How COVID-19 affects voting for incumbents: Evidence from local elections in France*

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Abstract

How do voters react to an ongoing natural threat? We address this question by investigating voters' reactions to the early spread of COVID-19 in the 2020 French municipal elections. Using a novel, fine-grained measure of the circulation of the virus based on excess-mortality data, we find that support for incumbents increased in the areas that were particularly hit by the virus. Incumbents from both left and right gained votes in areas more strongly affected by COVID-19. The results are robust to a placebo test and hold across different methods, including regressions with lagged dependent variables, a differences-in-differences approach and propensity score matching. We also provide indirect evidence for two mechanisms that can explain our findings: an emotional channel related to feelings of fear and anxiety, and a prospective-voting channel, related to the ability of incumbents to act more swiftly against the diffusion of the virus than challengers.

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How do natural threats affect voting behavior? Several studies have addressed this question in relation to different types of catastrophic events, such as earthquakes, floods, and hurricanes. The general finding is that these events do influence voting, with incumbents either gaining or losing consensus, mainly depending on how they respond to the natural catastrophe. Virtually all these studies focus on whether and how people change voting preferences *after* a disaster has occurred. However, we do not know how voters respond to a threatening event *while* it is unfolding. How do voters react to an ongoing natural threat?

We address this question by investigating voters' reactions to the early spread of COVID-19 in France. COVID-19 differs from common natural disasters since it is a prolonged threat that does not result in physical destruction but spreads invisibly, potentially affecting all human beings. Like other infectious diseases (Campante, Depetris-Chauvin, and Durante 2020), COVID-19 generates fear, which, we argue, increases voters' tendency to support incumbent candidates as a means to obtain safety and security. This dynamic applied especially at the onset of the pandemic when high uncertainty surrounded the best ways of containing the virus and guaranteeing citizens' safety.

We focus on the municipal elections that took place in France on 15 March 2020, when SARS-Cov-2, the virus causing COVID-19, was already circulating in the country, albeit in low numbers.¹ We exploit the uneven diffusion of the virus throughout the country to test whether support for local incumbents increased in the municipalities that were particularly hard hit by COVID-19, using regression models that control for the lagged dependent variable and condition on

¹On 15 March 2020 the total number of cases of COVID-19 in France was 4,532 (source: COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University. Available at <https://github.com/CSSEGISandData/COVID-19> [Accessed on 1 November 2021]).

baseline mortality rates, a difference-in-differences approach, and propensity score matching. To estimate the “threat” of COVID-19, we developed a novel, fine-grained measure of the spread of the virus at the municipality level, using excess-mortality data weighed by the age and sex structure of the population. This measure accounts for the Infection Fatality Ratio (O’Driscoll et al. 2021) and allows us to address the problems of underreporting the circulation of the virus at the beginning of the pandemic using the number of cases (Russell et al. 2020).

Our findings show that votes for local incumbents increased as the threat of COVID-19 also increased. In the municipalities with a high circulation of the virus (tenth decile), the average vote for incumbents was 3.7 percentage points higher than in the places with a low circulation (first decile). The effects are not sensitive to the political affiliation of the incumbents, as support for incumbents increases regardless of whether they are left-wing, right-wing, or from other parties.

We also find suggestive evidence that the effect of COVID-19 on voting is more pronounced in the areas where people feel particularly anxious about the pandemic and where economic welfare has improved during the outgoing administration. This evidence supports our argument that, when threatened by the circulation of the virus at the beginning of the pandemic, voters turned to incumbents as a means of reducing fear and anxiety—an “emotional channel” in line with recent evidence in the United States (Bisbee and Honig 2021). In addition, following the logic of prospective voting, we argue that voters support incumbents to maintain continuity with the current administration as the most efficient means of tackling the virus, especially in areas where the incumbent mayors had performed well.

In the next section, we review existing research on the effects of natural disasters on voting and advance our arguments for why the early spread of COVID-19 should influence support for local incumbents. We then provide brief background information on the 2020 municipal elections in France, describe our data and methods, and present the results. In the conclusions, we summarize our findings and discuss the implications and potential limitations of our study.

NATURAL THREATS AND SUPPORT FOR INCUMBENTS

Research shows that voters punish or credit political candidates depending on how they respond to severe weather phenomena. For example, studies indicate that incumbent politicians lose support if their response to natural disasters is perceived as inadequate (Akarca and Tansel 2007; Eriksson 2016; Lay 2009). Voters also punish incumbents in the aftermath of severe weather events that cause economic damage, such as tornadoes and extreme rainfall (Cole, Healy, and Werker 2012; Gasper and Reeves 2011; Healy, Malhotra, and Mo 2010), and even in the case of events that are clearly out of politicians' control, such as shark attacks (Achen and Bartels 2016). On the other hand, there is evidence that voters reward governments and incumbent politicians who are seen as having responded well to natural disasters (Bechtel and Hainmueller 2011; Belloc, Drago, and Galbiati 2016; Healy and Malhotra 2009; Masiero and Santarossa 2021).²

The primary mechanism underlying voters' reaction after a disaster has occurred is retrospective voting (Fiorina 1981): on election day, voters sanction or reward politicians depending on how well

²On the debate on why incumbents might gain or suffer electorally after extreme weather events, see also Bechtel and Mannino (2020).

they responded to the damage caused by the natural catastrophe. At the beginning of the COVID-19 pandemic, however, it was unclear how to best respond to the circulation of the virus. As an invisible threat that does not lead to physical destruction and persists for an indefinite period, COVID-19 cannot be tackled with the same means used after a natural catastrophe. Relief spending and the type of reconstruction undertaken after natural disasters were not viable options for incumbent politicians at the beginning of the pandemic. This is especially true for local mayors who lacked the legal authority to introduce strong containment measures, such as lockdowns. Thus, the initial spread of COVID-19 should not have affected voting for local incumbents through retrospective evaluations since it was unclear how politicians ought to have responded to the pandemic.

The spread of COVID-19 also differs from the types of threats that lead people to “rally around the flag”, i.e., express greater support for incumbent political leaders following sudden, dramatic events (Baker and Oneal 2001; Lambert, Schott, and Scherer 2011; Mueller 1970). These threats concern mostly terrorist attacks (see for example Dinesen and Jæger 2013; Gaines 2002; Hetherington and Nelson 2003; Hinson and Vaishnav 2021; Perrin and Smolek 2009) or military crises (Baker and Oneal 2001) that boost presidential popularity and government support in the short term. Besides being related to “human” and not natural threats, rally effects are activated mostly by a sentiment of patriotism and by anger toward a clearly identifiable external aggressor (Lambert, Schott, and Scherer 2011). The threat of COVID-19, however, should not activate the same feelings of anger and patriotism, since there is not a deliberate attack behind the circulation of the virus (i.e., the virus did not “intend” to attack a population, as terrorists do), and there is no clearly identifiable human enemy against whom the population should mobilize.

Still, even if retrospective evaluations and rally effects should not play a (clear) role in explaining why the spread of COVID-19 would affect voting, there is evidence that incumbents' popularity increased across several countries at the start of the pandemic (De Vries et al. 2021; Jennings 2020). This boost in support occurred *before* most governments took active measures to contain the virus, thus making it unlikely that voters retrospectively rewarded their governments because of their specific response to the pandemic. Instead, we argue that two additional channels can explain why the threat posed by COVID-19 at the very beginning of the pandemic influenced the vote for incumbents. These channels lead us to the expectation that support for local incumbents would increase in the areas most severely hit by the pandemic.

The first is an emotional channel, concerning the fact that COVID-19 triggers fear and anxiety, as indicated by psychological studies (Hyland et al. 2020; Petzold et al. 2020). As with the Ebola virus, when it reached the US in 2014 (Campante, Depetris-Chauvin, and Durante 2020), at the beginning of the pandemic, COVID-19 represented an invisible threat against which there was no clear remedy, thus potentially inducing fear in the population. Different strands of theories indicate that sentiments of fear and anxiety lead to risk-aversion (for a review, see Wagner and Morisi 2019), which, in turn, should translate into increased support for incumbent candidates, as they represent a safer, status quo option compared to the risk of electing an as-yet-untested challenger.

Furthermore, according to terror-management theory (Greenberg, Solomon, and Pyszczynski 1997) and motivated-social-cognition theory (Jost et al. 2003), people are motivated to see the world as a secure place. Thus, in the presence of a fear-inducing threat such as COVID-19, they should turn their support toward incumbent politicians who offer an actual or symbolic sense of safety and security by representing the status quo. Indeed, evidence indicates that the spread of COVID-19 and

lockdown measures at the beginning of the pandemic increased support for candidates representing the “status quo” in the US (Bisbee and Honig 2021) and for incumbents and national governments in Europe (Bol et al. 2020; De Vries et al. 2021; Esaiasson et al. 2020).

The second channel refers to prospective voting based on the simple consideration that during a crisis “it is no good time for a change.”³ In line with the idea of prospective voting (Lockerbie 1991; Rosema 2006), voters compare how challengers versus incumbents will perform in relation to containing the virus. Anticipating that the threat of COVID-19 is going to last, and given that virtually no candidate has a track record in dealing with a pandemic, voters might consider that incumbents will perform better simply because they have had several years of experience with the local administration and can swiftly mobilize all the available local resources. In other words, in a scenario of a looming threat, voters might prefer to maintain continuity with the current administration as the most efficient means of tackling the virus and restoring safety. On the other hand, choosing a challenger over the incumbent might delay the necessary response to the pandemic due to the period of transition to the new administration.

Both the emotional channel and the prospective-voting channel lead us to the expectation that support for incumbents should increase in the areas where the spread of COVID-19 was higher at the early stage of the pandemic. According to these theoretical channels, support for incumbents should increase regardless of their political affiliation, as voters threatened by COVID-19 turn to incumbents mainly because they represent the status quo. Previous studies, however, indicate that it is mostly

³This channel applies to voting while a threat is present in the population, as in the case of COVID-19, or to voters anticipating that natural disasters might occur in the near future (Leininger and Schaub 2020).

right-wing incumbents that gain from military threats because their aggressive defense strategies are seen as more in line with citizens' need for protection compared to other parties' strategies (Berrebi and Klor 2008; Getmansky and Zeitzoff 2014). Although the spread of COVID-19 differs from military threats, if right-wing incumbents are better suited to reducing anxiety and addressing citizens' need for safety and security, we might expect voters to increase support for right-wing incumbents in particular, when the circulation of the virus is high.

MUNICIPAL ELECTIONS IN FRANCE

On March 15, 2020 French voters went to the polls to choose the mayors of all of the nearly 35,000 municipalities in the country. Municipal elections in France are held every six years, and, depending on the size of municipality, consist of one or up to two rounds. In small municipalities with under 1,000 inhabitants, voters choose lists of candidates and are allowed to cast a vote for more than a single candidate in a majoritarian system.⁴ In larger towns and cities with more than 1,000 inhabitants, elections consist of one or two rounds. In the first round, all lists of candidates standing for the election compete against each other. In case no list obtains more than 50 percent of the vote, a run-off election is held in which all the lists that obtained more than 10 percent of the votes compete again for election. This second round is usually held two weeks after the first round.

In 2020 the first round of the municipal elections was held as scheduled, despite a partial lockdown in some places. However, as the number of cases of COVID-19 continued to increase, the

⁴In addition, the candidates in towns with less than 1000 inhabitants are not required to declare any political affiliation.

day after the first round of the elections, President Macron announced that the second round would be postponed to an unspecified date, which was later set to June 28, 2020.

Compared to the previous local elections in 2014, turnout dropped substantially. While in 2014, 63.5 percent of eligible voters went to cast their ballot in the first round of the elections, on March 15, 2020 less than half of eligible voters (44.7 percent) went to vote. This drop in the participation was likely due to the circulation of the virus, as confirmed by a recent study (Noury et al. 2021).

DATA AND METHODS

Voting and census data

We retrieve electoral data for the municipal elections in 2020 and 2014 from the Ministry of the Interior.⁵ We consider only the municipalities that in both election rounds had more than 1000 inhabitants due to the differences in electoral rules explained above. We also exclude overseas territories and the cities of Paris, Marseille and Lyon, since the voting system also differs in these areas. After excluding these observations, we are left with a sample of 8,193 municipalities.

To determine which candidates running in 2020 were incumbents, we matched the names of those who were elected mayor in 2014 with the names of the 2020 candidates. This operation gives us our effective sample of 4,952 municipalities (around 56%) in which an incumbent was running in

⁵Source: first round of the 2020 election, <https://www.data.gouv.fr/fr/datasets/elections-municipales-2020-resultats/> (downloaded on June 10, 2020); second round of the 2020 election, <https://www.data.gouv.fr/fr/datasets/municipales-2020-resultats-2nd-tour/> (downloaded on July 1, 2020); 2014 election, <https://www.data.gouv.fr/fr/datasets/?organization=534ff91a3a7292c64a77f53&q=%C3%A9lections%20municipales%202014> (downloaded on June 10, 2020).

2020.⁶ Our outcome of interest is the share of votes for the incumbents in the first round of the municipal elections in 2020. Crucially, in all regression models we include the vote share for the same candidates in 2014, which allows us to estimate whether the spread of COVID-19 influences the *change* in vote shares for incumbents in 2020 compared to 2014.

We also retrieve information about the political affiliation of the incumbent candidates to test for heterogeneous effects depending on the incumbents' political leaning. In 2014, all candidates competing in municipalities above 1000 inhabitants had to indicate their political affiliation, which was then classified by the Ministry of the Interior. We use this information to distinguish between incumbents related to left-wing parties (22%), right-wing parties (47%), and a residual category including mostly candidates with no clear left-right affiliation and a few centrist candidates (31%). In Table A3 we provide detailed information about each political group.

Furthermore, we collect census data at the municipality level from the year 2017 to control for key socio-economic indicators that might confound the relationship between the spread of COVID-19 and voting for incumbents.⁷ Specifically, in each model we include measures of population density, male over female ratio, the share of people aged above 65, the share of immigrants, the share of

⁶Balance statistics indicate that municipalities with and without incumbents are statistically indistinguishable across all our indicators, apart from population density and turnout in 2014, as municipalities with an incumbent are more densely populated and have a higher turnout in 2014 than municipalities without an incumbent (see Table A1).

⁷Source: French national institute for statistics. On immigration and professions: <https://www.insee.fr/fr/statistiques/4515919?sommaire=4516115&q=immigr%25C3%25A9%2520commune>. On median income: <https://www.insee.fr/fr/statistiques/4507225?sommaire=4507229#dictionnaire>. On demographic characteristics: <https://www.insee.fr/fr/statistiques/1893204>. Data downloaded on September 28, 2020.

blue-collar workers, the share of unemployed inhabitants, and the median income of households in the municipality.⁸ We use the logged transformation for each of these variables (apart from the median income) in order to account for the presence of outliers. Furthermore, we control for the level of turnout in 2014 to account for imbalances in voters' electoral participation at the municipality level. (For summary statistics, see Table A2).

Estimating the spread of COVID-19

Estimating the prevalence of COVID-19 at the municipality level is challenging, because of scattered data availability and the low reliability of common measures. For instance, reported cases of COVID-19 at the beginning of the pandemic were sensitive to differences in testing frequencies across the country and underestimated the circulation of the virus (Russell et al. 2020). The number of hospitalisations, on the other hand, is a more reliable indicator, but this data is not available at the municipality level, since hospitals are located only in few cities.

We decided, therefore, to use death records, which are publicly available and systematically recorded at the municipality level. In particular, we compute excess mortality in each municipality, by comparing the number of deaths after the elections in 2020, with the number of deaths in the same period in the previous years.

Excess mortality has been presented as a reliable method to estimate the number of COVID-19 cases, because mortality appears fairly stable over a period of a few years, making extreme mortality

⁸A directed acyclic graph (DAG) justifying the choice of control variables is included in the supplementary Figure A1.

events clearly visible in the form of peaks (Beaney et al. 2020; Karlinsky and Kobak 2021). Yearly influenza outbreaks, for instance, are clearly identifiable in country-wide weekly mortality records (see Figure B.1).

In order to compute the excess mortality (or excess hazard) at the municipality level we collected all mortality records between 2015 and 2020.⁹ We then estimated excess mortality around the time of the first round of elections by comparing mortality figures to those of the same period 2015–2019, thus avoiding seasonal variability. Aggregated mortality rates seem reasonably stable over the last half-decade for the period considered (see Figure B.2). Given the delay between infection and death, we consider all deaths occurring between the election day (March 15, 2020) up to six weeks later.¹⁰

Authors such as Beaney et al. (2020) have argued that excess death may be related indirectly to COVID-19 through the saturation of hospital facilities, interruption of preventative programmes or the impact of social restrictions on physical and mental health. However, it seems unlikely that these factors played a strong role at the very beginning of the pandemic. Instead, researchers have argued that the probability of dying from COVID-19 once infected by the virus (Infection Fatality Ratio, IFR) is heavily determined by age and sex¹¹ (O’Driscoll et al. 2021) and that excess mortality should be weighed by these factors if we intend to use it as a proxy for the circulation of the virus. In this sense, a 5% excess mortality in a relatively young city indicates that SARS-Cov-2, the virus

⁹Dates and places of deaths are recorded at the municipality level and available in open access at <https://www.data.gouv.fr/fr/datasets/fichier-des-personnes-decedees/>. We downloaded these data on July 6, 2020.

¹⁰In a supplementary analysis, we consider a shorter time window of four weeks, obtaining substantially similar results (see Table A5).

¹¹It also depends on other factors such as health infrastructure, which however, has been shown to be relatively constant country-wide (Gianicolo et al. 2021).

causing COVID-19, is circulating *more* than in a relatively old city with the same level of excess death, since young people are less likely to die from COVID-19 than elderly people. Therefore, we build a model to estimate COVID-19 prevalence at the municipality level from mortality data and use it as a novel measure describing the spread of COVID-19 which weights excess death by age and sex-specific infection fatality ratios, to better estimate the number of cases.

Specifically, use a Poisson mortality model where the municipality-level baseline hazard over the 6 weeks period is considered constant between 2015 and 2019 and death counts in 2020 result from the baseline hazard plus an excess hazard due to COVID-19. Baseline mortality is modulated by an age and sex effect. We account for the Infection Fatality Ratio (obtained from O’Driscoll et al. 2021) and estimate a municipality-level measure of prevalence based on age and sex specific baseline hazard for each municipality. Population data is obtained from Census data from 2010 to 2017 then either linearly or log-linearly extrapolated for 2018-2020 (see details in Appendix B.2).¹² (For detailed information on how we computed our measure, see Appendix B.) To deal with the presence of outliers among the municipalities, in the regression models we use either a decile version (treated as a continuous variable) or a quartile version of our measure (to test for non-linear effects). In supplementary analyses, we show that substantially similar results are obtained using a logged transformation or a quintile version of our measure (see Tables A4 and A5).

¹²Data on the age structure of the populations at the municipal level can be openly accessed at https://statistiques-locales.insee.fr/#c=indicator&i=pop_depuis_1876.dens&s=2017&view=map1. We downloaded these data on 10th July 2020. These data were only available up to the year 2017, which is why we extrapolated population sizes for the three years 2018-2020. We downloaded information on sex distribution from <https://www.insee.fr/fr/statistiques/1893204> on 28th September 2020.

Estimating the effect on incumbent voting

In order to estimate the effect of COVID-19 on incumbent vote shares, we estimate OLS regression models in the form

$$I_{m,d,20} = \alpha + \beta Cov_{m,20} + \gamma X_{c,t-1} + \eta I_{m,d,14} + \lambda_d + \epsilon_{m,d,t} \quad (1)$$

where $I_{m,d,20}$ is the vote share received by the incumbent in a given municipality m in 2020; $Cov_{m,20}$ measures the spread of COVID-19 in a given municipality in 2020; $X_{c,t-1}$ is a vector including the municipality-level census variables presented above (measured in 2017), in addition to the level of turnout in 2014 and a measure of baseline mortality. The baseline mortality is the municipality-specific probability to die during the period prior to the onset of the pandemic. Controlling for this measure is especially important since it captures various contributions to mortality—both observed and unobserved—thereby adjusting the otherwise quite diverse set of municipalities in terms of expected future mortality. $I_{m,d,14}$ is the incumbent's vote share in the election 2014; and λ_d are county (*Département*) fixed effects that remove time invariant factors at this level from our estimations.

Our parameter of interest is β . Since our models include the lagged dependent variable (i.e., vote for incumbents in 2014), β measures the *change* in incumbent support between the two elections related to the spread of COVID-19, all else being equal. We opted for this specification because it allows for more flexibility in the way the independent variable can be specified. Below we show that

our results also hold in a difference-in-differences framework, when matching municipalities using propensity scores and a punishing caliper, and are robust to a placebo test.

RESULTS

Figure 1 presents the results of our regression models. Both plots show that vote shares for incumbents are substantially higher where COVID-19 is more widespread. The left-hand plot indicates that support for local incumbents is 3.7 percentage points higher in the municipalities with high circulation of the virus (tenth decile) than in the municipalities with low circulation (first decile) – an increase that is statistically significant at $p < 0.001$. While in the latter group of municipalities the estimated, average vote share for local incumbents in the first round of the elections was 70.9 percent, in the former group it was 74.6 percent.

If we divide our measure of the spread of COVID-19 in quartiles, we find that the effect of the virus on voting is not linear. As the right-hand plot of Figure 1 indicates, the increase in votes occurs mostly in the third and fourth quartiles compared to the first and second. The average vote share for incumbents in the municipalities located in the fourth quartile of the distribution of COVID-19 spread is 2.6 percentage points higher than the vote share in the municipalities with relatively low circulation (first quartile) – a difference that is statistically significant at $p < 0.01$.

The effect of COVID-19 does not seem to vary depending on the political affiliation of incumbents. If we interact our measure of the spread of the virus with a categorical variable indicating whether the incumbent is affiliated to a left-wing party, a right-wing party or another party, we do not find statistically significant interactions (see Table A6). Figure 2 plots the results of the interactions,

Figure 1. *Effect of COVID-19 on vote for incumbents in 2020*

Note: Coefficient plots from OLS regressions of vote for incumbents in 2020 on local spread of COVID-19 controlling for vote for incumbents in 2014 and additional municipality-level covariates. Markers are point estimates, lines are 95% confidence intervals. For complete regression estimates, see Table A4.

showing that, as the prevalence of COVID-19 increases, votes for incumbents increase in a similar fashion regardless of the incumbents' political affiliation. Thus, we cannot confirm previous studies showing that it is mostly right-wing candidates who gain support when voters are under threat (Berrebi and Klor 2008; Getmansky and Zeitzoff 2014). Instead, our results indicate that support for incumbents increased "across the board" in the areas that were particularly hit by the virus.

Figure 2. Effect of COVID-19 on vote for incumbents in 2020

Note: Coefficient plots from OLS regressions of vote for incumbents in 2020 on local spread of COVID-19 interacted with the political affiliation of the incumbent. Markers are point estimates, lines are 95% confidence intervals. For complete regression estimates, see Table A6.

Robustness checks and placebo tests

We implement alternative specifications of our models and conduct additional analyses to test the robustness of our results. First, we run the models using alternative specifications of our measure of the spread of COVID-19. We find substantially similar results if we use either a logged or a quintile version of our independent variable (see Models 3 and 4 in Table A4), or if we estimate the spread of COVID-19 using excess-mortality data registered four (instead of six) weeks after the first round of elections (see Table A5).

Second, we use propensity score matching to increase our confidence that municipalities with low and high prevalence of COVID-19 are statistically indistinguishable across all available indicators, apart from our measure of COVID-19. We divide our sample in treated and control observations, defining municipalities as ‘treated’ if they fall into the top two quartiles of municipalities affected by the spread of COVID-19. We then calculate the propensity score (the likelihood of a municipality being heavily affected by COVID-19) using the full set of control variables. Next, we match treatment and control observations with very similar propensity scores one-to-one applying a punishing caliper. Only matches whose propensity scores differ by no more than 0.025 points are retained. We then run our models on the sample of matched municipalities, and find substantially the same results: moving from the first to the tenth decile of COVID-19 spread is associated with an increase of 3.4 percentage points in votes for incumbents (see Table A7).

Third, we check if our results hold in a difference-in-differences (DiD) framework that compares within-municipality changes in incumbent vote shares across treatment and control municipalities over time. A ‘naive’ comparison of differences shows that the change in incumbent vote shares in treated vs. control municipalities between 2014 and 2020 differed by 1.43 percentage points (see Table A10). This estimate of the DiD increases to 1.76 percentage points if we calculate the model in a regression framework using municipality fixed effects and controlling for changes in our control variables over time (see Table A11).

Lastly, we conduct placebo tests using vote shares for incumbents in 2014 as our outcome. We retrieve information from the 2008 elections to determine which candidates in 2014 were

incumbents.¹³ We then run the same models, using votes for incumbents in 2014 as dependent variable and including their vote shares in 2008 among the predictors. Reassuringly, we find no differences in support for incumbents in 2014 depending on the circulation of the virus in 2020 (see Table A8).

Mechanisms

According to our theoretical framework, the effect of the early spread of COVID-19 on support for local incumbents can be explained by two channels: an emotional channel related to feelings of fear and anxiety, and a prospective-voting channel, related to the idea that the local administration led by the incumbent should be able to act more swiftly against the diffusion of the virus than a new administration led by a challenger. Although we cannot test these channels "directly" using aggregate data at the municipality level, we attempt to test them indirectly using additional data that can plausibly work as proxies for our mechanisms.

To test the emotional channel, we retrieved data from a national survey conducted by IPSOS,¹⁴ in which the respondents were asked how frequently they "experienced a feeling of nervousness, anxiety or tension" or they were "unable to stop worrying or controlling your worries" in the past two weeks. As response categories, they could choose between "almost everyday", "more than

¹³Because of a change in the electoral system, there are only 543 municipalities in which the electoral system did not change between 2008 and 2014, and an incumbent was running in 2014. We retrieved the list of mayors elected during the 2008 election from Tricaud (2019).

¹⁴The survey was conducted from 7 to 14 April 2020 with a representative sample of 5,000 French adults. Source: Ipsos, <https://www.data.gouv.fr/fr/datasets/datacovid-barometre-COVID-19/>, data downloaded on 14th June 2020.

half of the time", "several days", or "never". We combine the responses to these two items into an additive index of perceived anxiety, rescaled from 0 (corresponding to "never experiencing anxiety") to 1 ("experiencing it almost every day").

Although the respondents' municipality of residence is not available in the survey, there is information about the county of residence and the size of the municipality of residence divided in five categories ("rural", "between 2000 and 19,999 inhabitants", "between 20,000 and 99,999", "100,000 inhabitants or more", "greater Paris"). Using this information, we grouped the respondents by county and municipality size, and then calculated the average level of perceived anxiety for all the respondents living in the municipalities of the same size within each county. With this operation we obtain 316 observations that we combine with our original dataset, matching by county and municipality size.

We then introduce the aggregate measure of anxiety in our regression models and interact it with our measure of the spread of COVID-19, clustering standard errors at the level of municipality-size within county. If voters support incumbents as a means of reducing the fear and anxiety induced by the pandemic, we should find that votes for incumbents in 2020 increase especially where the circulation of the virus is high *and* people are particularly anxious about the pandemic. Our results indicate that this is indeed the case. We find a positive and marginally significant ($p < 0.1$) interaction between aggregate levels of anxiety and the spread of COVID-19. The left-hand panel of figure 3 visualizes this result: while there is no association between the circulation of the virus and voting for incumbents in the areas where people (on average) do not feel anxious, in the areas with higher levels of anxiety this correlation is substantial. This finding supports the idea that, under the threat

of the virus, voters turn to incumbent candidates in search of safety and as a way to reduce fear and anxiety. In the absence of anxiety, the threat of COVID-19 does not affect voting.

Figure 3. Testing mechanisms underlying the effect of COVID-19

Note: The coefficients indicate the effect of the local spread of COVID-19 on voting for incumbents in 2020 by categories of the interacted variables specified on the y-axis. Coefficients plots from OLS regressions controlling for vote for incumbents in 2014 and additional municipality-level covariates. Markers are point estimates, lines are 95% confidence intervals. For complete regression estimates, see Table A9.

Testing our second channel proves even more challenging, since we assume that voters (on average) would prefer incumbents over challengers to avoid the potential delays that might result from changing the political representatives of the local administration. Still, if this reasoning is correct, we can hypothesize that voters should be particularly prone to confirm incumbent mayors that have

performed well during the last administration. The idea is that politicians who performed well in the former administration - even in domains that are unrelated to public healthcare - might also perform well in the next administration when facing the urgent task of dealing with the pandemic.

As indirect measures of past performance, we retrieve data about the median income and the unemployment rate at the municipality level in 2014, and compute the change between 2014 and 2017. If the median income increased and the unemployment rate decreased over time, voters might be particularly satisfied with their local mayors, even if these trends might be unrelated to the local administration's performance. Thus, they should be particularly likely to vote for incumbents where the diffusion of COVID-19 is high and mayors have performed well in the past, since past performance can be used as an indicator of future performance against the pandemic.

To test this expectation, we introduced our measures of change in the regression models. We find a positive and statistically significant interaction between the change in median income and the spread of COVID-19 (see Table A9). As the centre-plot of figure 3 shows, the association between the spread of COVID-19 and the vote for incumbents becomes substantial and statistically significant as median income increased between 2014 and 2017. The right-hand plot of figure 3 shows the interaction between the change in the unemployment rate and the spread of COVID-19. In line with the expectations, we find that the spread of COVID-19 only influenced voting in places where the unemployment rate decreased between 2014 and 2017.

CONCLUSIONS

From personal health to material welfare, the COVID-19 pandemic has disrupted human lives at an unprecedented scale. Consistent with research on natural disasters, we find that the threat of COVID-19 has also affected voting behavior. Focusing on municipal elections that took place in France at the beginning of the pandemic in spring 2020, we find that support for incumbents increased in the areas particularly hard hit by the virus. The effect is not sensitive to candidates' political affiliation, meaning that incumbents from both the left and the right obtained higher vote shares in areas more strongly affected by the pandemic. The results are robust to a placebo test and hold across different methods, including regressions with lagged dependent variables, a differences-in-differences approach and propensity score matching.

While previous studies have focused on the aftermath of natural disasters, we provide novel evidence for how voters react to such disasters while they are unfolding. Furthermore, we show that natural threats can boost support for incumbents even in the absence of retrospective evaluations. At the very beginning of the pandemic, it was unclear how to best respond to the circulation of the virus, and local candidates lacked the legal authority to introduce strong containment measures, giving voters little to evaluate. This finding is in line with recent evidence that incumbents' popularity increased across several countries *before* governments took active measures to reduce the spread of COVID-19 (De Vries et al. 2021; Jennings 2020).

Setting retrospective evaluations aside, we argue that voters support incumbents as a means to reduce the fear and anxiety generated by the circulation of the virus (Campante, Depetris-Chauvin, and Durante 2020). We provide indirect evidence for this emotional channel, by showing that

votes for incumbents increased especially in areas where the circulation of the virus was high and people felt particularly anxious about the pandemic. A relevant implication of this mechanism is that incumbents benefit from the presence of external threats simply by virtue of representing the status quo, *regardless* of their performance or political leaning. In this sense, our findings can be interpreted as further evidence of a status-quo bias in voting for political candidates (see for example Alesina and Passarelli 2019; Morgenstern and Zechmeister 2001; Morisi et al. 2021; Quattrone and Tversky 1988), which is heightened in the presence of fear-inducing threats (Bisbee and Honig 2021).

We further argue that a prospective-voting channel can also explain our results. Voters, we reason, believe that incumbents can act more swiftly than challengers against the looming threat of the pandemic, simply because they represent continuity with the current administration. Although we cannot test this mechanism directly, we hypothesise that this mechanism should especially benefit mayors with a positive administrative record. Voters might infer that a candidate that performed well in one domain, might perform equally well in handling the pandemic - even if these domains are unrelated. In line with this reasoning, we find that voters are particularly likely to support incumbents where the threat of COVID-19 is high and welfare improved over the last electoral cycle.

Further research should attempt to clarify the mechanisms underlying the effects of natural threats on support for incumbents in the absence of retrospective evaluations. While we argue that both an emotional channel and a prospective-voting channel might explain such effects, we lack individual-level data that can address these mechanisms directly. We also call for further research into the nature of rally-around-the-flag effects. While our findings resemble the sudden jump in support for incumbent candidates following terrorist attacks or military crises - i.e., the type of

events that lead people to rally around the flag (Baker and Oneal 2001; Lambert, Schott, and Scherer 2011; Mueller 1970) - the threat of COVID-19 fundamentally differs from these types of threats. By lacking the intention to attack a population, COVID-19 should not activate the same feelings of anger and revenge that according to Lambert, Schott, and Scherer (2011) explain rally effects. Further research should test whether facing a natural threat (such as COVID-19) or a human threat (such as a terrorist attack) are associated to different emotional states of fear or anger, which, in turn, lead to different behavioral outcomes (for a review, see Wagner and Morisi 2019).

Lastly, we should not overstate the "power" of the incumbency status in influencing voting behavior. Although the effects we detect can change the outcome of elections, they are likely to be short-lived, in line with research on the effects of terrorist attacks (Dinesen and Jæger 2013). As the pandemic unfolds, a number of considerations will probably influence voters' decisions, including the evaluation of how incumbents and political representatives responded to the spread of the virus. Indeed, evidence indicates that support for governments in Western democracies has decreased in the course of the pandemic (Jørgensen et al. 2021). In this sense, voters are not blind to the performance of their political representatives. After the initial emotional reaction to the spread of COVID-19 it is likely that other considerations will soon shape the calculus of voters again.

Competing interests

Competing interests: The authors declare none

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SUPPLEMENTARY INFORMATION

A. Additional analyses

TABLE A1 *Predictors of city with incumbent (vs. no incumbent)*

	City with incumbent (vs city without incumbent)	
Covid-19 spread (deciles)	-0.007	(0.008)
Population density (logged)	0.092**	(0.028)
Male to female ratio (logged)	0.326	(0.280)
Share of immigrants (logged)	0.036	(0.036)
Share of blue collars (logged)	-0.083	(0.092)
Share of unemployed (logged)	-0.089	(0.104)
Share of aged 65+ (logged)	-0.020	(0.109)
Median household income	-0.002	(0.001)
Baseline mortality (logged)	0.052	(0.031)
Turnout 2014	1.177***	(0.315)
County fixed effects	Yes	
<i>N</i>	8913	
Pseudo- <i>R</i> ²	.018	

Note: Logistic regression of city with incumbent vs city without incumbent.

Coefficients are log-odds with standard errors in parentheses

* p<.05, ** p<.01, *** p<.001

Figure A1. DAG justifying the choice of control variables.

Note: Directed acyclic graph (DAG) showing the interrelationship between factors predicting mortality from COVID-19 and factors directly affecting incumbent support. Potential confounders highlighted with a black outline. We control for these factors in our regression model. Names in the diagram refer to the following publications: Cai and Goehring (2020), Carozzi (2020), Clark et al. (2020), Koopmans (2020), Kuchler, Russel, and Stroebel (2020), Patel et al. (2020), Qiu, Chen, and Shi (2020), and Williamson et al. (2020)

TABLE A2 *Summary statistics*

	Count	Mean	SD	Min	Max
Incumbent vote share 2020	4952	72.71	24.93	7.78	100
Incumbent vote share 2014	4952	68.04	22.41	20.66	100
Covid-19 spread	4952	0.01	0.03	0.001	0.99
Covid-19 spread (logged, normalized)	4952	0.27	0.12	0	1
Population density (logged)	4952	5.32	1.22	1.57	9.887
Male to female ratio (logged)	4952	-0.05	0.09	-0.40	0.94
Share of immigrants (logged)	4952	-3.24	0.94	-6.31	-0.69
Share of blue collars (logged)	4952	-2.28	0.40	-4.95	-1.24
Share of unemployed (logged)	4952	-2.21	0.37	-3.92	-0.92
Share of people aged 65+ (logged)	4952	-1.61	0.30	-3.25	-0.66
Median household income (hundreds of euros)	4952	218.83	33.43	133.2	449.9
Baseline mortality (logged)	4952	-7.47	0.86	-9.49	-2.23
Turnout 2014	4952	0.67	0.09	0.32	0.98

Note: Summary statistics for municipalities with more than 1000 inhabitants and an incumbent candidate in 2020.

TABLE A3 *Political affiliation of incumbents*

Political affiliation in 2014	Name of the list	2014 abbreviation	Frequency	Percent
Left-wing	Front de gauche	FG	16	0.32
	Parti de gauche	PG	2	0.04
	Parti communiste français	COM	38	0.77
	Parti socialiste	SOC	267	5.39
	Union de la gauche	UG	208	4.20
	Divers gauche	DVG	1,016	20.52
	Europe-Ecologie-Les Verts	VEC	6	0.12
Centre / Unclear	Modem	MDM	16	0.32
	Union du centre	UC	16	0.32
	Union des démocrates et indépendants	UDI	144	2.91
	Divers	DIV	887	17.91
Right-wing	Les Républicains	UMP	243	4.91
	Union de la droite	UD	205	4.14
	Divers droite	DVD	1,878	37.92
	Rassemblement national	FN	7	0.14
	Extrême droite	EXD	3	0.06
Total			4,952	100

TABLE A4 *Effects of COVID-19 on voting for incumbents*

	<i>Vote share for incumbents in 2020 (first round)</i>			
	(1)	(2)	(3)	(4)
Covid-19 spread (deciles)	0.409*** (0.106)			
Covid-19 spread (r.c.=1st quart.)				
- 2nd quartile		0.587 (0.862)		
- 3rd quartile		2.565** (0.859)		
- 4th quartile		2.646** (0.855)		
Covid-19 spread (logged, normalized)			5.450* (2.541)	
Covid-19 spread (r.c.=1st quint.)				
- 2nd quintile				-0.260 (0.960)
- 3rd quintile				1.116 (0.965)
- 4th quintile				2.536** (0.947)
- 5th quintile				2.825** (0.958)
Incumbent vote share 2014	0.570*** (0.019)	0.570*** (0.019)	0.572*** (0.019)	0.571*** (0.019)
Population density (logged)	0.474 (0.422)	0.461 (0.422)	0.498 (0.422)	0.485 (0.422)
Male to female ratio (logged)	2.504 (3.878)	2.564 (3.880)	2.298 (3.883)	2.599 (3.880)
Share of immigrants (logged)	0.367 (0.514)	0.366 (0.514)	0.365 (0.514)	0.350 (0.514)
Share of blue collars (logged)	3.607** (1.291)	3.595** (1.293)	3.631** (1.293)	3.604** (1.292)
Share of unemployed (logged)	-4.497** (1.471)	-4.508** (1.471)	-4.418** (1.472)	-4.491** (1.471)
Share of aged 65+ (logged)	-2.532 (1.532)	-2.550 (1.532)	-2.636 (1.533)	-2.527 (1.532)
Median income (hundreds euros)	0.011 (0.018)	0.011 (0.018)	0.011 (0.018)	0.011 (0.018)
Baseline mortality (logged)	-0.833 (0.431)	-0.823 (0.431)	-0.785 (0.432)	-0.838 (0.432)
Turnout 2014	70.304*** (5.622)	70.255*** (5.629)	70.741*** (5.628)	70.464*** (5.627)
County fixed-effects	Yes			
Constant	-30.925*** (6.653)	-30.027*** (6.638)	-30.349*** (6.685)	-30.182*** (6.644)
<i>N</i>	4,952	4,952	4,952	49,52
<i>R</i> ²	0.308	0.308	0.306	0.308

Note: OLS regression coefficients with standard errors in parentheses. Covid-19 spread: excess mortality weighted by age and sex-specific infection fatality ratios. All variables measured at the municipality level. * p<.05, ** p<.01, *** p<.001

TABLE A5 *Effects of COVID-19 on voting for incumbents (alternative specification of COVID-19 spread)*

	<i>Vote share for incumbents in 2020 (first round)</i>			
	(1)	(2)	(3)	(4)
Covid-19 spread (deciles)	0.357*** (0.106)			
Covid-19 spread (r.c.=1st quart.)				
- 2nd quartile		-0.091 (0.862)		
- 3rd quartile		1.519 (0.864)		
- 4th quartile		2.603** (0.857)		
Covid-19 spread (logged, normalized)			3.906 (2.721)	
Covid-19 spread (r.c.=1st quint.)				
- 2nd quintile				1.080 (0.961)
- 3rd quintile				0.932 (0.966)
- 4th quintile				2.819** (0.958)
- 5th quintile				2.704** (0.962)
Incumbent vote share 2014	0.570*** (0.019)	0.571*** (0.019)	0.572*** (0.019)	0.570*** (0.019)
Municipality-level covariates			Yes	
Baseline mortality			Yes	
Turnout 2014			Yes	
County fixed-effects			Yes	
<i>N</i>	4952	4952	4952	4952
<i>R</i> ²	0.307	0.308	0.306	0.308

Note: OLS regression coefficients with standard errors in parentheses. Covid-19 spread: excess mortality (4 weeks after election) weighted by age and sex-specific infection fatality ratios. The models include the same covariates included in Table A4. * $p < .05$, ** $p < .01$, *** $p < .001$

TABLE A6 *Interactions with political affiliation of incumbents*

	<i>Vote share for incumbents in 2020 (first round)</i>			
	(1)	(2)	(3)	(4)
Covid-19 spread (deciles)	0.399* (0.185)	0.374 (0.232)		
Covid-19 spread (r.c.=1st quart.)				
- 2nd quartile			-0.064 (1.526)	-0.893 (1.781)
- 3rd quartile			2.087 (1.529)	0.451 (1.864)
- 4th quartile			2.492 (1.504)	1.587 (1.857)
Incumbent (centre/unclear)	r.c.	0.736 (1.846)	r.c.	0.045 (1.707)
Incumbent (left-wing)	-0.736 (1.846)	r.c.	-0.045 (1.707)	r.c.
Incumbent (right-wing)	-1.752 (1.505)	-1.016 (1.728)	-2.691 (1.396)	-2.646 (1.599)
Centrist incumbent X Covid-19	r.c.	0.025 (0.296)		
Left-wing incumbent X Covid-19	-0.025 (0.296)	r.c.		
Right-wing incumbent X Covid-19	0.038 (0.238)	0.063 (0.277)		
Centrist incumbent X Covid-19 2nd q.			r.c.	0.829 (2.339)
Left-wing incumbent X Covid-19 2nd q.			-0.829 (2.339)	r.c.
Right-wing incumbent X Covid-19 2nd q.			1.881 (1.979)	2.711 (2.186)
Centrist incumbent X Covid-19 2nd q.			r.c.	1.636 (2.407)
Left-wing incumbent X Covid-19 3rd q.			-1.636 (2.407)	r.c.
Right-wing incumbent X Covid-19 3rd q.			1.872 (1.960)	3.508 (2.232)
Centrist incumbent X Covid-19 4th q.			r.c.	0.904 (2.388)
Left-wing incumbent X Covid-19 4th q.			-0.904 (2.388)	r.c.
Right-wing incumbent X Covid-19 4th q.			0.810 (1.936)	1.714 (2.226)
Municipality-level covariates			Yes	
Baseline mortality			Yes	
Turnout 2014			Yes	
County fixed-effects			Yes	
<i>N</i>	4952	4952	4952	4952
<i>R</i> ²	0.309	0.309	0.309	0.309

Note: OLS regression coefficients with standard errors in parentheses. The models include the same covariates included in Table A4. * p<.05, ** p<.01, *** p<.001

TABLE A7 *Propensity score matching*

	<i>Vote share for incumbents in 2020 (first round)</i>	
	(1)	(2)
Covid-19 spread (deciles)	0.380*** (0.115)	
Covid-19 spread (r.c.=1st quart.)		
- 2nd quartile		0.845 (0.952)
- 3rd quartile		2.608** (0.940)
- 4th quartile		2.469** (0.933)
Incumbent vote share 2014	0.575*** (0.021)	0.574*** (0.021)
Municipality-level covariates		Yes
Baseline mortality		Yes
Turnout 2014		Yes
County fixed-effects		Yes
<i>N</i>	4122	4122
<i>R</i> ²	0.309	0.309

Note: OLS regression coefficients with standard errors in parentheses. Sample of matched municipalities. The models include the same covariates included in Table A4. * p<.05, ** p<.01, *** p<.001

TABLE A8 *Placebo test: effect of COVID-19 on vote for incumbents in 2014*

	<i>Vote share for incumbents in 2014 (first round)</i>	
	(1)	(2)
Covid-19 spread (deciles)	0.072 (0.239)	
Covid-19 spread (r.c.=1st quart.)		
- 2nd quartile		1.509 (2.107)
-3rd quartile		1.773 (2.150)
-4th quartile		0.547 (1.976)
Incumbent vote share 2008	0.295** (0.107)	0.294** (0.107)
Municipality-level covariates		Yes
Baseline mortality		Yes
County fixed-effects		Yes
<i>N</i>	543	543
<i>R</i> ²	0.205	0.206

Note: OLS regression coefficients with standard errors in parentheses. Dependent variable: vote share for incumbents in 2014 (first round). The models include the same covariates included in Table A4 (apart from turnout in 2014). * p<.05, ** p<.01, *** p<.001

TABLE A9 *Testing mechanisms with interaction models*

	<i>Vote share for incumbents in 2020 (first round)</i>		
	(1)	(2)	(3)
Covid-19 spread (deciles)	-0.076 (0.304)	0.086 (0.192)	0.567** (0.216)
Perceived anxiety (0-1)	-4.981 (4.586)		
Covid-19 X anxiety	1.272+ (0.747)		
Change in median income		-0.324* (0.144)	
Covid-19 X income change		0.043* (0.022)	
Change in unemployment rate			0.292 (0.352)
Covid-19 X unemployment change			-0.031 (0.037)
County fixed-effects	No	Yes	Yes
Municipality-level covariates	Yes	Yes	Yes
Baseline mortality	Yes	Yes	Yes
Turnout 2014	Yes	Yes	Yes
<i>N</i>	4820	4952	4952
<i>R</i> ²	0.277	0.309	0.308

Note: OLS regression coefficients with standard errors in parentheses. Column 1: standard errors clustered at the level of municipality-size within county. Change in median household income: hundreds of euros. The models include the same covariates included in Table A4. + $p < 0.1$, * $p < .05$, ** $p < .01$, *** $p < .001$

TABLE A10 *'Manual' DiD*

Treatment status	Election		Diff
	2014	2020	
Control	68.98	73.04	4.06
Treated	68.07	73.56	5.49
Diff	-0.91	0.52	1.43

Note: Raw incumbent vote shares in treated vs. untreated municipalities in 2014 vs. 2020. Treatment defined as being in the third or fourth quartile of municipalities affected by COVID-19.

TABLE A11 *DiD in regression framework*

	<i>Vote share for incumbents in 2020 (first round)</i>	
	(1)	(2)
Treated towns	-0.839 (0.635)	0.041 (0.604)
2020 (vs. 2014) election	3.785*** (0.494)	13.671*** (0.788)
Treated×2020 election	1.763** (0.680)	1.759* (0.697)
Share of immigrants (logged)		-3.190*** (0.301)
Share of blue collars (logged)		11.636*** (0.866)
Share of unemployed (logged)		-14.374*** (1.047)
Median household income		0.001*** (0.000)
Constant	68.463*** (0.459)	32.626*** (2.438)
<i>N</i>	9904	9901
<i>R</i> ²	0.010	0.117

Note: Regression coefficients with bootstrapped standard errors in parentheses. Treatment defined as being in the third or fourth quartile of municipalities affected by Covid-19. * $p < .05$, ** $p < .01$, *** $p < .001$

B. Estimating the spread of COVID-19

Figure B.1. Weekly death count in France between 2001 and 2020, as of April 14th 2020. Large peaks are clearly visible and correspond to extreme mortality events: the 2003 heat wave, yearly flu outbreaks and the 2020 pandemic.

Nombre quotidien de décès en France, 2001-2020

En rouge, l'année 2020, en gris les années 2001 à 2019. En bleu foncé : 2003

Sources : Fichier des décès sur data.gouv.fr et Fichier des décès sur insee.fr (24 avril 2020) | Graphique : B. Coulmont

Note: Mortality records from data.gouv.fr and from INSEE.fr, image by B. Coulmont.

Figure B.2. Number of recorded death on each year, aggregated at country level and during the period of interest.

B.1. Population extrapolation

Population data at the municipality level is only available with a 3-year lag¹⁴. To obtain population data for 2018, 2019 and 2020, we extrapolated the population from the previous years by estimating the municipality-specific evolution trend over the years 2010-2017. We added up the population of the municipalities that merged in 2020 but were distinct at some point in the past.

We consider three basic extrapolation models:

- constant population

- linear increase with time

- linear increase with time on the log scale

To predict the population in 2019 and 2020 for each municipality, we aim to use the best model according to a simplicity criterion and a goodness of fit criterion. More precisely, this can be formalised in the following four models. Let N_{mt} be the population of municipality m at year t :

¹⁴Source: <https://www.insee.fr/fr/statistiques/1893204>, data downloaded on 24th September 2020

$$N_{mt} = N_m + \epsilon \quad (2)$$

$$\log N_{mt} = \log N_m + \epsilon \quad (3)$$

$$N_{mt} = \alpha + \beta t + \epsilon \quad (4)$$

$$\log N_{mt} = \alpha + \beta t + \epsilon \quad (5)$$

$$\epsilon \sim \text{Normal}(0, \sigma) \quad (6)$$

For our simplicity criterion, we deem reasonable to rank the models by increasing complexity using the following order: 1) constant population (Equation (2)), 2) constant population on the log scale (Equation (3)), 3) linearly trend (Equation (4)) 4) linear trend on the log scale (Equation (5)).

For each model and each municipality, our goodness of fit criterion is the Akaike Information Criterion (AIC, Sakamoto, Ishiguro, and Kitagawa 1986). A difference of AIC of 3 is sometimes considered as reasonable evidence in favor of one of the two models (Burnham, Anderson, and Huyvaert 2011). When the difference between the best model according to the AIC criterion and a simpler model according to the complexity criterion is smaller than 3, we prefer the simpler model. Therefore, our mixed criteria model selection procedure consists of choosing the simplest model within a radius of 3 of the best model according to the AIC. We also considered the Bayesian Information Criterion (Sakamoto, Ishiguro, and Kitagawa 1986) instead of AIC and obtained similar results.

Figure B.3. Random selection of municipalities with population larger than 1000. The dark points indicate observed data, the light points indicate extrapolated data. The panel label denotes the INSEE code for the municipality considered.

For the 34972 municipalities considered, the constant model (Equation (2)) was chosen 8 times (0.02%), the log-constant model (Equation (3)) 5559 times (16%) and the log-linear model 29405 times (84%). Figure B.3 shows a random sample of the municipalities with the data used for fitting the extrapolation model and the extrapolation. In all cases, the extrapolation seems reasonable. Figure B.4 shows the cities where the goodness of fit of the selected model, measured by R^2 , are the worst among the 34972 municipalities. Even in this worst case scenario, we see that the extrapolation is not predicting unrealistic values, thus confirming the reliability of our approach.

To obtain population estimates in age and sex categories for each municipality, we use the detailed 2017 census data¹⁵ to estimate the proportion of the population in each age and sex categories for each municipality. We then assume these proportions to remain constant between 2015 and 2020

¹⁵<https://www.insee.fr/fr/statistiques/1893204>

Figure B.4. Worst fitting municipalities among the 34972 municipalities. The dark points indicate observed data, the light points indicate extrapolated data. The panel label denotes the INSEE code for the municipality considered.

and redistribute the total population of the municipalities at each year in each age and sex category according to these proportions.

B.2. Estimating the COVID-19 threat from excess mortality data

Excess mortality models. We model excess mortality in 2020 compared to the previous years through a Poisson model with municipality-specific intensities. We first introduce a basic model for excess mortality which does not take into account the age of the deceased. The purpose of the basic model is to show the added value of the main model, which accounts for the dependence on age and sex of the probability to die once infected (Infection Fatality Ratio, IFR).

For the basic model, let Y_{mt} denote the number of deaths between March 15th and six weeks later in municipality m at year t , and let N_{mt} denote the population of that municipality on that year t . We make the common assumption (see for instance O’Driscoll et al. 2021; Blangiardo et al. 2020) that mortality follows a Poisson distribution with a baseline-municipality specific hazard h_m for $2015 \leq t \leq 2019$ plus a municipality-specific excess hazard h_m^+ for $t = 2020$:

$$Y_{mt} \sim \text{Poisson}(N_{mt} h_m) \text{ if } t \neq 2020 \tag{7}$$

$$Y_{mt} \sim \text{Poisson}(N_{mt} (h_m + h_m^+)) \text{ if } t = 2020$$

In this model, h_m^+ characterises the severity of the COVID-19 outbreak in the municipality. A natural consequence of this model is that the excess probability to die from COVID-19 is the same for every person in any given municipality, which we know to be an oversimplification of reality. We therefore introduce a model accounting for the differential probability of dying from COVID-19

infection depending on age and sex, which has been estimated using data from various countries in O’Driscoll et al. 2021.

Starting from the mortality records, we attribute each death record to a 5-year age-class matching the classes defined by O’Driscoll et al. (2021). We therefore use the best age resolution available for the age-specific Infection Fatality Rate.

We discard death records for children under 10 and for people over 80 because excess death in these age classes can be linked to a variety of causes and are not very informative about the level of COVID-19 spread (see notably the dispersion of Infection Fatality Rate for young children and people over 80 on Figure 1.b. of O’Driscoll et al. 2021).

Let Y_{mtas} denote the number of deaths between March 15th and six weeks later in municipality m at year t in age class a for sex s , and let N_{mtas} denote the population in that age and sex class of that municipality at year t . As in the previous section, we assume that mortality follows a Poisson distribution with a baseline municipality-age-sex specific hazard h_{mas} for $t \in 2015 : 2019$ plus a municipality specific excess hazard h_{mas}^+ for $t = 2020$, where the excess hazard involves the COVID-19 prevalence in the municipality v_m and the age-specific Infection Fatality Ratio ρ_{as} .

We define an age-class continuous variable x_a indicating the index of the age-class (which corresponds to a binning of the age, thus proportional to age) which we scale and center. We further define a sex-class binary variable x_s where the value 1 corresponds to males. These quantities are combined together in the following model:

$$\begin{aligned}
Y_{mtas} &\sim \text{Poisson}(N_{mtas}, h_{mas}) \text{ if } t \neq 2020 \\
Y_{mtas} &\sim \text{Poisson}(N_{mtas}, h_{mas} + h_{mas}^+) \text{ if } t = 2020 \\
\log h_{mas} &= \log h_m + \beta_{age}x_a + \beta_{sex}x_s \\
h_{mas}^+ &= \nu_m \rho_{as}
\end{aligned} \tag{8}$$

h_m is the baseline hazard in municipality m for females in the central age-class. β_{age} and β_{sex} are the country-wide age and sex effects on the baseline mortality.

Note that in this model the prevalence ν_m is a municipality-level quantity, which is the same for all age and sex classes. We use ν_m to characterize the severity of the COVID-19 outbreak in municipality m .

Prior structure. A striking feature of the excess hazard due to COVID-19 in 2020 is that in the period considered, only a few hotspots of COVID infection were scattered around the country, which implies that most municipalities were not affected yet. As a consequence, it is realistic for most h_m^+ and ν_m values to have a negligible value.

We include this insight in the model by performing inference using the Bayesian framework and specifying a sparsity-inducing Lasso prior (Park and Casella 2008) h_m^+ and ν_m , and resorting to Maximum a Posteriori (MAP) estimation. We use the following prior structure for the first model, *not* accounting for the age and sex-specific IFR:

$$\begin{aligned}
h_m &\sim \log\mathcal{N}(\mu, \sigma) \\
h_m^+ &\sim \exp(\lambda) \\
\mu &\sim \mathcal{N}(-5, 5) \\
\sigma &\sim \mathcal{N}^+(1, 20) \\
\lambda &\sim \text{Gamma}(0.001, 0.001)
\end{aligned} \tag{9}$$

where $\mathcal{N}$ denotes the Normal distribution, $\mathcal{N}^+$ denotes the truncated Normal distribution on the positive real numbers and $\log\mathcal{N}^+$ denotes the lognormal distribution.

We use the following prior structure for the second model which accounts for the age and sex-specific IFR:

$$\begin{aligned}
h_m &\sim \log\mathcal{N}(\mu, \sigma) \\
v_m &\sim \exp(\lambda) \\
\mu &\sim \mathcal{N}(-5, 5) \\
\sigma &\sim \mathcal{N}^+(1, 20) \\
\lambda &\sim \text{Gamma}(0.001, 0.001) \\
\beta_{age}, \beta_{sex} &\sim \mathcal{N}(0, 2)
\end{aligned} \tag{10}$$

We use very vague priors on the location and scale parameters for the baseline mortality. For h_m^+ and v_m we chose a prior on $\mathbb{R}^+$ with positive mass at 0 to allow for shrinkage of the MAP to 0. Rather than using cross-validation to select the optimal penalty parameter, we follow the

recommendations of Park and Casella (2008) and Casella et al. (2010) and use a Gamma distribution for the Lasso parameter λ , although we place this prior on λ rather than λ^2 since we do not have conjugacy constraints.

This is essentially the same prior structure for both models, with for the second model a weakly informative prior on the age and sex effect on the baseline mortality. Since the sex covariate is binary and the age covariate is scaled and centred, the priors allows everything from negligible to large positive or negative effects.

Inference. Given the large number of municipalities, the previous models have a large number of parameter, on the order of 60 000. This renders standard Monte Carlo Markov Chain inference very time consuming. Since the goal of this analysis is to obtain point estimates for the municipality-level excess hazard or the municipality-level prevalence, we resort to Variational Inference, which is known for good performance in obtaining point estimates for a posterior distribution (Blei, Kucukelbir, and McAuliffe 2017). We use a stochastic variational inference algorithm (Kucukelbir et al. 2015) through the interface available in Stan (Stan Development Team 2021). Sparsity is obtained by calculating MAP values conditional on the optimal value of the penalty parameter λ , estimated by the median marginal posterior distribution on λ . Optimisation of the posterior to obtain the MAP is performed using the default Limited-memory Broyden–Fletcher–Goldfarb–Shanno (LBFGS) algorithm implementation in Stan.

B.3. Estimated values and validation

Posterior predictive model checking. Figure B.5 compares the two estimations of COVID-19 outbreak severity to a naive estimate, the empirical excess hazard, aggregated at the regional level. The empirical excess hazard is obtained by dividing the number of deaths by the population size for each year, then subtracting to the empirical hazard for 2020 the mean hazard for the previous years. This empirical estimate does not take into account population size and is thus sensitive to outliers. The model-based excess hazard (Equation (7)) and the prevalence (Equation (8)) are more robust because they take into account the size of the population in the Poisson intensity and they benefit from the country-wide shrinkage (Equations (9) and (10)) for the baseline mortality estimates and from the lasso penalty.

This increased robustness is expected to play a role at the municipality level, where populations may be small and fluctuations large. At the regional level, with larger aggregated population, the model-based estimate of excess hazard and the empirical estimates should be close, and this is indeed what we see on Figure B.5, where we see large excess hazard in the Grand-Est region and the Île-de-France region, as expected.

Since the prevalence measure takes into account the age structure of the population it can provide different values depending on the age at death of the people on the mortality records. Indeed, we see that our assessment of the severity of the COVID-19 outbreak is fairly different from the basic excess hazard model ((Equation (7))), with the Île-de-France region now much more severely affected than the other regions. Because of the comparatively older population in the Grand-Est region, a COVID-19 outbreak comparable to other regions caused a large excess mortality. Conversely, the

prevalence measure reveals that although excess hazard was not the highest in the Île de France region, the COVID-19 outbreak was particularly severe, given the markedly younger population in counties such as Seine-Saint-Denis.

We perform posterior predictive checks for our main model (Equation (8)), where we predict the number of deaths for each municipality based on our MAP estimates and compare them with the observed number of death. Figure B.6 shows that predictions based on the MAP estimates perform generally well. The 95% prediction interval mostly cover the true value, with an average coverage of 99% , which suggest that the data is slightly under-dispersed compared to a Poisson error model.

Validation by comparison with external measures. We compare our measure of the spread of COVID-19 (prevalence) with other measures obtained from publicly available data. These measures are rarely available at the municipality level and may require aggregating prevalence at the county or regional level. First, we use county-level data from hospitals, such as the number of hospitalised people, the number of people in intensive care or the number of deceased per inhabitant.¹⁶ These measures should be relatively noise-free, assuming that the quality of hospital reporting is high, but they are still partial, as they document only the gravest cases of COVID-19 infection. These data contain information closely related to the excess number of death, and we observe a correlation with our prevalence measure (Figure B.7).

¹⁶Source: data.gouv.fr. Available at <https://www.data.gouv.fr/fr/datasets/donnees-hospitalieres-relatives-a-lepidemie-de-covid-19/>

Figure B.5. Three measures of COVID-19 severity aggregated at the regional level.

Figure B.6. Posterior predictive check for the prevalence model (Equation (8)). The mean predictive estimate for the number of death in each age and sex category, for each municipality and each year is plotted against the observed number of deaths. The prediction is performed using the MAP estimates for the parameters. The vertical segments denotes the 95% prediction interval, they have a light colour if the cover the observed data and a dark colour if they do not. The identity line is denoted in red.

Figure B.7. Correlation between the COVID-19 outbreak severity measure and various measures from the departmental level hospital dataset.

Second, we retrieve data from the CoviPrev survey¹⁷, which tracked the evolution of mental health and general behavior - such as adoption of preventative measures - in the French population since March 23, 2020. These data are recorded at the regional level. Figure B.8 shows a strong correlation between the spread of Covid-19 and anxiety at the regional level, lending support to our measure of the level of threat perceived by the voters.

Third, we use data compiled by Noury et al. (2021) who estimate the spread of COVID-19 using the distance to the COVID-19 hotspots known to be active at the time of the election. This measure can be compared directly with our measure since it is available at the municipality level. As expected, our measure of prevalence is negatively correlated with the log-distance of the municipalities to the nearest COVID-19 hotspot (Figure B.9).

Since our measure of prevalence can be imprecise for municipalities with a small population, if we remove all municipalities with a population below 10000, we find a marked increase in the magnitude of the correlation (Figure B.9, bottom).

¹⁷Source:<https://www.santepubliquefrance.fr/etudes-et-enquetes/coviprev-une-enquete-pour-suivre-l-evolution-des-comportements-et-de-la-sante-mentale-pendant-l-epidemie-de-COVID-19>

Figure B.8. Correlation between the COVID-19 outbreak severity measure and the level of anxiety reported during the first week after the election. Every measure is at the regional level.

Figure B.9. Correlation between the COVID-19 outbreak severity measure and the log-distance between each municipality and the nearest COVID-19 hotspot, as measured in Noury et al. 2021. The bottom figure is the same correlation, computed only on municipalities with a population larger or equal to 10000.

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