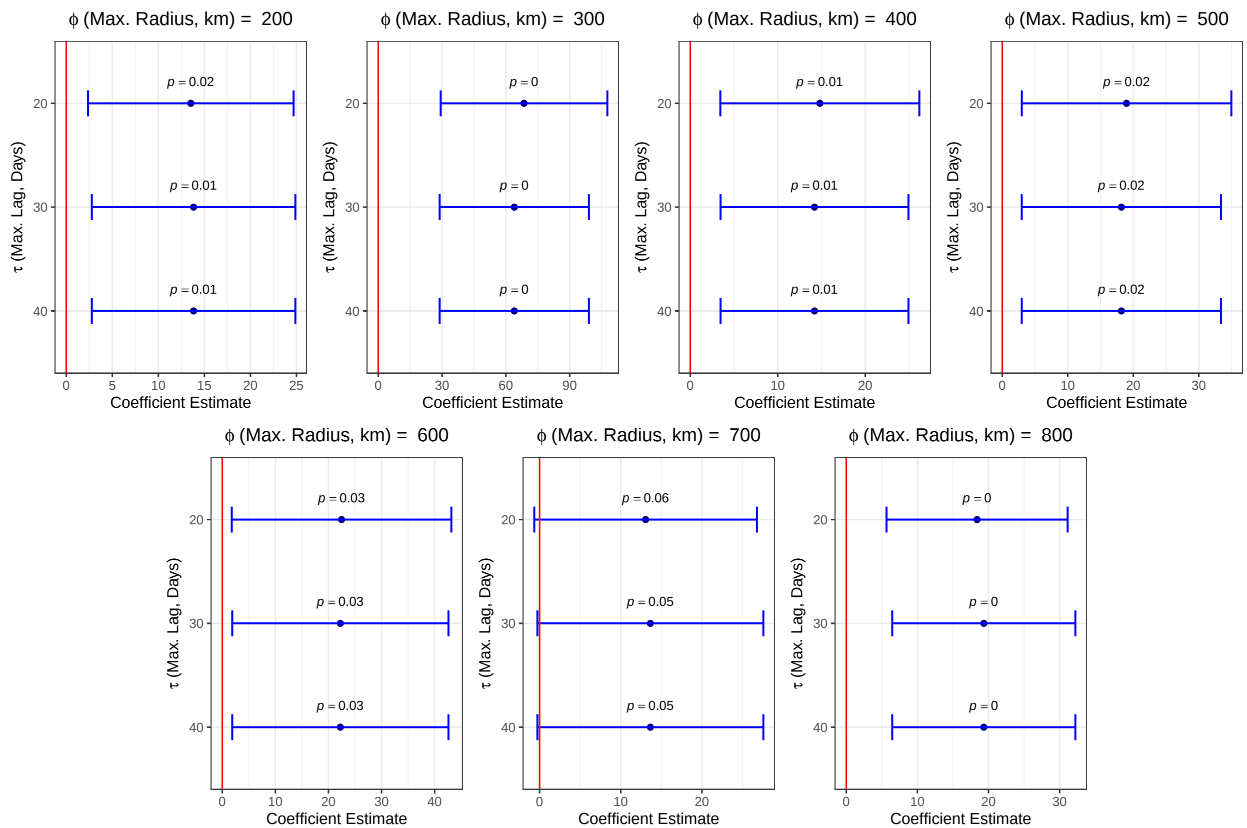
Notes: This table provides summary statistics for variables in our analysis of COVID-19's impact on support for the RN in the first round of the 2020 French municipal elections. The sample comprises approximately 10,000 French municipalities with at least 1,000 inhabitants in 2014 and 2020.

TABLE A12. Balance Table: French Municipalities With and Without Superspreader Events before First Round of 2020 Elections

	Munic. without SSEs		Munic. with SSEs		T-Test: Diff. in Means		
	Mean	St. Dev.	Mean	St. Dev.	t	p	p^*_{1000}
RN vote share (%), 2014	0.01	0.04	0.07	0.10	-0.87	0.55	0.51
Log RN voters, 2014	0.40	1.63	3.43	4.85	0.88	0.54	0.53
Population per km^2, 2019	474.89	1,330.45	503.70	572.27	-0.07	0.95	0.52
Share of people aged < 25, 2019	0.10	0.02	0.10	0.02	-0.20	0.87	0.51
Share of people aged 75+, 2019	0.10	0.04	0.10	0.01	-0.29	0.82	0.54
Share of men, 2019	0.49	0.02	0.49	0.03	0.15	0.91	0.51
Share of recent migrants, 2019	0.002	0.004	0.001	0.002	0.94	0.52	0.54
Δ Recent migrant share, 2013-2019	0.0002	0.003	-0.001	0.003	0.49	0.71	0.54
Share aged > 15 not in education, 2019	0.78	0.04	0.78	0.03	-0.07	0.96	0.54
Share of industrial employment, 2019	0.15	0.13	0.09	0.05	1.70	0.34	0.54
Share of employed people, 2019	0.44	0.08	0.45	0.01	-1.82	0.32	0.51
Share manual employment, 2019	0.23	0.09	0.18	0.08	0.89	0.54	0.54
Number of residences, 2019	1,924.08	3,287.32	2,429.22	2,604.48	-0.27	0.83	0.51

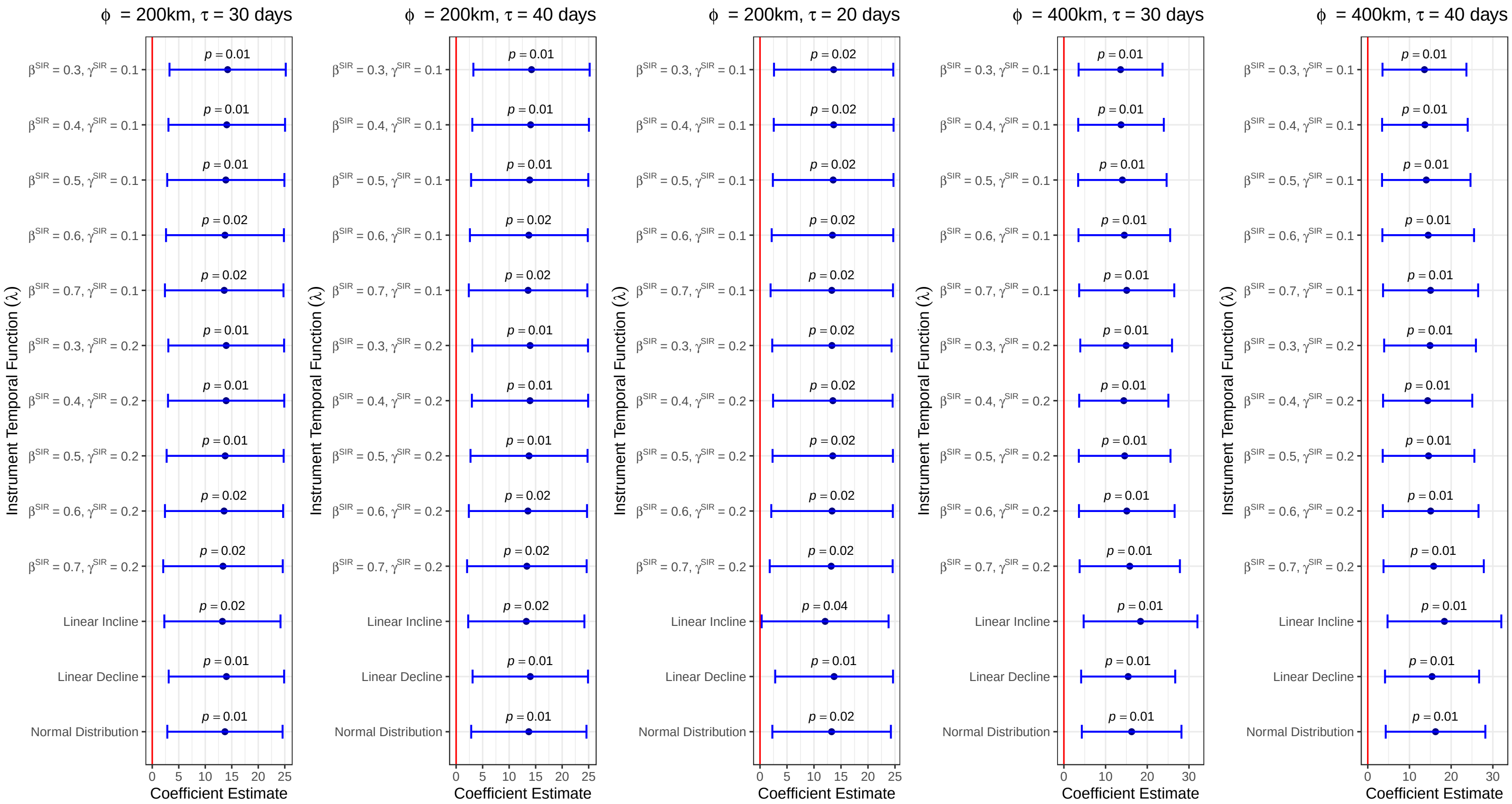
Notes: Comparison of French municipalities (*communes*) with and without SSEs before the first round of the 2020 municipal elections (15 March) on measures and predictors of populist support before the COVID-19 pandemic. The last three columns report the results of a two-sample *t*-test — regular and bootstrapped with 1,000 samples — for the difference in means between the two sets of municipalities.

FIGURE A10. Second-Stage Results with Varying Instrument Parameters



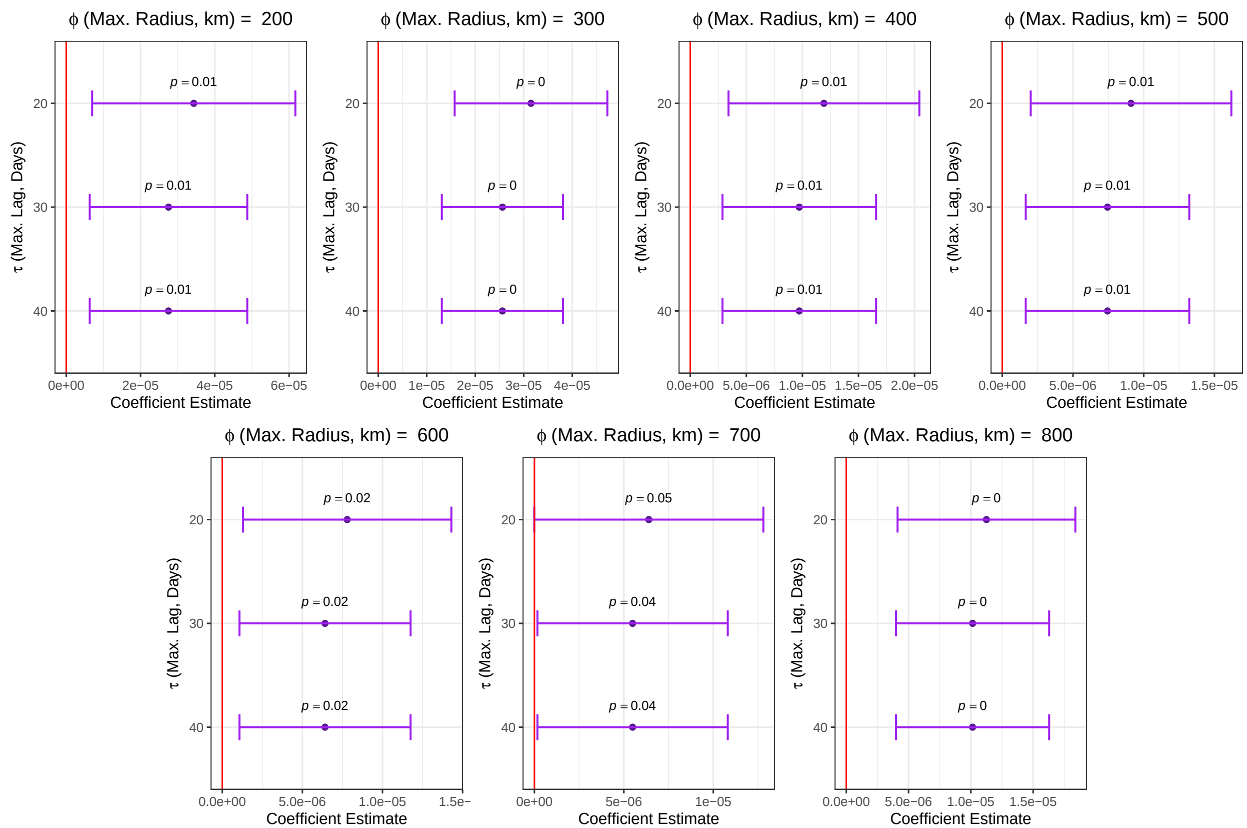
Notes: Municipality-election-level 2SLS estimates from Equation 6 with 95% confidence intervals based on robust standard errors clustered by municipality. The maximum distance (ϕ in Equation 1) and time lag (τ) used to construct the SSE exposure instrument varies across models. All models include municipality and election fixed effects and control for the male-female ratio, population density, the share of young people, the share of elderly people, the share of people with no schooling, the share of industrial workers, the manual share of employment, the share of recent overseas migrants, the total number of RN voters, and the size of the housing stock.

FIGURE A11. Second-Stage Results with Alternative Temporal Functions



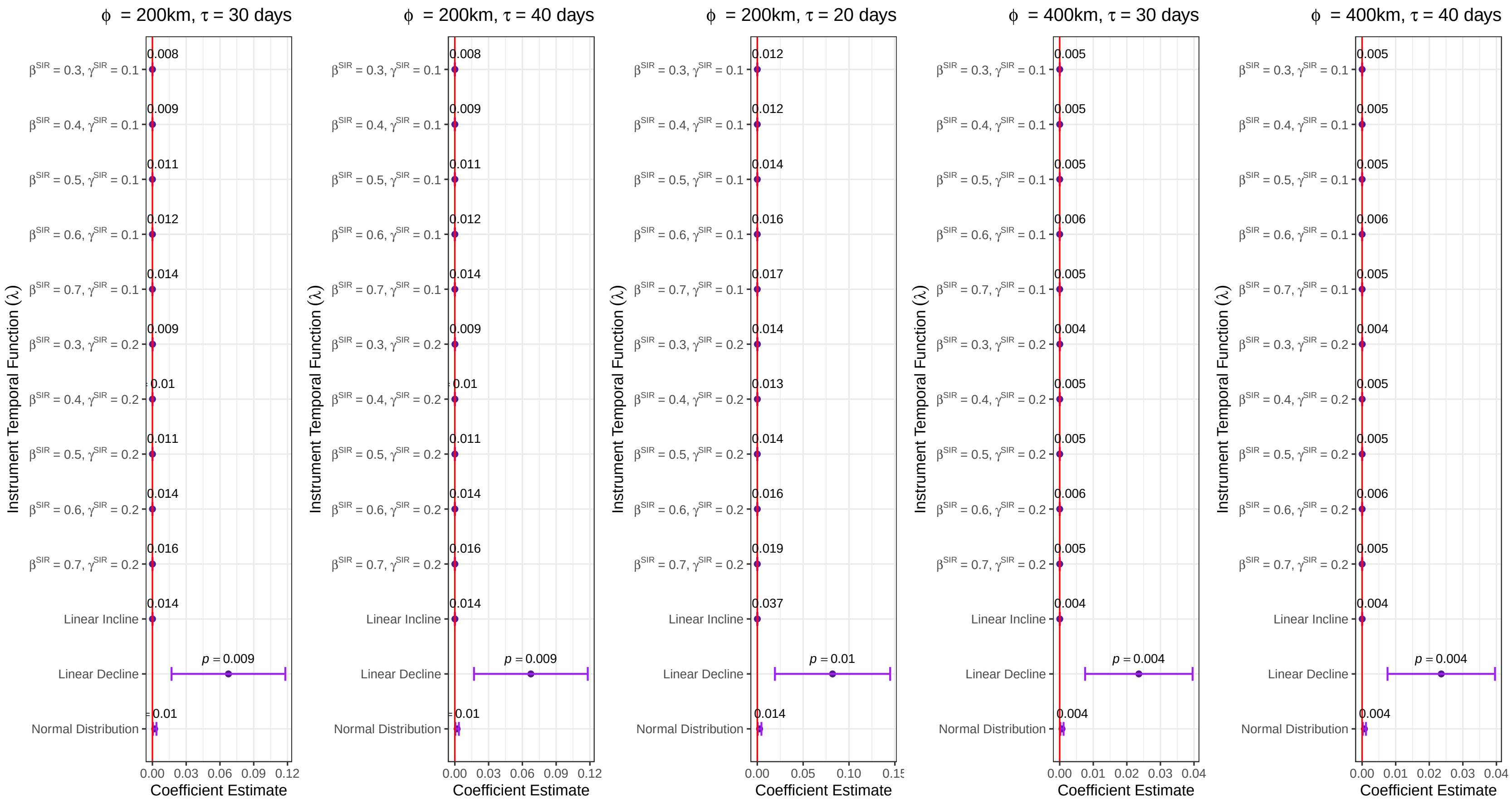
Notes: Municipality-election-level 2SLS estimates from Equation 6 with 95% confidence intervals based on robust standard errors clustered by NUTS-3 region. The distribution of temporal weights attached to the SSE exposure instrument (λ in Equation 1) varies across models. All models include municipality and election fixed effects and control for the male-female ratio, population density, the share of young people, the share of elderly people, the share of people with no schooling, the share of industrial workers, the manual share of employment, the share of recent overseas migrants, the total number of RN voters, and the size of the housing stock.

FIGURE A12. SSE Exposure and RN Support with Varying Instrument Parameters



Notes: Municipality-election-level OLS estimates from the specification reported in Panel B of Table 5 with 95% confidence intervals based on robust standard errors clustered by municipality. The maximum distance (ϕ in Equation 1) and time lag (τ) used to construct the SSE exposure instrument varies across models. All models include municipality and election fixed effects and control for the male-female ratio, population density, the share of young people, the share of elderly people, the share of people with no schooling, the share of industrial workers, the manual share of employment, the share of recent overseas migrants, the total number of RN voters, and the size of the housing stock.

FIGURE A13. SSE Exposure and RN Support with Alternative Temporal Functions



Notes: Municipality-election-level OLS estimates from the specification reported in Panel B of Table 5 with 95% confidence intervals based on robust standard errors clustered by municipality. As per the legend, the distribution of temporal weights attached to the SSE exposure treatment (λ in Equation 1) varies across models. All models include municipality and election fixed effects and control for the male-female ratio, population density, the share of young people, the share of elderly people, the share of people with no schooling, the share of industrial workers, the manual share of employment, the share of recent overseas migrants, the total number of RN voters, and the size of the housing stock.

TABLE A13. PLACEBO ANALYSIS: FUTURE COVID-19 EXPOSURE AND POPULIST SUPPORT IN THE 2008 AND 2014 FRENCH MUNICIPAL ELECTIONS

Outcome: RN Vote Share (mean = 0.01)	(1)	(2)	(3)	(4)	(5)
Panel A: 2SLS Estimates (Instrument = Future SSE Exposure)					
Log Cumulative COVID Cases	2.641	2.641	3.438	3.617	3.617
per 10,000 Pop. (Instrumented)	(2.867)	(2.867)	(2.875)	(2.962)	(2.962)
First-Stage F-Statistic	360.504	360.504	340.269	391.678	391.678
Panel B: OLS Estimates (Treatment = Instrument)					
Future SSE Exposure Instrument	0.00001	0.00001	0.00002	0.00001	0.00001
	(0.00002)	(0.00002)	(0.00002)	(0.00001)	(0.00001)
Instrument Maximum Radius (ϕ)	200	200	200	400	400
Instrument Maximum Lag (τ)	30	40	20	30	40
Municipality FE	✓	✓	✓	✓	✓
Election (2008/2014) FE	✓	✓	✓	✓	✓
Municipality-Level Controls	✓	✓	✓	✓	✓
N	12,119	12,119	12,119	12,119	12,119

Notes: Municipality-election-level 2SLS (panel A) and OLS (panel B) estimates with robust standard errors, clustered by municipality, in parentheses. Controls (measured as of 2008 or 2013): male-female ratio, population density, share of young people, share of people with no schooling, share of industrial workers, share of unemployed people, manual share of employment, logged total RN voters. A small number of controls from Table 5 could not be included due to multicollinearity. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE A14. Populist Support and Twitter Engagement in French Municipal Elections

Outcome: RN Vote Share 2020	(1)	(2)	(3)
Panel A. Treatment: Twitter Engagement with RN			
Log RN Mentions per 1,000 Pop.	0.003		
	(0.003)		
Log RN Retweets per 1,000 Pop.		0.005***	
		(0.001)	
Log RN Likes per 1,000 Pop.			0.004***
			(0.001)
Panel B. Treatment: Unique Twitter Users Engaging with RN			
Log RN Mentions per 1,000 Pop.	0.004		
	(0.003)		
Log RN Retweets per 1,000 Pop.		0.006***	
		(0.001)	
Log RN Likes per 1,000 Pop.			0.004***
			(0.001)
NUTS-3 FE	✓	✓	✓
Municipality-Level Controls	✓	✓	✓
RN Vote Share 2014	✓	✓	✓
Mean Outcome Variable	0.005	0.005	0.005
N (Municipalities)	9,302	9,302	9,302

Notes: This table presents OLS estimates of the association between the RN's level of Twitter engagement and subsequent vote share in the first round of the 2020 French municipal elections (on 15 March). The controls are the same as in Table 5 aside from the number of RN voters, which is replaced by the RN's vote share in the 2014 elections. Robust standard errors, in parentheses, are clustered at the NUTS-3 level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

F British Survey Analysis

TABLE A15. Association between Local and Personal Exposure to COVID-19 in UK

Outcome:	Infected with COVID (1)	Close Family/ Friend Infected (2)	Acquaintance Died from COVID (3)
Panel A: BES Wave 21 (May 2021)			
Log Cumulative COVID-19 Cases per 10,000 Pop.	0.052***	0.076***	0.043***
	(0.011)	(0.016)	(0.012)
Mean Outcome Variable	0.155	0.329	0.215
N	11,104	12,353	11,800
Panel B: BES Wave 20 (June 2020)			
Log Cumulative COVID-19 Cases per 10,000 Pop.	0.035**	0.030*	0.091***
	(0.014)	(0.016)	(0.020)
Mean Outcome Variable	0.137	0.161	0.177
N	488	603	577
Controls	✓	✓	✓
Local Authority FE	✓	✓	✓

Notes: Respondent-level OLS estimates of the association between local and personal exposure to COVID-19 in the United Kingdom in 2020 and 2021; robust standard errors, clustered by local authority, are in parentheses. Controls: ethnicity, gender, education level, homeownership, religion, gross income. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE A16. Severity of Individual COVID-19 Exposure and Populist Voting Preferences

Outcome: Populist Vote Likely	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Severity of COVID Infection (1-5)	0.003	0.050								
	(0.010)	(0.038)								
Severity of Family COVID Infection (1-6)			-0.001	-0.013						
			(0.005)	(0.023)						
Severity of Someone Close's COVID Infection (1-6)					-0.006	-0.002				
					(0.006)	(0.041)				
Infected with COVID (0/1) × Age							0.001**	0.003		
							(0.000)	(0.015)		
Close to Someone Infected with COVID (0/1) × Age									0.000	0.007
									(0.000)	(0.013)
Respondent-Level Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Wave FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Local Authority FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Respondent FE		✓		✓		✓		✓		✓
Mean Outcome Variable	0.22	0.19	0.18	0.19	0.15	0.16	0.19	0.20	0.20	0.20
N	2,636	696	4,202	936	1,812	196	17,816	7,940	20,152	9,886

Notes: Respondent-wave-level OLS estimates with robust standard errors, clustered by respondent, in parentheses. Controls: left-right ideology, age, education level, gross income, employment status, social class, homeownership, household size. The three measures of personal COVID-19 severity have an ordinal scale where 1 = "Could still do all daily activities"; 2 = "Had to stop some daily activities"; 3 = "Most daily activities were not possible"; 4 = "Required hospitalisation"; 5 = "Required ventilation"; and 6 = "They passed away." $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Full Questions and Response Options

This section provides the full text and response options for the questions used in our analyses of the BES panel. We begin with the analysis of COVID-19's impact on voting intentions.

Populist Voting

- "How likely is it that you would ever vote for each of the following parties?" Options: "UKIP"; "Greens"; "BNP"; "The Independent Group"; "The Brexit Party/Reform UK"; "Alba Party." Answer scale: 0-10 ordinal, where 0 = "Very unlikely" and 10 = "Very likely." In Table 6, *Populist Vote Not Very Unlikely* is equal to 1 if the response for "UKIP" or "The Brexit Party/Reform UK" is greater than 0; *Populist Vote Likely* is equal to 1 if this response is greater than 4.

In our investigation of causal mechanisms, we analyze responses to eight questions in Wave 20 of the BES, which we group into six categories: *confidence in institutions*, *financial situation*, *anxiety*, *opposition to government response*, *out-group hostility*, and *social isolation*.

Confidence in Institutions

- "How much trust do you have in Members of Parliament in general?" Answer scale: 1-7 ordinal, where 1 = "No trust" and 7 = "A great deal of trust."
- "How much do you trust the Parliament at Westminster?" Answer scale: 1-7 ordinal, where 1 = "No trust" and 7 = "A great deal of trust."

Financial Situation

- "How does the financial situation of your household now compare with what it was 12 months ago?" Answer scale: 1-5 ordinal, where 1 = "Got a lot worse"; 2 = "Got a little worse"; 3 = "Stayed the same"; 4 = "Got a little better"; 5 = "Got a lot better."

- "How do you think the general economic situation in this country has changed over the last 12 months?" Answer scale: 1-5 ordinal, where 1 = "Got a lot worse" and 5 = "Got a lot better."

Anxiety

- "Overall, how anxious did you feel yesterday?" Answer scale: 0-10 ordinal, where 0 = "Not at all anxious" and 10 = "Completely anxious."
- "Overall, how satisfied are you with your life nowadays?" Answer scale: 0-10 ordinal, where 0 = "Not at all satsified" and 10 = "Completely satisfied."
- "Overall, to what extent do you feel that the things you do in your life are worthwhile?" Answer scale: 0-10 ordinal, where 0 = "Not at all worthwhile" and 10 = "Completely worthwhile."
- "Overall, how happy did you feel yesterday?" Answer scale: 0-10 ordinal, where 0 = "Not at all happy" and 10 = "Completely happy."

Opposition to Government Response

- "How well do you think the UK government has handled: The coronavirus lockdown?" Answer scale: 1-5 ordinal, where 1 = "Very badly" and 5 = "Very well."
- "How well do you think the UK government has handled: The testing of the population for coronavirus?" Answer scale: 1-5 ordinal, where 1 = "Very badly" and 5 = "Very well."
- "In March, the government ordered a "lockdown" requiring people to stay at home most of the time to help reduce the spread of the coronavirus. A lockdown like this substantially reduces economic activity. How strongly do you support or oppose a lockdown being in place at this time?" Answer scale: 0-10 ordinal, where 0 = "Strongly oppose lockdown" and 10 = "Strongly support lockdown."

Outgroup Hostility

- "And do you think that immigration undermines or enriches Britain's cultural life?" Answer scale: 1-7 ordinal, where 1 is the minimum and 7 is the maximum.
- "Some people think that the UK should allow many more immigrants to come to the UK to live and others think that the UK should allow many fewer immigrants. Where would you place yourself [...] on this scale?" Answer scale: 1-10 ordinal, where 0 = "Many fewer" and 10 = "Many more."
- "Do you think that Britain should allow more or fewer of the following kinds of people to come and live in Britain? Asylum Seekers." Answer scale: 0-10 ordinal, where 1 = "Many fewer" and 10 = "Many more."

Social Isolation

- "If you need help on short notice in the following areas, would you personally know someone who would be able to help you out within one week?...None of these" (areas: give you sound advice on your work; help you with small jobs around the house; do your shopping if you are ill or look after your home or pets if you go away; lend you money; discuss politics with you; give you sound advice on legal or money matters; give you a good reference for a job; help you to find somewhere to live if you had to move home). Answer scale: binary 0/1.
- "Do you personally know anyone with the following occupations that you could reach on short notice, say within a week?...None of these" (occupations: works for your local council; is a local councillor; is in a position to hire other people; has a profession such as a lawyer, teacher or accountant?). Answer scale: 1-4 categorical, where 1 = "No, I do not know any such person"; 2 = "Yes, I know such a person and could reach them by the internet"; 3 = "Yes, I know such a person and could reach them by internet and in other ways"; 4 = "Yes, I know such a person and could reach them by internet and in other ways." In Table 7, *No Professional Network* is equal to 1 if respondents select option 1 and to 0 otherwise.

- “Do you personally know anyone who knows a lot about the following things and who you could reach on short notice, say within a week?...None of these” (items: is a reliable tradesman; can speak another language fluently; knows how to fix problems with computers; knows a lot about government regulations; has good contacts with the local newspaper radio or TV; knows a lot about health and fitness). Answer scale: 1-4 categorical, where 1 = “No, I do not know any such person”; 2 = “Yes, I know such a person and could reach them by the internet”; 3 = “Yes, I know such a person and could reach them by internet and in other ways”; 4 = “Yes, I know such a person and could reach them by internet and in other ways.” In Table 7, *No Skilled Network* is equal to 1 if respondents select option 1 and to 0 otherwise.

Control Variables

In both sets of analyses, we control for several socioeconomic and demographic variables, some of which we convert into categorical form:

- Age: ordinal scale.
- Gender: 1-2 categorical scale, where 1 = “Male” and 2 = “Female.”
- White: dummy variable based on the question, “To which of these groups do you consider you belong?” Variable is equal to 1 if respondents answer “White British” and to 0 otherwise.
- Educated: dummy variable based on the question: “What is the highest educational or work-related qualification you have?” Response options: 1 = “No formal qualifications”; 2 = “Youth training certificate/skillseekers”; 3 = “Recognised trade apprenticeship completed”; 4 = “Clerical and commercial”; 5 = “City & Guilds certificate”; 6 = “City & Guilds certificate - advanced”; 7 = “ONC”; 8 = “CSE grades 2-5”; 9 = “CSE grade 1, GCE O level, GCSE, School Certificate”; 10 = “Scottish Ordinary/ Lower Certificate”; 11 = “GCE A level or Higher Certificate”; 12 = “Scottish Higher Certificate”; 13 = “Nursing qualification (e.g. SEN, SRN, SCM, RGN)”; 14 = “Teaching qualification (not degree)”; 15 = “University diploma”; 16 = “University or CNAA first degree (e.g. BA, B.Sc, B.Ed)”; 17 = “University or CNAA higher degree (e.g. M.Sc, Ph.D)”; 18 = “Other

technical, professional or higher qualification." Variable is equal to 1 if the respondent's answer is above the sample mean and to 0 otherwise.

- Religious: dummy variable based on the question, "Do you regard yourself as belonging to any particular religion, and if so, to which of these do you belong?" Answer options: 1 = "No, I do not regard myself as belonging to any particular religion"; 2 = "Church of England/Anglican/Episcopal"; 3 = "Roman Catholic"; 4 = "Presbyterian/Church of Scotland"; 5 = "Methodist"; 6 = "Baptist"; 7 = "Orthodox Christian"; 8 = "Pentecostal (e.g. Assemblies of God, Elim Pentecostal Church, New Testament Church of God, Redeemed Christian Church of God)"; 9 = "Evangelical – independent/non-denominational (e.g. FIEC, Pioneer, Vineyard, Newfrontiers)"; 10 = "United Reformed Church"; 11 = "Free Presbyterian"; 12 = "Brethren"; 13 = "Judaism"; 14 = "Hinduism"; 15 = "Islam"; 16 = "Sikhism"; 17 = "Buddhism"; 18 = "Other." Variable is equal to 1 if respondent select option 1 and to 0 otherwise.
- Homeowner: dummy variable based on the question, "Do you own or rent the home in which you live?" Response options: 1 = "Own - outright"; 2 = "Own – with a mortgage"; 3 = "Own (part-own) – through shared ownership scheme (i.e. pay part mortgage, part rent)"; 4 = "Rent – from a private landlord"; 5 = "Rent – from my local authority"; 6 = "Rent – from a housing association"; 7 = "Neither – I live with my parents, family or friends but pay some rent to them"; 8 = "Neither – I live rent-free with my parents, family or friends"; 9 = "Other." Variable is equal to 1 if respondents select options 1-3 and to 0 otherwise.
- Left-right scale: "In politics people sometimes talk of left and right. Where would you place yourself on the following scale?" Answer scale: 0-10 ordinal, where 0 = "left" and 10 = "right."

G Dutch Survey Analysis

TABLE A17. Personal COVID-19 Exposure and Populist Voting Preferences in the Netherlands

Outcome: Populist Voting Intention	(1)	(2)	(3)	(4)
Infected with COVID	0.069**		0.104***	
	(0.034)		(0.034)	
Family or Household		0.065**		0.101***
Affected by COVID		0.030)		(0.032)
Individual-Level Controls	✓	✓	✓	✓
Weighting Factor			✓	✓
Mean Outcome Var.	0.109	0.114	0.109	0.114
N	1,310	1,459	1,310	1,459

Notes: Individual-level OLS estimates with robust standard errors in parentheses. All models control for age, gender, education level, occupation, and household position; in columns 3 and 4, observations are weighted by an age × gender × education factor. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Full Questions and Response Options

Populist Voting Intention The full questions in the LISS panel survey on "consequences of COVID for the quality of society" (CentERdata, 2020) that we employ in our analysis of voting intentions are:

- "If *Tweede Kamer* (House of Representatives) elections were to be held right now, would you vote?" Answer scale: 17 categories. In Table A17, *Populist Voting Intention* is equal to 1 if respondents select option 6 ("Forum voor Democratie (pro-direct democracy party)") or 10 ("PVV (Party for Freedom)") 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, where 0 = "No"; 1 = "Yes."

In Table A17, *Family or Household Affected by COVID-19* is equal to 1 if respondents select option 1 and to 0 otherwise.

Control Variables 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.

Causal Mechanisms In our investigation 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 (All Waves)

- "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" and 10 = "full confidence."

Financial Situation (All Waves)

- "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."
- "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" and 10 = "very satisfied."
- "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" and 100 = "I am sure that I will lose my job."

Social Isolation (All Waves)

- "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 (All Waves)

- “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” and 5 = “much more dejected.”
- “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” and 5 = “very little.”

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” and 5 = “completely agree.”

- “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.”
- “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.”
- “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.”

Outgroup 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” and 10 = “Severe friction.”
- “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” and 5 = “completely agree.”
- “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” and 10 = “completely entitled.”

H Mechanisms

TABLE A18. Lockdown Stringency and Populist Twitter Engagement

Outcome:	Log Populist Mentions (1)	Log Populist Retweets (2)	Log Populist Likes (3)
Lockdown Stringency	0.005**	0.039***	0.031***
(Instrumented)	(0.002)	(0.007)	(0.006)
NUTS-3 FE	✓	✓	✓
Day FE	✓	✓	✓
First-Stage F-Statistic	45.647	45.647	45.647
Mean Outcome Var.	0.09	0.84	0.98
N	119,393	119,393	119,393

Notes: NUTS-3-day-level 2SLS estimates with robust standard errors, clustered by NUTS-3 region, in parentheses. The specification is a modified version of our instrumental variables analysis of COVID-19's impact on populist Twitter engagement (Equations 3 and 4) in which lockdown stringency index is the endogenous regressor. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE A19. The "Supply" of Twitter Discourse: Populists versus Non-Populists

Outcome:	Probability COVID-19 is Mentioned		Log Tweets Mentioning COVID-19		Log All Tweets	
	(1)	(2)	(3)	(4)	(5)	(6)
Right-Wing Populist Author	-0.023	-0.021	0.057	0.058	0.230	0.231
	(0.030)	(0.030)	(0.102)	(0.102)	(0.211)	(0.211)
Log COVID Cases per 10k Pop.	Daily	Cumul.	Daily	Cumul.	Daily	Cumul.
Leader Account	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓	✓
Mean Outcome Variable	0.14	0.14	0.40	0.40	1.57	1.57
N	42,597	42,597	4,996	4,996	4,996	4,996

Notes: Columns 1 and 2 report estimates from a tweet-day-level linear probability model predicting whether a given tweet mentions COVID-19 conditional on whether the author is a populist. In columns 3-6, where the data have an author-day panel structure, the outcome variable is instead the logarithm of daily tweets that mention COVID-19 (columns 3-4) or the logarithm of all daily tweets (columns 5-6). Robust standard errors, in parentheses, are clustered by author. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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