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Government-sponsored disinformation and the severity of respiratory infection epidemics including COVID-19: A global analysis, 2001–2020

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ABSTRACT

Internet misinformation and government-sponsored disinformation campaigns have been criticized for their presumed/hypothesized role in worsening the coronavirus disease 2019 (COVID-19) pandemic. We hypothesize that these government-sponsored disinformation campaigns have been positively associated with infectious disease epidemics, including COVID-19, over the last two decades. By integrating global surveys from the Digital Society Project, Global Burden of Disease, and other data sources across 149 countries for the period 2001–2019, we examined the association between government-sponsored disinformation and the spread of respiratory infections before the COVID-19 outbreak. Then, building on those results, we applied a negative binomial regression model to estimate the associations between government-sponsored disinformation and the confirmed cases and deaths related to COVID-19 during the first 300 days of the outbreak in each country and before vaccination began. After controlling for climatic, public health, socioeconomic, and political factors, we found that government-sponsored disinformation was significantly associated with the incidence and prevalence percentages of respiratory infections in susceptible populations during the period 2001–2019. The results also show that disinformation is significantly associated with the incidence rate ratio (IRR) of cases of COVID-19. The findings imply that governments may contain the damage associated with pandemics by ending their sponsorship of disinformation campaigns.

1. Introduction

Coronavirus disease 2019 (COVID-19) has caused a worldwide medical crisis that began in 2020. As the COVID-19 pandemic has escalated, accurate and inaccurate information has spread on the Internet (Islam et al., 2020). The World Health Organization (WHO) has warned of the risk of an "infodemic" wherein an overwhelming amount of circulating information discredits professional advice and prevents accurate information from reaching its target audience (WHO, 2020). Some studies have found that people's exposure to misinformation may be associated with their violation of epidemic prevention regulations or resistance to vaccination (Lee et al., 2020; Hornik et al., 2021; Loomba et al., 2021; Prandi and Primiero, 2020), and the sources of this misinformation can be traced back to political leadership in the government. For example, one study found the name of former U.S. president Donald Trump appeared in 37.9% of misinformation conversations about the COVID-19 pandemic (Evanega et al., 2020). These findings imply that attempts to conceal or distort information about the disease may contribute to its spread globally.

Most public health studies on information issues have emphasized only the spread and effects of misinformation (Roozenbeek et al., 2020) and not considered "disinformation." In contrast to misinformation, which refers to simply false information, disinformation refers to false information that is spread deliberately to deceive people. Unsurprisingly, political leaders, especially those who have undermined democratic institutions, adopt disinformation as an instrument for gaining support and reducing resistance, especially during crucial political moments such as elections and wars (Guriev and Treisman, 2019). In the digital era, recent studies have uncovered that more than two dozen governments have been deeply involved in disinformation campaigns to pursue their own domestic or international purposes (Bennett and Livingston, 2018; Bradshaw and Howard, 2018).

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The relationship between such disinformation campaigns and disease spread warrants investigation particularly in the case of the COVID-19 outbreak. Some governments adopt authoritarian strategies including disinformation and censorship to protect against political accountability and criticism over the spread of epidemics. However, the effects of such activities are unclear (Edgell et al., 2021). In this paper, we hypothesize that political disinformation may lead to worse public health outcomes. By examining comprehensive data on respiratory infections from 149 countries from 2001 to 2020, the present study discovered that government-sponsored disinformation is positively associated with the spread of respiratory infections including COVID-19. The findings imply that governments may contain the damage associated with pandemics by ending their sponsorship of disinformation campaigns.

2. Government-sponsored disinformation and epidemics

Disinformation is widely understood as being misleading content produced to further political goals, generate profits, or maliciously deceive. It may be utilized by politicians to manipulate public perception and reshape the collective decisions of the majority (Stewart et al., 2019). As an effective political tool in the digital era, one of the major origins of disinformation is a variety of agents sponsored by governments (Bradshaw and Howard, 2018). The actors disseminating government-sponsored disinformation include government-based cyber troops working as civil servants to influence public opinion (King et al., 2017), politicians and parties utilizing social media to reach their political intentions, private contractors hired by the government to promote domestic and international propaganda, volunteers that collaborate with governments, and citizens who have prominent influence on the internet and are paid by governments to spread disinformation (Bennett and Livingston, 2020).

Accompanied by the development of the internet, government-sponsored disinformation has become a global issue over the last two decades. Comparative political studies have noted that autocracies create more fake news than democracies, while the public in democracies has also severely suffered from it (Bradshaw and Howard, 2018). In contrast to democratic governments that are elected to provide public goods through majority rule, nondemocratic governments have leaders who remain in office by gaining support from a small group of political elites without checks and balances. Autocratic governments, therefore, face the constant threat of mass protests from large numbers of disenfranchised people (De Mesquita and Smith, 2003; Acemoglu and Robinson, 2006). In the digital age, autocracies prefer to use informational instruments such as censorship and disinformation to compromise potential protests, particularly during political crises (Guriev and Treisman, 2019). For example, a recent study revealed that autocracies such as China, Russia, and Iran used internet censorship as a reactive strategy to suppress civil society after the Arab Spring (Chang and Lin, 2020). The political effects of government-sponsored disinformation and internet censorship on disease spread, however, remains understudied.

As a tool for maintaining political stability in the government's favor; however, disinformation may lead to dysfunction in public health systems, as well as more infections from disease. In this paper, we highlight some suspected political, informational, and institutional processes to explain the positive association between government-sponsored disinformation and the exacerbation of infectious diseases—measured by the incidence, prevalence, and death percentages of respiratory infection before the COVID-19 pandemic—and how this disinformation was associated with the number of confirmed cases (henceforth, cases) of and deaths due to the COVID-19 pandemic.

2.1. Political incentives to spread disinformation about epidemics

As the COVID-19 outbreak has made apparent, some government incumbents accountable for controlling the disease neglected the risk and failed to prevent its spread. The failure of leadership to control the disease stimulated blame avoidance behaviors (Weaver, 1986; Baekkeskov and Rubin, 2017; Zahariadis et al., 2020), which sometimes took the form of internet censorship and government-sponsored disinformation. The Chinese government has been criticized for its alleged ignorance and suppression of information at the beginning of the COVID-19 epidemic (Petersen et al., 2020), while Chinese diplomats have openly accused the United States of spreading the disease, with the Iranian and Russian governments also supporting this conspiracy theory (Whiskeyman and Berger, 2021). In Iran, the government disseminated contradictory information on national COVID-19 fatalities. On February 10, 2020, the Iranian government falsely claimed that the country had no cases of coronavirus, but a 63-year-old woman died of COVID-19 on the same day. Finally, on February 19, the Iranian regime admitted that coronavirus had spread in Iran, 9 days after the first reported death (Dubowitz and Ghasseminejad, 2020). Under the cloud of poor transparency and disinformation regarding the epidemic in Iran, the country saw severe outcomes, with 55,223 deaths as of December 31, 2020.

Disinformation as blame avoidance behavior by political leaders was exhibited not only in autocratic countries, but also occurred in some democratic countries (Flinders, 2020). For example, during his US presidency, Donald Trump understated the risk of the COVID-19 pandemic by accusing the political opposition of conspiracy and the media of exaggeration (Calvillo et al., 2020). His statements about hydroxychloroquine as a "miracle cure" also misled the public to employ false treatments (Evanega et al., 2020). This misinformation about the disease could directly result in ineffective coping by people and undermine their institutional trust in public health agencies. However, the suspected "disinformation" from democratic leadership, in contrast to autocracies, still encountered effective checks and balances by parliaments, medical professionals, free media, and voters.

2.2. Disinformation and ineffective coping

Some case studies have shown that reliable and transparent government-sponsored epidemic information could have alerted public health institutions and susceptible populations early and led them to take effective preventive behaviors before the COVID-19 pandemic. For example, a key lesson learned from the severe acute respiratory syndrome (SARS) experience in Singapore was the importance of rapid and accurate information to support effective decision making. The innovation of frequent information reviews effectively guided local public health decisions during the H1N1-2009 epidemic (Tan, 2006; Tay et al., 2010). In contrast, government-sponsored disinformation disrupts the mechanisms of information exchange among public health institutions and other bodies, which can lead to ineffective coping, such as perceptions of low risk and the slow development of preventive behaviors at both the individual level, and preparedness delays and resource misallocation at the institutional level.

COVID-19 studies have demonstrated that people's belief in misinformation reduced the likelihood that they would take preventive measures such as mask wearing, social distancing, and complying with official guidelines (Lee et al., 2020; Hornik et al., 2021; Pickles et al., 2021). Case studies of Iran have revealed that government-sponsored disinformation typically results in ineffective coping by individuals and public health institutions and that the disinformation can elevate disease incidence and prevalence in an epidemic (e.g., Bastani and Bahrami, 2020). In addition, in contrast to democracies, autocracies such as Iran, China, Russia, and North Korea are likely to refuse information sharing and regulations promoted by the global health system during a pandemic (Burkle, 2020). When governments disseminate disinformation or suppress valid information, therefore, we expect that it is difficult for public health institutions and citizens to protect themselves from the spread of the disease.

2.3. Disinformation and institutional distrust

Misinformation is likely to trigger institutional distrust in public authorities and thus directs citizens' attention away from professional advice and instead towards skeptics and harmful treatments (Brainard and Hunter, 2019) harmful treatments (Brainard and Hunter, 2019). Disinformation could be associated even more strongly with dire outcomes. Studies conducted before the COVID-19 pandemic have illustrated that distrust of government or the medical profession creates obstacles to preventing epidemics by reducing people's compliance with official messages related to disease containment and by engendering inadequate medical service utilization. For example, studies investigating Ebola outbreaks discovered that respondents with misinformation and low trust in the government were less likely to comply with social distancing policies or take precautions against the epidemic (Blair et al., 2017; Vinck et al., 2019).

Recent global studies on COVID-19 have reported that trust in public institutions, but not general social trust, has a negative association with the disease incidence ratio and deaths related to the pandemic (Elgar et al., 2020). For example, online survey studies confirmed that trust in government amplified compliance with official health guidelines (Pak et al., 2021); evidence from a geographic information system in European countries revealed the same pattern—the higher the political trust, the lower the regional and national human mobility (Bargain and Aminjonov, 2020). Survey studies conducted in both China and Europe have demonstrated that higher political trust before the outbreak was associated with lower incidence and mortality rates (Ye and Lyu, 2020; Oksanen et al., 2020). In addition, studies conducted in the United States have shown a negative relationship between institutional trust in science and the public health system and belief in misinformation (Dhanani and Franz, 2020; Agley and Xiao, 2021) and that both trust and information sources influence the probability that individuals will perform preventive behaviors (Fridman et al., 2020). International comparative studies have also found that distrusting citizens may not comply with regulations because of their underestimation of the risk of non-compliance (Jennings et al., 2021). Therefore, government-sponsored disinformation may result in distrust of public health institutions and be positively associated with the incidence and prevalence of disease.

In this study, cross-national data on vaccination is not included, although other studies suggest that misinformation could result in the spread of epidemics by reducing the willingness to receive vaccination. Studies before COVID-19 have revealed that vaccination-related information on Twitter is associated with regional vaccination rates in the United States and public confidence in vaccination in Russia (Salathé and Khandelwal, 2011; Broniatowski et al., 2018). Based on a global survey, Lunz Trujillo and Motta (2021) found that country-level internet connectivity is associated with individual-level vaccine skepticism. A recent study on the acceptance of COVID-19 vaccines also demonstrated that misinformation exposure significantly reduced the willingness of people to accept a vaccine in the UK and USA (Loomba et al., 2021). As these studies implied, government-sponsored disinformation may reduce the acceptance and coverage of vaccination and thus are likely to be positively associated with the incidence and prevalence of epidemics.

To sum up, blame avoidance and other interests of politicians may stimulate government-sponsored disinformation and internet censorship efforts during epidemics. The disinformation might be associated with ineffective coping by people and institutions, and contribute to institutional distrust of governments and public health systems. The ineffective coping, and resistance to official guidelines of preventive behaviors and vaccination because of the distrust, might facilitate the spread of disease in epidemics. Accordingly, we expect government-sponsored disinformation to be positively associated with the incidence and prevalence measures of respiratory infections including COVID-19.

3. Materials and methods

In this study, we investigate the relationship between government-sponsored disinformation and respiratory infections before the COVID-19 pandemic using data from the period 2000–2019 in high-dimensional fixed-effects (HDFE) regression (Guimaraes and Portugal, 2010) models. We then also examine the relationship between government-sponsored disinformation and cases of and deaths from COVID-19 in the first 300 days after the first case of COVID-19 in each of the 149 countries in our study. Although previous studies have applied the Poisson model (i.e., Elgar et al., 2020), we detected an over-dispersion issue in the COVID-19 dataset. Therefore, following another study (Oztig and Askin, 2020), we analyzed the COVID-19 cases and deaths data using the robust negative binomial regression model.

For the HDFE regression, we integrated data from the Global Burden of Disease Study (GBD, 2020), World Development Indicators (WDI, 2020), Digital Society Project (DSP) dataset (Mechkova et al., 2020), Variety of Democracy (V-Dem) measurements (Coppedge et al., 2020), and other surveys from 149 countries conducted during the period 2000–2019. We employed three epidemiological variables for respiratory infections—the standardized incidence percentage, prevalence percentage, and death percentage, from all causes of disease. We applied the difference of the lagged year ($Y_t - Y_{t-1} = \Delta Y_t$, also called first difference estimator) for each of the three and set these as the dependent variable in the HDFE regression models to estimate the effects of government-sponsored disinformation. For the robust negative binomial regression model, we gathered data from the COVID-19 Weekly Epidemiological Update from the WHO (2020) and incorporated the accumulated cases and deaths from 149 countries for the first 300 days after the first case in each and controlled for the GBD respiratory infection percentages, as well as public health, socioeconomic and political factors in 2019 before the outbreak.

3.1. Government-sponsored disinformation

Government-sponsored disinformation, the key independent variable of this study, was obtained from the DSP dataset (version 3.0). It covers 179 countries globally and includes 35 indicators such as online censorship, disinformation campaigns, polarization and politicization of social media, etc. The timeframe was from 2000 to 2020. The data was collected through expert-coded surveys. For each country, five regional experts were recruited to answer surveys regarding the interaction between digital society and politics in a state according to their professions (Mechkova et al., 2020). However, these experts do not provide answers about the situation in their homeland countries. The answers were standardized and applied to generate indicators according to the methodological procedure developed by scholars of V-Dem (Coppedge et al., 2020), another international data project, to evaluate the different dimensions of digital society globally.

The DSP project involves an expert survey on the question "How often do the government and its agents use social media to disseminate misleading viewpoints or false information to influence its population?" The responses are given on a 5-point Likert scale. A score of 0 refers to extremely often; the government disseminates false information on all key political issues. A score of 1 corresponds to often; the government disseminates false information on many key political issues. A score of 2 refers to about half the time; the government disseminates false information on some key political issues. A score of 3 corresponds to rarely; the government disseminates false information on only a few key political issues. A score of 4 indicates never or almost never. In the project, a lower value implies the higher tendency of governments to spread disinformation on social media. Each country expert made an ordinal judgement in the questionnaire. To standardize the scale, the V-dem team then developed Linearized Original Scale Posterior Prediction estimates for each question as the linearized median to serve as the point evaluation for the specific country-year (Pemstein et al. (2021). The same variable suggested by the V-Dem methodologists has been applied to study the democratic landslide during the COVID-19 pandemic (Edgell et al., 2021). We reversed the order of point estimates values in this study and linearly converted them into a 0%–100% range according to maximum and minimum country-year values. The transformed estimates did not change the statistical results (except for the reversed correlation scale) but simply made it easier to explain the degree of the disinformation in reality. Thus, we considered higher values to signify higher frequency of a government generating and spreading disinformation in its territory.

Fig. 1 presents the average scores for government-sponsored disinformation campaigns globally. As seen in the figure, the disinformation index of the worst-scoring 20 countries is considerably higher than the global average and has been continually increasing in the most recent decade, whereas the scores of the developed OECD countries are lower than the global average but also rapidly increasing. The figure also details the highest levels of government-sponsored disinformation campaigns in the world. The five countries experiencing the highest levels of such disinformation campaigns in 2019 were Venezuela, Azerbaijan, Burundi, Russia, and China, which are autocracies or fragile states with little respect for free speech.

The risk of a population being influenced by online disinformation campaigns may depend on the population's exposure to the internet (Lunz Trujillo and Motta, 2021). Accordingly, we collected data on the percentage of the population using the internet from the WDI database. Nevertheless, the effects of internet coverage could be complex. Although the internet may facilitate the establishment of a digital infrastructure favorable for people's well-being, including their health, it can also be a tool for the government to manipulate and spread disinformation on epidemics. In addition, a study noted that the blocking of information for political censorship might be applied by governments to underreport the numbers of cases and deaths related to COVID-19 (Karabulut et al., 2021). We employed an internet censorship variable described below to control for the tentative effects of the censorship on underreporting epidemics.

The DSP project involves another expert survey question "How frequently does the government censor political information (text, audio, images, or video) on the Internet by filtering (blocking access to certain websites)?" The responses are also on a 5-point Likert scale from 0 (extremely often), 1 (often), 2 (sometimes), 3 (rarely), to 4 (never) (Mechkova et al., 2020). We also reversed the order of ordinary values and converted them into a 0%–100% range, that is, a higher value refers to stronger internet censorship by the government. It has been applied to study the effect of internet censorship on the activeness of civil society

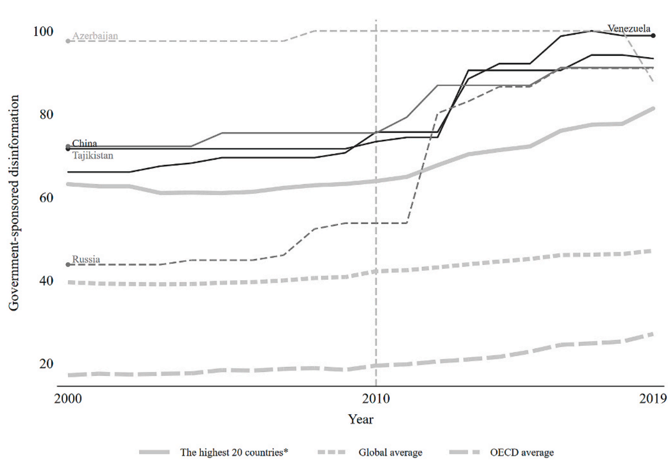

Fig. 1. Government-sponsored disinformation index. Average of the highest 5 countries and highest 20 countries, global average, and OECD average for 2000–2019.

and has been shown to be valid and reliable (Chang and Lin, 2020). In line with earlier findings (Karabulut et al., 2021), we assume that the degree of internet censorship is negatively associated with the numbers of confirmed cases and deaths from epidemics.

3.2. *Percentage of respiratory infections from all causes*

For our analysis on respiratory infections that had global consequences before COVID-19, including flu, coronaviruses, and pneumonia such as SARS and the Middle East respiratory syndrome (MERS), we used the incidence, prevalence, and death percentages of upper and lower respiratory tract infections as dependent variables (Skov et al., 1998). Data on upper respiratory infections incorporated cough, acute nasopharyngitis, sinusitis, pharyngitis, tonsillitis, laryngitis, tracheitis, epiglottitis, rhinitis, rhinosinusitis, rhinopharyngitis, and supraglottitis; while lower respiratory infections included death and disability resulting from clinician-diagnosed and self-reported cases of pneumonia, bronchiolitis, respiratory syncytial virus (RSV), and influenza-like illness. However, the GBD databases do not provide information on the different causes and details of the upper and lower respiratory infections. For the readers who are interested in the detailed analyses of upper and lower respiratory infections separately, please refer to the supplementary files.

The GBD database contains three types of variables for respiratory infections: number of infections, growth rate of infections in the population, and percentage of infections from all causes of disease. Prevalence refers to the proportion of persons in total who have a condition during the specific year, whereas incidence refers to the proportion or rate of persons who newly develop a condition during the year. We selected percentages (incidence, prevalence, and death) rather than rates as indicators to present the severity of the influence of respiratory infections. We discovered that there are some difficulties in applying the number or rate of some infectious diseases in the GBD. In developing countries, a large proportion of deaths may not be attributed to a specific cause by medical professionals. For example, the number or rate of deaths from respiratory infections may be inaccurate because of underreporting or misclassification. We noticed that the standard deviation of death and incidence rates of the respiratory infections is much greater in developing countries than in developed countries and this reduced the associations between socio-economic conditions and the diseases. Applying the percentages of respiratory infections from all causes can limit the range of the standard deviation and moderate the heteroscedasticity in the data of the respiratory infections in developing countries. Therefore, we use percentages rather than rates or numbers of cases and deaths to estimate the influence of respiratory infections before COVID-19. The statistical results of percentages and rates of respiratory infections using the same models are very similar and also significant (please refer to the supplementary files).

The death, incidence, and prevalence percentages of respiratory infections from all causes showed some positive correlations to government-sponsored disinformation. As illustrated in Fig. 2 via a simple regression line, for example, government-sponsored disinformation indexes in the previous year were positively associated with the death percentages of respiratory infections during the period 2001–2019 (the country points are the average values).

3.3. *Cases and deaths of COVID-19*

We also used the number of cases and deaths of COVID-19 in the first 300 days after the first case was reported in each country and before vaccinations began as the dependent variable to investigate the association between government-sponsored disinformation and the spread of the pandemic. The United Kingdom was the first country to administer vaccinations to citizens; this occurred 311 days after the first case was reported. We also applied data from different periods until the end of 2020 and 365 days after the first case for comparison with the GBD

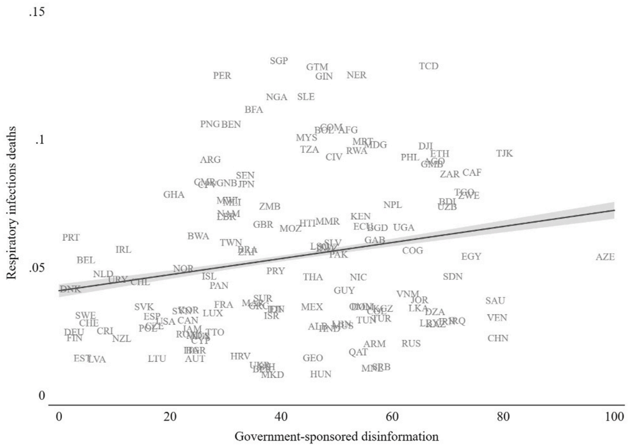

Fig. 2. Correlation between government-sponsored disinformation and the percentage of deaths from respiratory infections, with the average points for 149 countries.

records. Although the statistical results were similar to those for the first 300 days, the integration of COVID-19 data with the respiratory infection percentages in the GBD for comparison remained difficult. The incidence and prevalence percentages of COVID-19 were much lower than those of previous aggregated respiratory infections, and their interactions from 2020 are complicated. Therefore, we estimated the relationship between government-sponsored disinformation and the incidence rate ratio (IRR) of cases and deaths separately by using the negative binomial regression model.

3.4. Control variables

Factors influencing the cross-national comparison of respiratory infections are complex. First, we adopted control variables from various sources, such as temperature and precipitation from the Climatic Research Unit dataset (Harris et al., 2020). Second, we used population density as a proxy to measure "social and physical distancing" in relation to exposure to pandemics. Third, given the evidence that older populations are more vulnerable to diseases than younger populations, we incorporated life expectancy and measured the influence of demographic structure (Wu and McGoogan, 2020). In addition, we introduced infant mortality rate and the number of physicians (doctors) per 1000 people to control for the varying quality of public health systems (Zweifel and Navia, 2003). To estimate differences in economic development and industrialization, we applied the natural logarithm of gross domestic product (GDP) per capita [ln(GDPpc)] adjusted for purchasing power parity and the percentage of the rural population from the WDI database (Zhang et al., 2021). Scholars have argued that democracies typically perform better during epidemics than authoritarian governments (Justesen, 2012). However, the performance of democracies during the COVID-19 pandemic could be an exception (Karabulut et al., 2021). Therefore, we used Polity V, a widely used political science database covering 167 countries from 1800 to 2018, to measure the level of democracy. The Polity score ranges from −10 to +10, with −10 signifying the most autocratic country and +10 signifying the most democratic country (Marshall and Marshall, 2019). Finally, to account for global health inequality (Elgar et al., 2020), we introduced domestic income inequality by using the Gini coefficient of net income (Gini, 0%–100%) from the Standardized World Income Inequality Database (Solt, 2020), which comprises income inequality indicators from 196 countries for the period 1960 to the present.

3.5. Data integration

After integrating data from different sources, we selected 2001–2019 as the study period because the DSP disinformation survey started in 2000. Therefore, in the COVID-19 models, we incorporated the explanatory variables of 2019 from the integrated database. Second, we selected 191 countries from the COVID-19 database and deleted those that reported no cases of or deaths due to COVID-19 to the WHO in 2020. As Rocco et al. (2021) suggested, including these missing numbers made their data less reliable. Third, we kept the 163 countries with complete data of government-sponsored disinformation in the DSP dataset. Fourth, we checked the control variables and found that most of the missing data was for physicians per 1000 people (namely, physician density) and Gini coefficients. We removed countries that reported only two points or fewer of any control variable in the two decades because retaining them may have reduced the reliability of data imputation. After deleting 14 countries with almost no information of physician density and Gini coefficients, we retained a nearly balanced panel of 149 countries, which is similar to the country list of Edgell et al. (2021) on COVID-19, for the period 2000–2019. For the control variables still affected by missing data, namely ln(GDPpc), Gini, physician density and internet coverage, we covered the missing data by Bayesian bootstrapping multiple imputations using the Amelia II program (Honaker et al., 2011). Table 1 lists the data sources, and Table 2 presents the original descriptive statistics of the variables (standardized later in the models).

3.6. Regression models

We separately estimated the effects of government-sponsored disinformation on GBD respiratory infections (2001–2019, Table 3) and on COVID-19 (2020, Table 4) by using different models. We used standardized HDFE regression to estimate a first difference estimator that comprised year and country dummy and independent variables of the previous year. The advantage of this fixed-effect model is that it excludes the effects of unobserved time-invariant variables (e.g., geographic region and national religion). The period effect was reduced using the year dummy variables in our models. Except for temperature and precipitation, the independent variables of the previous year reduced endogeneity problems among health outcome, government-sponsored disinformation, and other control variables. As shown in Fig. 3, the incidence percentage of respiratory infections in the GBD in 2019 was positively correlated with the number of COVID-19 cases in 2020, and the 20 countries with the highest scores on the government-sponsored disinformation index were more severely affected by the pandemic than the global average.

We applied the robust negative binomial regression model and the independent variables of the closest year (2018–2019) to estimate the COVID-19 cases and deaths in the first 300 days after the first case. The key variable in these models was the government-sponsored disinformation index in 2019; the national population in 2019 was used as the exposure variable to calculate the IRR of cases, and the number of cases was used as the exposure variable to calculate the IRR of deaths. In the model estimating the COVID-19 cases, the control variables included the incidence percentage of respiratory infections in 2019, whereas in the model estimating the COVID-19 deaths, the control variables included the percentage of respiratory infections that resulted in death in 2019. Both models controlled for temperature (2020), precipitation (2020), infant mortality (2019), life expectancy (2018), ln(GDPpc) (2018), physician density (2018), ln(population density) (2019), rural population (2019), democracy (2018), Gini (2018), and Internet coverage (2019).

Table 1
Data sources.

Variable	Measurement	Data Source
COVID-19 cases	Country-level COVID-19 number of confirmed cases 300 days after the first case	World Health Organization (WHO)
COVID-19 deaths	Country-level COVID-19 number of deaths 300 days after the first case	WHO
Respiratory infection incidence	$Incidence_{i,c,t} = \frac{New\ cases_{i,c,t}}{New\ cases\ from\ all\ causes\ of\ disease_{c,t}}$, where i = upper, lower, and total respiratory infections; c = country id; t = year $\Delta Incidence_{i,c,t} = Incidence_{i,c,t} - Incidence_{i,c,t-1}$	Global Burden of Disease Study (2019) (GBD)
Respiratory infection prevalence	$Prevalence_{i,c,t} = \frac{Total\ cases_{i,c,t}}{Total\ cases\ from\ all\ causes\ of\ disease_{c,t}}$, $\Delta Prevalence_{i,c,t} = Prevalence_{i,c,t} - Prevalence_{i,c,t-1}$	GBD 2019
Respiratory infection deaths	$Deaths_{i,c,t} = \frac{Deaths_{i,c,t}}{Deaths\ from\ all\ causes\ of\ disease_{c,t}}$, $\Delta Deaths_{i,c,t} = Deaths_{i,c,t} - Deaths_{i,c,t-1}$	GBD 2019
Temperature	Annual mean of monthly average daily mean temperature; unit: °C	Climatic Research Unit 4.05 (CRU)
Precipitation	Annual mean of precipitation (mm)	CRU
Infant mortality	Mortality rate, infant (per 1000 live births)	World Development Indicators (WDI)
Physician density*	Number of physicians per 1,000 people	WDI
Life expectancy	Life expectancy at birth, total (years)	WDI
ln(GDPpc)*	GDP per capita, Purchasing Power Parity (PPP, constant 2017 international $)	WDI
ln(population density)	Population density (people per sq. km of land area)	WDI
Rural population	Rural population (% of total population)	WDI
Democracy	Polity score, autocracies (−10 to −6); anocracies (−5 to +5); democracies (+6 to +10)	Polity V
Gini*	Estimate of Gini index of inequality in equivalized (square root scale) household disposable (posttax, posttransfer) income, using Luxembourg Income Study data as the standard	Standardized World Income Inequality Database 9.1
Internet coverage*	Individuals using the Internet (% of population)	WDI
Internet censorship*	Censorship attempts including Internet filtering (blocking access to certain websites or browsers), denial-of-service attacks, and partial or total Internet shutdowns	Varieties of Democracy 11.1 (V-Dem)
Disinformation	Domestic government dissemination of false information	V-Dem 11.1

Note: *We applied Bayesian multiple imputation in Amelia II to the following five control variables: physician density: (N = 1,820, missing = 1,011); ln (GDPpc): (N = 2,816, missing = 15); Gini: (N = 2,447, missing = 384); Internet coverage: (N = 2,745, missing = 86); and Internet censorship: (N = 2,827, missing = 4).

4. Results

4.1. Respiratory infections in the period 2001–2019

Table 3 presents the coefficients of the standardized HDFE regression models, with model (1) estimating the annual change (first difference estimator) in the incidence percentage (ΔIncidence), model (2) estimating the annual change in the prevalence percentage (ΔPrevalence), and model (3) estimating the annual change in the death percentage (ΔDeath). The results of all three models were standardized; therefore, the coefficients could easily show whether the percentage of the explanatory variable change in the year is positively or negatively associated with the unit of standard errors of ΔIncidence, ΔPrevalence, and ΔDeath in the lagged year.

Table 2
Description of variables.

Variables	Mean	SD	Min	Max
COVID-19 cases*	439,761.544	1,327,059.235	53	1,0618,459
COVID-19 deaths*	10,771.322	30,973.697	2	246,131
Respiratory infections incidence (%)	0.438	0.064	0.271	0.590
Respiratory infections prevalence (%)	0.034	0.006	0.016	0.051
Respiratory infections deaths (%)	0.054	0.033	0.008	0.164
Upper respiratory infections incidence (%)	0.427	0.066	0.259	0.581
Upper respiratory infections prevalence (%)	0.033	0.006	0.015	0.049
Upper respiratory infections deaths (%)	0.000	0.000	0.000	0.002
Lower respiratory infections incidence (%)	0.011	0.003	0.004	0.021
Lower respiratory infections prevalence (%)	0.001	0.000	0.000	0.003
Lower respiratory infections deaths (%)	0.053	0.032	0.007	0.163
Temperature	17.309	7.636	−8.680	27.878
Precipitation	1,097.906	754.050	15.389	4,501.800
Infant mortality	29.238	27.473	1.600	139.500
Physician density	1.646	1.312	0.001	7.120
Life expectancy	69.324	9.735	39.441	84.211
ln(GDP pc)	9.179	1.196	6.447	11.652
ln(Population density)	4.108	1.348	0.779	8.981
Rural population	43.051	22.030	0.000	91.754
Democracy	4.519	5.802	−10.000	10.000
Gini	39.332	8.489	22.580	67.439
Internet coverage	30.985	29.197	0.000	99.653
Internet censorship	24.587	22.265	0.000	100.000
Disinformation	41.835	21.412	0.000	100.000

Note: N = 2,831. The year range for data on respiratory infections is 2001–2019 and that for other variables is 2000–2018. *COVID-19 cases and deaths on the 300th day since the 1st case reported.

In these models, the key explanatory variable—the index of government-sponsored disinformation in the previous year—consistently exhibited significant positive associations with ΔIncidence and ΔPrevalence. The relationship between the index of government-sponsored disinformation and ΔDeath was positive but non-significant. In addition, along with the effect of disinformation, internet coverage (indicating informational infrastructure) was significantly negatively associated with the prevalence percentages, whereas internet censorship was also negatively associated with the incidence percentage.

Except for the results of the key explanatory variable, some results of control variables related to public health were consistent with the predictions in the literature; for example, population density was positively associated with the prevalence percentage of respiratory infections, and the physician density was negatively associated with the percentage of respiratory infections. Income inequality was positively associated with epidemics, as measured by the prevalence percentage (Pinzón-Rondón et al., 2016) and as reported in recent studies on COVID-19 (Elgar et al.,

Table 3
Government-sponsored disinformation and respiratory infections: standardized high dimensional fixed-effects regression.

	Respiratory infections		
	Δ Incidence (1)	Δ Prevalence (2)	Δ Deaths (3)
Temperature	0.029	−0.042	−0.035
	(0.024)	(0.022)	(0.024)
Precipitation	−0.000	0.000	−0.000
	(0.000)	(0.000)	(0.000)
Infant mortality (*t*-1)	0.651	0.021	0.035
	(0.404)	(0.142)	(0.412)
Physician density (*t*-1)	−0.018	−0.163*	−0.075
	(0.054)	(0.070)	(0.051)
Life expectancy (*t*-1)	0.502	0.382	−0.358
	(0.263)	(0.200)	(0.255)
ln(GDP pc) (*t*-1)	−0.408	0.029	−0.394
	(0.290)	(0.159)	(0.214)
ln(Population density) (*t*-1)	0.661	0.816**	−0.608
	(0.461)	(0.266)	(0.429)
Rural population (*t*-1)	0.213	−0.112	−0.124
	(0.165)	(0.222)	(0.156)
Democracy (*t*-1)	0.001	0.004	−0.003
	(0.016)	(0.016)	(0.014)
Gini (*t*-1)	0.128	0.416**	0.059
	(0.094)	(0.156)	(0.083)
Internet coverage (*t*-1)	−0.181	−0.251***	−0.049
	(0.093)	(0.063)	(0.091)
Internet censorship (*t*-1)	−0.193*	−0.103	−0.046
	(0.098)	(0.094)	(0.077)
Disinformation (*t*-1)	0.270*	0.345*	0.108
	(0.122)	(0.160)	(0.107)
Constant	−0.365	0.710	0.713
	(0.415)	(0.406)	(0.406)
Country fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
R^2	0.136	0.156	0.229
Adjusted R^2	0.078	0.099	0.177

Note: N = 2,831. Coefficient of linear regression absorbing multiple levels of fixed-effects model; robust standard errors in parentheses. *$p < .05$, **$p < .01$, ***$p < .001$, two-tailed test.

2020), but its effect on the death percentage for all respiratory infections was nonsignificant. The proportion of rural population, related to underdevelopment, is also positively associated with the incidence percentage. Nevertheless, the effect of some control variables, such as climatic factors and economic development, were nonsignificant. Although the populations of democratic countries are usually healthier than those of nondemocratic countries (Bollyky et al., 2019), the effects of regime type on the incidence, prevalence, and death percentages of respiratory infections were not significant. Democracies performed better than autocracies only in preventing high prevalence percentages of lower respiratory infections in our further investigations.

4.2. Cases and deaths related to COVID-19 (over ~300 days)

Table 4 presents the results of the robust negative binomial regression models for the COVID-19 data. The coefficients reflected the IRR calculated from the national population (that is, the exposure of the models); if the coefficient is higher than 1, the independent variable is positively associated with the IRR of cases and deaths, whereas if the coefficient is lower than 1, the independent variable is negatively associated with the IRR, in the cross-national comparison. Following similar model designs employed in recent COVID-19 studies (Oztig and Askin, 2020), model (4) was constructed to estimate the results for the IRR of the cases on the basis of the national population whereas model (5) was constructed to estimate the results for deaths on the basis of the exposure of cases in the first 300 days.

In the model of cases, the government-sponsored disinformation index in 2019 was significantly positively associated with the IRR of COVID-19 in the first 300 days. It was positively associated with the IRR

Table 4
Government-sponsored disinformation and COVID-19: negative binomial regression.

	COVID-19	
	Cases (4)	Deaths (5)
Respiratory infections incidence	1.000	
	(0.000)	
Respiratory infections deaths		1.000
		(0.000)
Temperature	0.979	0.993
	(0.023)	(0.011)
Precipitation	1.000*	1.000
	(0.000)	(0.000)
Infant mortality	0.975**	1.004
	(0.009)	(0.007)
Physician density	1.196	0.885*
	(0.113)	(0.050)
Life expectancy	1.007	1.051*
	(0.030)	(0.021)
ln(GDP pc)	1.724**	0.857
	(0.294)	(0.119)
ln(Population density)	1.063	0.907
	(0.067)	(0.046)
Rural population	0.996	1.001
	(0.006)	(0.004)
Democracy	1.022	1.008
	(0.021)	(0.014)
Gini	1.042***	1.005
	(0.011)	(0.009)
Internet coverage	0.995	0.997
	(0.005)	(0.004)
Internet censorship	0.991	0.995
	(0.005)	(0.003)
Disinformation	1.011**	1.006
	(0.004)	(0.003)
Exposure variable	Population	COVID-19 cases
Dispersion parameter	0.938	0.353***
	(0.122)	(0.045)
Log likelihood	−1,878.135	−1,190.340
Pseudo R^2	0.035	0.010

Note: N = 149. The variables, Respiratory infections incidence and Respiratory infections deaths, use case number instead of percentage. The variables, Temperature and Precipitation were for 2020, Infant mortality, ln(GDP pc), ln (Population density), Rural population, Internet coverage, Internet censorship, and Disinformation were for 2019, and the others were for 2018. Incidence rate ratios of negative binomial regression model; robust standard errors in parentheses. *$p < .05$, **$p < .01$, ***$p < .001$.

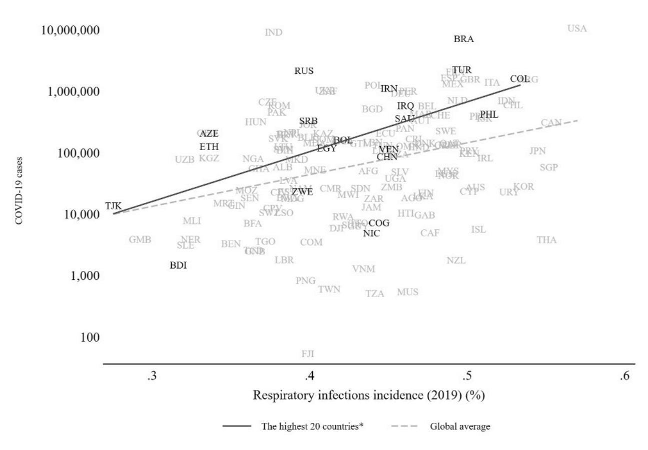

Fig. 3. Correlation between the incidence percentage of respiratory infections in 2019 and that of COVID-19 in 2020, in the highest 20 countries where government-sponsored disinformation is prevalent, and the global average of 149 countries.

of the deaths related to COVID-19 but nonsignificant. In contrast, internet censorship and internet coverage was associated with lower reported number of both cases and deaths during the pandemic but at only marginal significance ($p < .1$). The major results of informational variables are consistent with those of the HDFE models of respiratory infections for the period 2001–2019.

In the negative binomial regression models on COVID-19, the Gini coefficient was significantly positively associated with cases (Elgar et al., 2020), while the effects of some control variables were different from their effects in the HDFE models of respiratory infections before the pandemic. For instance, infant mortality became significantly negatively associated with the IRR of cases. Moreover, another variable—physician density was negatively associated with the IRR of deaths. Some results of control variables are consistent with those of recent studies on COVID-19. Economic development, measured using ln(GDPpc), was significantly positively correlated with the IRR of cases but negatively correlated with the IRR of deaths related to COVID-19 (Zhang et al., 2021). In contrast, life expectancy was significantly positively associated with the IRR of deaths (Shams et al., 2020).

The non-significant correlation between democracy and the impact of COVID-19, in contrast to the positive correlation between democracy and other health indicators, could have been a result of a higher detection capacity in the medical systems of these countries (Richards, 2020), but it may reflect some ignored health inequalities, institutional vulnerabilities (Karabulut et al., 2021), and the "pandemic backsliding" of illiberal regulations in democracies (Edgell et al., 2021). We note that one study found no association between governments' illiberal measures (including disinformation) and the logged COVID-19 mortality rate over the period March to December 2020 (Edgell et al., 2021). We discovered that government-sponsored disinformation was positively and significantly associated with cases but not with deaths. The results imply that the mortality of the pandemic might be determined by the capacity of public health systems, such as the measure of physician density, but that factors such as informational systems or nondemocratic reactions are less relevant.

5. Conclusion

This study hypothesized a positive association between political disinformation and its impacts on epidemics in light of political and institutional processes. The findings reveal that government-sponsored disinformation is associated with the incidence and prevalence of respiratory infections during the period 2001–2019, before the COVID-19 pandemic. Government-sponsored disinformation is also positively associated with the IRR of cases of COVID-19 before vaccination program implementation. In contrast to literature focusing only on the effects of misinformation and preventive behaviors at the individual level during the COVID-19 pandemic, the present study integrated evidence from global surveys and revealed the adverse effects of government-sponsored disinformation on the management of epidemics over the last two decades. We found that disinformation is positively and significantly associated with the incidence and prevalence of respiratory infections including COVID-19, though its positive relationship with mortality of these respiratory infections was not significant.

This study has some limitations. First of all, the disinformation index focused on only government sources and not on other disinformation and misinformation sources. Also, the DSP database is expert-rated and inevitably subjective. However, it is the only existing global database regarding the interaction between politics and social media. Second, the pooled category of respiratory infections and the percentages of all disease causes could not be directly compared with the IRRs for a single pandemic. Data on both cases and deaths in the GBD and COVID-19 databases might not only present the impacts of the respiratory infections but also reflect differing levels of capacity among various public health systems and transparency among governments. The data on respiratory infections may be censored deliberately or underreported unintentionally by developing countries. For the application of the GBD database, we suggest that adopting the percentages of a specific type of epidemic from all causes might be a relatively more reliable choice than the rates or numbers. However, the database of epidemics might consider some adjustments to address the variation from the different capacity of public health systems. Despite these limitations, this study may be the first to present cross-national evidence of the association between political disinformation and the spread of epidemics including COVID-19.

Our study also implies that the quality of data during the COVID-19 pandemic is an endogenous factor of informational politics. The internet censorship of autocracies tends to systematically underreport the morbidity and mortality of the pandemic. Iran is a vivid example of intentionally underreporting and also disseminating fake news. There is also evidence of deliberate inaccuracies and concealment of COVID-19 infections in lower- or middle-income countries (Richards, 2020). Rocco et al. (2021) revealed that subnational COVID-19 data quality, including mortality, is associated with media independence. Hansen et al. (2021) pointed out that in the United States, counties were more likely to release information about COVID-19 when there was a stronger opposition (Democrats) before the US presidential election. In our analysis, governments that applied censorship and spread fake news as blame avoidance behaviors may also intentionally underreport the numbers of infected and deaths. After all, concealing the numbers of cases and deaths during the pandemic is also a form of political disinformation. Therefore, we may have underestimated the association between disinformation and the severity of pandemics. The real damage of disinformation may be greater than the current findings show.

Based on our findings, we suggest countering disinformation during the COVID-19 pandemic. First, we would ask that governments immediately stop sponsoring disinformation for blame avoiding or regarding the disease as a strategy for gaining political advantage in domestic and international conflicts. Also, we would propose that the international community and global civil society act to prevent governments from sponsoring disinformation campaigns and internet censorship. In practice, fact-checking authorities managed by civil associations may be established to efficiently refute fake news. Eliminating fake news in civil society may help curb the spread of infections. In sum, to control the pandemic, fighting disinformation can play a key role.

Credit author statement

Thung-Hong Lin: Principal Investigator, Writing, Methodology, Chun-Chih Chang: Integration of Political Theory. Ming-Chiao Chang: Review of Medical Literature, Ya-Hsuan Chou: Formal analysis, Visualization.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2022.114744.

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