# Government-Sponsored Fake News Worsens Epidemics of Respiratory Infections Including the Coronavirus: Global Survey

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# Government-Sponsored Fake News Deteriorates Epidemics of Respiratory Infections: A Global Survey, 2000-2017

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## Abstract

The growth of the coronavirus disease 2019 (COVID-19) pandemic has prompted some government-sponsored Internet disinformation campaigns. We assumed that government-sponsored disinformation may deteriorate infectious disease epidemics through three mechanisms: ineffective coping, institutional distrust, and stigma avoidances. By employing global surveys across 144 countries for the period 2000–2017, we examined the association between government-sponsored disinformation and the spread of respiratory infections before the COVID-19 outbreak. After controlling for climatic, public health, socioeconomic, and political factors, we observed that government-sponsored disinformation significantly increased the incidence, prevalence, and death percentages of respiratory infections in populations. These empirical results thus deliver a warning: To contain the damage from pandemics, governments must immediately stop sponsoring disinformation campaigns. Because these respiratory infections share a common transmission pathway with COVID-19, our findings shed light on the mechanisms through which information environments play a major role in the management of modern pandemics.

## Introduction

Coronavirus disease 2019 (COVID-19) has engendered a worldwide medical crisis since the beginning of 2020. As the COVID-19 pandemic grows, accurate and inaccurate information has spread on the Internet. The World Health Organization (WHO) warned of the risk of an "infodemic," in which an overwhelming amount of circulating information discredits professional advice and prevents accurate information from reaching its target audience. Attempts to conceal or distort information on the disease may account for its uncontrolled spread globally. In the social science literature, disinformation refers to false information that is spread deliberately to deceive people. Disinformation has been applied by politicians and criminals long before the digital era. Government-sponsored disinformation campaigns have been publicly criticized; however, the relationship between such campaigns and disease spread has rarely received attention in scientific studies before the COVID-19 outbreak.

Accordingly, the relationship between government-sponsored disinformation and the spread of infectious diseases warrants investigation. Studies on the mechanisms underlying informational causes of diseases have focused on individual-level analyses or simulations in single regions or populations. By examining global surveys from 144 countries from 2000 to 2017, the present study discovered that government-sponsored disinformation may increase the spread of respiratory infections. Because respiratory infections share a common transmission path with COVID-19, this result is critical for understanding the spread of modern pandemics.

## Government-sponsored Disinformation and Epidemic

Politicians frequently adopt informational instruments such as bots and trolls to manipulate public perception and reshape the collective decisions of the majority. Compared with their opponents, incumbents typically have more incentives and resources to employ disinformation campaigns, undermine opponents' interactions, and revive patriotism by creating imagined foreign enemies. Comparative political studies have noted that autocracies may create more fake news than do democracies. In contrast to democratic governments elected to provide public goods through majority rule, the leaders of nondemocratic governments remain in office by gaining support from a small group of political elites. Autocratic governments, therefore, face the constant threat of mass protests from large numbers of disenfranchised people.

In the digital age, autocracies prefer to use informational instruments to compromise potential protests, particularly during political crises and natural disasters. For example, a recent study revealed that autocracies used Internet censorship as a reactive strategy to suppress civil society after the Arab Spring. Figure 1 presents the top 10 countries experiencing government-sponsored disinformation campaigns, according to the Digital Society Project (DSP) dataset (2000–2018) released in 2019. The scores indicate the highest levels of government-sponsored disinformation campaigns in the world. The top 10 countries experiencing disinformation campaigns in 2017 are listed as follows: Azerbaijan, Venezuela, Russia, China, Tajikistan, Cambodia, Iran, Turkmenistan, Zimbabwe, and Burundi. Moreover, these countries are mainly autocracies or fragile states.

Disinformation is a tool used to maintain political stability in a government's favor; however, if not used carefully, it may also lead to unintended consequences, including the collapse of public health systems and more infections and death from disease. The Chinese government has been criticized for its ignorance and suppression of information on COVID-19. Chinese diplomats have openly accused the United States of spreading the disease, with the Iranian and Russian governments also supporting this theory. In Iran, the government gave contradictory information on national COVID-19 fatalities. That Iran, Russia, and China could not contain the outbreak in its early stages may not be a coincidence. Figure 2 indicates that the top 10 countries involving disinformation campaigns received significantly higher fatality rates from various respiratory infections similar to COVID-19 from 2000 to 2017 than did countries not involving disinformation campaigns. In this article, we highlight three mechanisms—ineffective coping, institutional distrust, and stigma avoidance—to explain the association between government-sponsored disinformation and the exacerbation of infectious diseases.

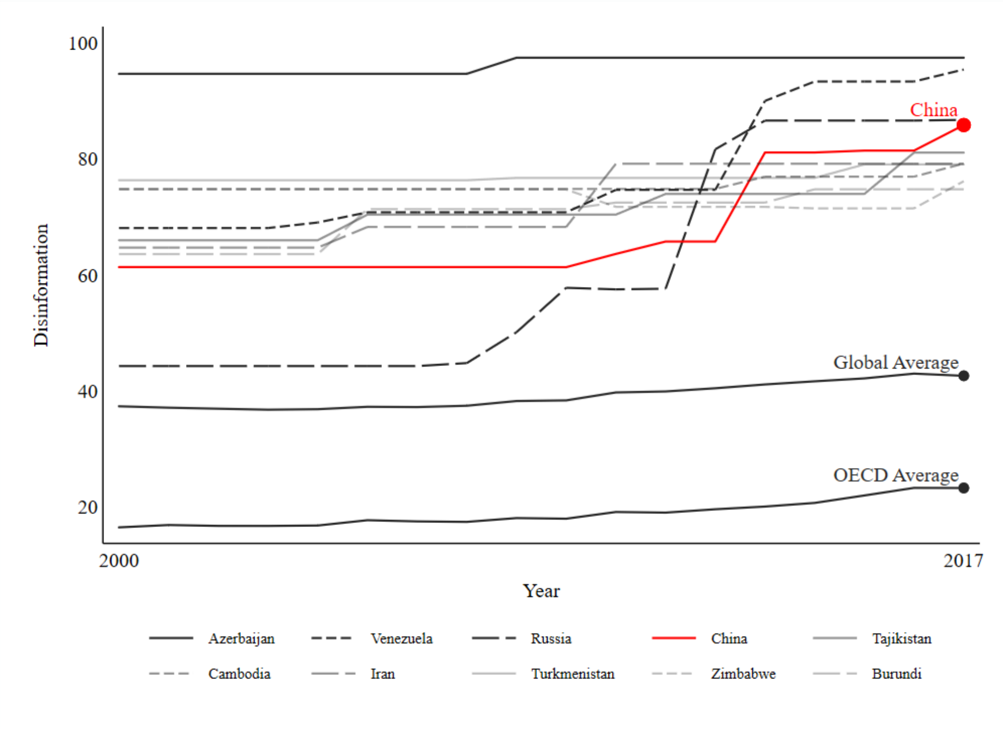


**Figure 1. Government-sponsored disinformation, global and top 10 countries trends, 2000-2017**

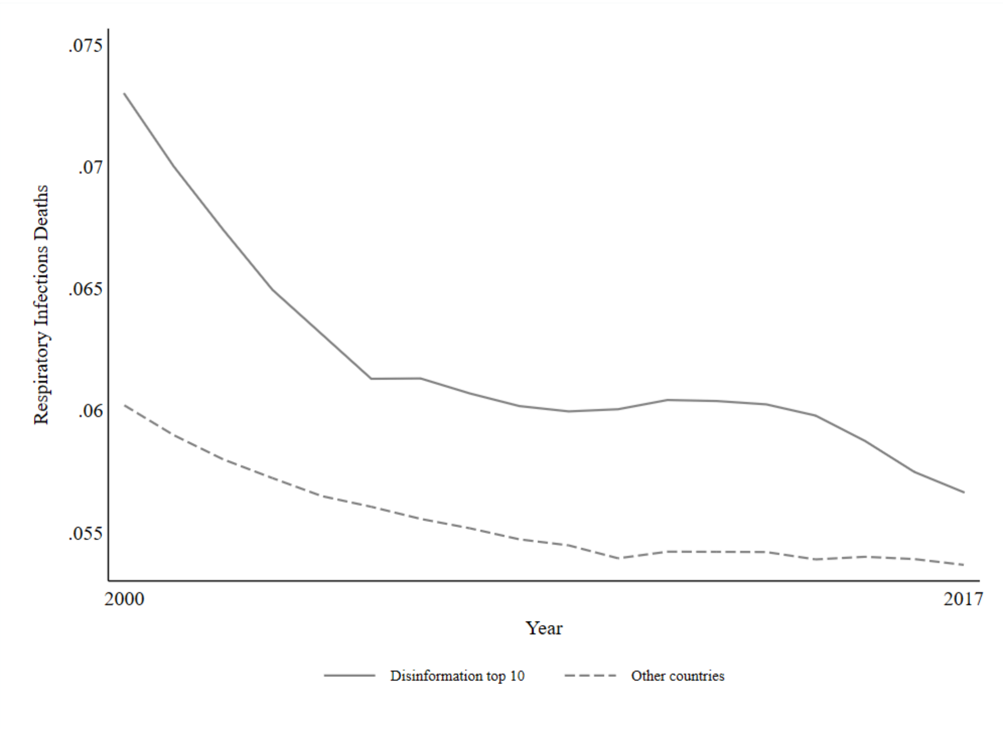


**Figure 2. Respiratory infections deaths percentage, global and top 10 countries trends, 2000-2017**

## Ineffective Coping

Government-sponsored disinformation disrupts the mechanisms of information exchange among public health institutions and other bodies, which leads to ineffective coping at the individual level—such as perceptions of low risk and the slow development of coping behavior—and delays in preparedness and resource misallocation at the institutional level. For example, a key lesson learned from the severe acute respiratory syndrome (SARS) experience in Singapore is the importance of rapid and accurate information for effective decision-making. The innovation of frequent information reviews effectively guided local public health decisions during the H1N1-2009 epidemic. However, when governments disseminate disinformation or suppress valid information, containing diseases becomes arduous. The case of Iran during the COVID-19 pandemic is a typical example of this. On February 10, 2020, the Iranian government falsely claimed that, "…there are no cases of coronavirus in the country and our citizens should only follow news released by the Health Ministry on the coronavirus." However, an Iranian woman died of the coronavirus disease on the same day. The lack of transparency on the epidemic in Iran has resulted in severe outcomes and led to more than 6,200 deaths by May 5, 2020. In addition, studies have revealed that autocracies sponsoring disinformation are more likely to refuse foreign aid and regulations promoted by the global health system. Cases in such countries reveal that government-sponsored disinformation typically results in ineffective coping by individuals and institutions and amplifies the incidence of an epidemic.

## Institutional Distrust

Government-sponsored disinformation triggers institutional distrust in public authorities and thus directs citizens' attention from professional advice to harmful treatments (Brainard and Hunter, 2019). Distrust of the government or the medical profession creates obstacles to the prevention of epidemics through two mechanisms: reducing people's compliance with official messages for disease containment and engendering inadequate medical service utilization. Blair et al. (2017) investigated the 2014–15 Ebola virus disease in Liberia and discovered that respondents with low trust in the government were less likely to comply with government-mandated social distancing policies or take precautions against Ebola in their homes. During the 2018–2019 Ebola outbreak in the Democratic Republic of the Congo, mistrust of the local authorities and misinformation on Ebola prevented people from receiving formal medical treatment (Vinck, 2019). Alsan and Wanamaker (2017) argued that the revelation of the Tuskegee Study of Untreated Syphilis in the African American Male, which undermined trust in the medical profession among older black men, increased the mortality of the affected population. Moreover, studies have revealed that vaccination-related information on Twitter determines regional vaccination rates in the United States and public confidence in vaccination in Russia (Salathé and Khandelwal, 2011; Broniatowski, 2018). Accordingly, institutional distrust amplifies the incidence and prevalence of epidemics.

## Stigma Avoidance

Government-sponsored disinformation exacerbates the stigmatization of infected people; accordingly, infected people may attempt to evade detection and medical treatment, a behavior that may worsen the damage caused by epidemics. Stigmatization engenders fear and prejudice against infected individuals or the entire groups or communities they belong to and may even result in violence against the stigmatized group. The literature reveals that stigmatization and discrimination have adverse effects on public health efforts geared toward managing diseases such as mental illness, leprosy, and epilepsy. Stigmatization sets barriers to health care seeking; additionally, the social marginalization caused by stigma can lead to poverty and neglect, which elevates the susceptibility of populations to diseases. During the 2003 SARS outbreak, infected people who experienced stigma and discrimination intentionally avoided community detection. Recently, the stigmatization of wearing a face mask may have resulted in the outbreak of COVID-19 in Western countries. As suggested by the experience gained from SARS and COVID-19, avoiding stigmatization may increase illness and death during pandemics (Person et al., 2004).

Although we linked the mechanisms ineffective coping, institutional distrust, and stigma avoidance to the indicators incidence, prevalence, and death rate of respiratory infections, respectively, these mechanisms may interact and amplify all three indicators of health losses from epidemics. For example, a population's ineffective coping with an epidemic because of government-sponsored disinformation can challenge institutional trust in authorities; this is exemplified by criticism of the performance of the WHO and Chinese government during the COVID-19 outbreak. Moreover, stigmatization induced by disinformation distorts the risk perception of the public, which may cause mass panic in the population and ineffective coping by politicians and professionals. In stigmatized groups, institutional distrust toward health authorities can lead to resistance against cooperation during public health emergencies. Overall, through ineffective coping, institutional distrust, stigma avoidance, and their interactions, government-sponsored disinformation may have deteriorated the public's morbidity and mortality from previous respiratory infections, and the COVID-19 outbreak may not be an exception.

## Data Sources and Method

In this study, we integrated data from the Global Burden of Disease Study (GBD), World Development Indicators (WDI) V-Dem-DSP dataset, and surveys from 144 countries conducted during 2000–2017 to investigate the relationship between government-sponsored disinformation and previous respiratory infections that are similar to COVID-19. We applied three epidemiological variables for respiratory infections—namely standardized incidence percentage, prevalence percentage, and death percentage—and high-dimensional fix-effect (HDFE) regression (Guimaraes and Portugal, 2010) models to estimate the effects of government-sponsored disinformation. After climatic, public health, socioeconomic, and political factors were controlled for, the results revealed that government-sponsored disinformation increased the incidence, prevalence, and death percentages of respiratory infections in populations.

## Percentages of Respiratory Infections in All Causes

To investigate coronavirus pandemics such as SARS and Middle East respiratory syndrome (MERS) that engendered global consequences, we applied the incidence, prevalence, and death percentages of upper and lower respiratory tract infections as dependent variables (Skov, 1998). The GBD database provides three types of variables for respiratory infections: number of infections, growth rate of infections in the population, and percentage of all causes of infection. We selected percentages (incidence, prevalence, and death) rather than rates as indicators to evaluate the severity of the influence of respiratory infections. We discovered that the rate of disease may be biased for various reasons. For example, the rate of death from a specific cause may be inaccurate because of underreporting or misclassification. In developing countries, a large proportion of deaths may not be given a specific cause by medical professionals. Furthermore, in developed countries, the cause of death may be certified by medical professionals who have no prior contact or access to the medical records of the deceased. This may lead to a higher rate of respiratory infections in developed countries. We assumed that bias has a comprehensive effect on all types of diseases. However, after assessing the percentages of respiratory infections from all causes, we observed that developing countries experienced more infections than did developed countries. Therefore, to eliminate bias, we applied percentages rather than rates, which indicate proportions among all types of diseases. Nevertheless, we estimated prevalence and incidence rates in the same models, and we noted that the effects exerted by government-sponsored disinformation on these rates were nearly identical to those exerted on the percentages; by contrast, the effects exerted on death rates differed from those exerted on death percentages. We discovered that some findings in the literature and most of our estimations are consistent; nonetheless, achieving a consensus between the public health and social science fields in terms of a suitable epidemiological dependent variable for international comparison is difficult.

## +Upper and Lower Respiratory Tract Infections

We separated respiratory infections (our dependent variables) into upper respiratory tract infections and lower respiratory tract infections and then applied the same models to assess the effects of disinformation on the indicators. Tables A1 and A2 indicate that in the models for upper respiratory tract infections, disinformation significantly amplified the incidence, prevalence, and death percentages; however, in the models for lower respiratory tract infections, disinformation significantly amplified only the death percentage. This suggests that upper respiratory tract infections dominated the patterns of incidence and prevalence percentages and that lower respiratory tract infections dominated the patterns of death percentages. Separating infections into upper and lower respiratory tract infections matched our expectations regarding the relationship between government-sponsored disinformation and epidemics. Accordingly, government-sponsored disinformation worsens the influence of both types of infections (please see the Appendix for more details).

However, applying this separation to coronavirus diseases would be difficult because diagnoses may vary depending on the clinical stage at which records are taken. For example, viruses mainly infect the upper respiratory tract. Nevertheless, viruses may also invade the lungs or lead to bacterial infection, causing lower respiratory tract infections, which can be deadly. The influenza virus infects both the upper and lower respiratory tracts and leads to primary viral pneumonia or even secondary bacterial pneumonia (Taubenberger, 2008). Therefore, we suggest combining respiratory infections into one category for observation. We believe that combining respiratory infections into a single category is favorable for measuring health outcomes for diseases caused by coronaviruses such as SARS, MERS, and COVID-19.

## Government-sponsored Disinformation

Data on government-sponsored disinformation were obtained from the V-Dem-DSP dataset. The V-Dem-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?" In the V-Dem project, a lower value was considered to imply the tendency of domestic governments to spread disinformation on social media. We reversed the order of variable values in this study and converted it into a 0%–100% range according to maximum and minimum values. We considered higher values to signify a higher frequency of a government generating and spreading disinformation in its territory.

The risk of a population being influenced by online disinformation campaigns depends on the population's exposure to the Internet. Accordingly, we collected data on Internet coverage from the WDI database; the data indicate the percentage of the population using the Internet. Internet coverage may facilitate the establishment of a digital infrastructure that is favorable for people's well-being, including their health, but can also be a tool for the government to manipulate and spread disinformation on epidemics.

## Control Variables

Factors shaping 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, 2014). Second, we applied population density to measure "social and physical distancing" in relation to exposure to pandemics. In addition, because evidence indicates that aging populations are more vulnerable to diseases than younger populations, we applied life expectancy and measured the influence of demographic structure (Wu and McGoogan, 2019). Third, we introduced infant mortality rates 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 (Deaton, 2010). Scholars have argued that democracies typically perform better during epidemics than do authoritarian governments. Therefore, we used Polity IV, 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 countries and +10 signifying the most democratic countries (Marshall et al., 2014). Finally, to account for global health inequality (Wilkinson, 1997), we introduced domestic income inequality by using the Gini coefficient of net income (Gini, 0%–100%) from the Standardized World Income Inequality Database (Solt, 2019), which comprises income inequality indicators from 196 countries from 1960 to the present. After deleting countries with too many missing or outdated values from 2018 in these sources, we retained a nearly balanced panel of 144 countries for the period from 2000 to 2017.

## Imputation of Missing Data

After integrating data from different sources, we discovered that some data points for three control variables, namely lnGDPpc, Gini, and Internet coverage, were missing. We conducted imputations for these missing points in the data of some developing countries as follows:

(1) We selected 2000–2017 as the study period because the DSP disinformation survey began from that year. In addition, extending the panel to the years following 2017 would be difficult because the missing data are amplified in some databases, such as the WDIs from 2017. (2) We selected countries with the most reliable and complete data. We removed countries for which more than one-third of possible data points were missing in the time series of our major variables (missing > 6/18); this is because retaining them may have reduced data reliability through imputation. After this procedure, we analyzed 144 countries in total.

(3) We managed the missing data by using the Amelia II program (King et al., 2001). Specifically, we executed multiple imputations through Bayesian bootstrapping, including 310 socioeconomic and political variables from the WDI database (2019; 178 variables), Penn World Table v9.0 (32 variables), Freedom House (2020; 2 variables), Polity IV (2018; 2 variables), Climatic Research Unit v4.03 (4 variables), Archigos v4.1 (2 variables), Standard World Income Inequality Database v8.2 (2 variables), KOF Globalisation Index (2018; 6 variables), Global Financial Development Database (2019; 17 variables), International Centre for Tax and Development (2019; 14 variables), V-Dem v9.0 (46 variables), and Quality of Government Standard Data (January 2020;

5 variables). The final data input into a missing point were averaged 10 times (Lin, 2015). This procedure prevented additional intervention from the association between dependent variables and the key variable: government-sponsored disinformation.

[Tables 1 and 2]

Table 1 lists the data sources, and Table 2 presents the original descriptive statistics of variables (standardized later in the models). We used other variables in our study, including government and health expenditure divided by GDP to measure state capacity and the trade dependence ratio to measure globalization. Nevertheless, we discovered that most control variables were nonsignificant and irrelevant to the key variables in our models. Therefore, we removed these variables and present the significant ones in Table 3.

### Regression Model

We used a standardized HDFE regression model that comprised the following autoregressive terms: lagged dependent variables, year and country dummies, and lagged independent variables. The advantage of this HDFE regression model is its exclusion of the effects of unobserved time-invariant variables (e.g., geographic region and national religion). The autoregressive term was used to control for the continuity of lagged dependent variables, implying that these variables violated the parallel trend assumption of difference-in-difference regression models. The period effect was reduced using the year dummy variables in our models. Except for temperature and precipitation, the lagged independent variables of the previous year reduced endogeneity problems among health outcome, government-sponsored disinformation, and other control variables. We also applied Bayesian statistics to replicate the results and found that they were very robust.

## Analysis

Table 3 presents the coefficients of the standardized HDFE regression models, with model (1) estimating the incidence percentage, model (2) estimating the prevalence percentage, and model (3) estimating the standardized death percentage of respiratory infections. In these models, the key explanatory variable—the index of government-sponsored disinformation in its domestic population in the past year—consistently exhibited significantly positive associations with the dependent variables. In addition, Internet coverage reflected how the information system infrastructure could significantly reduce the incidence and prevalence percentages.

By applying model (3) for prediction, we observed that the disinformation index in the past year was positively associated with the standardized death percentage (standardized and centered to zero) and country-average points (Figure 3). This evidence supports our hypothesis that government-sponsored disinformation deteriorates respiratory infections in terms of morbidity and mortality.

[Table 3]

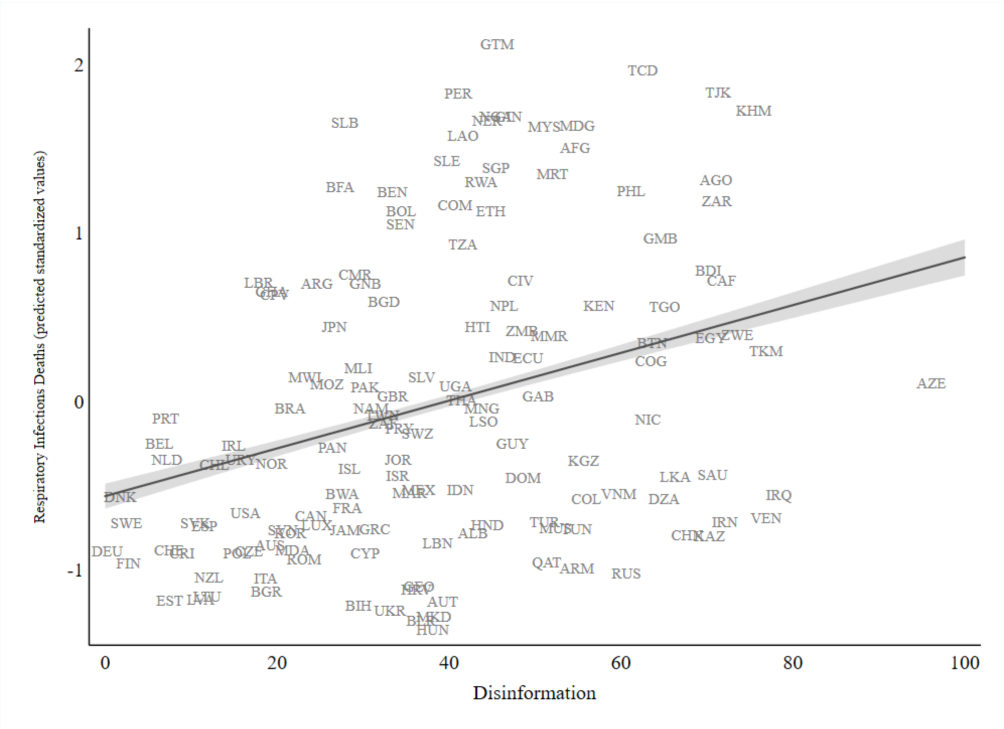


**Figure 3. Predicted association between government-sponsored disinformation and respiratory infections deaths percentage in 144 countries, 2000-2017**

Except for the results observed for the autoregressive terms, which exhibited a high correlation, the results observed for most other control variables were determined to be consistent with the predictions in the literature; nevertheless, some control variables were nonsignificant. A high average temperature could reduce the prevalence percentage, and high precipitation could reduce the standardized death percentage. The infant standardized death percentage was highly associated with the standardized death percentage of respiratory infections. Life expectancy related to aging populations could increase mortality and morbidity. Moreover, economic development could reduce the standardized death and incidence percentages. However, economic development was positively correlated with the prevalence percentage. The increase in the incidence percentage for rural populations may be attributed to the lack of public health resources. Income inequality amplified the standardized death and incidence percentages but not the prevalence percentage of respiratory infections (Pinzón-Rondón et al., 2016). Regime type could reduce the incidence percentage but was not significant for the standardized death or prevalence percentages in our models. Democracies performed better than did autocratic countries under some conditions and for some diseases. They also had greater economic development, lower infant mortality rates, and less disinformation than did countries with authoritarian governments (Bollyky, 2019). Therefore, the effects of democracy on the reduction of the standardized death percentage may have been mediated by other variables.

## Conclusion

This study presents an informational approach to depicting epidemics. The empirical findings reveal that ineffective coping, institutional distrust, and stigma avoidance resulting from government-sponsored disinformation could affect the incidence, prevalence, and death (three indicators discussed in the literature) associated with global epidemics of respiratory infections. Our study contributes to the literature by integrating theories and evidence from global surveys. Government-sponsored disinformation leads to institutional distrust, ineffective management, and stigma avoidance, and the corresponding adverse consequences are revealed by our empirical findings. Accordingly, our findings shed light on the mechanisms through which information environments play a major role in the management of epidemics.

This study has some limitations. For example, the pooled category of respiratory infections could not be applied to calculate the basic reproductive ratio of a single pandemic. Moreover, the disinformation indicators focused on only government sources and not on other misinformation sources. Despite these limitations, this study may be the first to present global evidence of the association between government-sponsored disinformation and the spread of epidemics.

On the basis of these findings, we propose the following steps to counter the global COVID-19 pandemic. First, governments must immediately stop sponsoring disinformation on the disease as a strategy for gaining political advantages in domestic and international conflicts. Disinformation as a political strategy deteriorates pandemics. Second, hidden or distorted information leads to ineffective coping and deteriorates respiratory infections, particularly the incidence of infections. Thus, transparent and instant information for the public is crucial. Accordingly, disease containment efforts should prioritize medical and public health knowledge along with disinformation control and political transparency. In practice, fact-checking authorities managed by civil associations may be established to refute fake news efficiently. Third, institutional distrust and stigmatization engendered by government-sponsored disinformation can deteriorate respiratory infections in terms of prevalence and mortality. Eliminating rumors and stigma in civil society may help curb the spread of pandemics.

# Tables and Figures

## Table 1 Data sources

| Variables | Measurement | Data Source |
|---|---|---|
| Respiratory Infections Deaths | The proportion of deaths for respiratory infections relative to deaths from all causes occurring in a population. | Global Burden of Disease Study 2017 (GBD) |
| Respiratory Infections Incidence | The proportion of new cases for respiratory infections in a year divided by the mid-year population size. | GBD |
| Respiratory Infections Prevalence | The proportion of people in a population who are a case of respiratory infections. | GBD |
| Upper Respiratory Infections Deaths | The proportion of deaths for upper respiratory infections relative to deaths from all causes occurring in a population. | GBD |
| Upper Respiratory Infections Incidence | The proportion of new cases for upper respiratory infections in a year divided by the mid-year population size. | GBD |
| Upper Respiratory Infections Prevalence | The proportion of people in a population who are a case of upper respiratory infections. | GBD |
| Lower Respiratory Infections Deaths | The proportion of deaths for lower respiratory infections relative to deaths from all causes occurring in a population. | GBD |
| Lower Respiratory Infections Incidence | The proportion of new cases for lower respiratory infections in a year divided by the mid-year population size. | GBD |
| Lower Respiratory Infections Prevalence | The proportion of people in a population who are a case of lower respiratory infections. | GBD |
| Temperature | Annual mean of monthly average daily mean temperature; units: degrees Celsius. | Climatic Research Unit 4.03 (CRU) |

| Variables | Measurement | Data Source |
|---|---|---|
| Precipitation | Annual mean of precipitation. | CRU |
| Infant Mortality | Mortality rate, infant (per 1,000 live births). | World Development Indicators (WDI) updated on December 20, 2019 |
| Life Expectancy | Life expectancy at birth, total (years). | WDI |
| ln(GDP pc)* | GDP per capita, PPP (constant 2011 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 IV 2018 |
| Gini* | Estimate of Gini index of inequality in equivalized (square root scale) household disposable (post-tax, post-transfer) income, using Luxembourg Income Study data as the standard. | Standardized World Income Inequality Database 8.2 (SWIID) |
| Internet Coverage* | Individuals using the Internet (% of population) | WDI |
| Disinformation | Government dissemination of domestic false information. | Varieties of Democracy 9 (V-Dem) |

Note: *We apply Bayesian multiple imputation by Amelia II to the following three control variables: ln(GDP pc): (N = 2,446, missing = 2); Gini: (N = 2,164, missing = 284); Internet Coverage: (N = 2,424, missing = 24).

**Table 2 Description of variables for 144 countries for the period 2000–2017.**

| Variables | Mean | SD | Min | Max |
|---|---|---|---|---|
| Respiratory Infections Deaths (%) | 0·056 | 0·034 | 0·008 | 0·173 |
| Respiratory Infections Incidence (%) | 0·460 | 0·088 | 0·249 | 0·636 |
| Respiratory Infections Prevalence (%) | 0·035 | 0·007 | 0·016 | 0·050 |
| Upper Respiratory Infections Deaths (%) | 0·000 | 0·000 | 0·000 | 0·002 |
| Upper Respiratory Infections Incidence (%) | 0·448 | 0·092 | 0·236 | 0·635 |
| Upper Respiratory Infections Prevalence (%) | 0·033 | 0·007 | 0·014 | 0·048 |
| Lower Respiratory Infections Deaths (%) | 0·055 | 0·034 | 0·007 | 0·171 |
| Lower Respiratory Infections Incidence (%) | 0·011 | 0·006 | 0·002 | 0·031 |
| Lower Respiratory Infections Prevalence (%) | 0·001 | 0·001 | 0·000 | 0·004 |
| Temperature | 16·906 | 7·739 | -7·620 | 27·445 |
| Precipitation | 1,110·355 | 734·545 | 21·011 | 3,563·602 |
| Infant Mortality | 31·025 | 28·630 | 1·600 | 142·400 |
| Life Expectancy | 68·888 | 9·966 | 39·441 | 83·985 |
| ln(GDP pc) | 9·014 | 1·233 | 6·301 | 11·728 |
| ln(Population Density) | 4·105 | 1·356 | 0·434 | 8·976 |
| Rural Population | 44·211 | 22·459 | 0·000 | 91·754 |
| Democracy | 4·558 | 5·833 | -10·000 | 10·000 |
| Gini | 39·206 | 8·305 | 22·449 | 66·191 |
| Internet Coverage | 28·063 | 28·547 | 0·000 | 98·240 |
| Disinformation | 38·908 | 20·744 | 0·000 | 100·000 |

Note: N = 2,448. The year range of respiratory infections data is 2001-2017 and that of the other variables 2000-2016.

**Table 3 Government-sponsored disinformation and respiratory infections: standardized HDFE regression**

| | Respiratory Infections | | |
|---|---|---|---|
| | **Incidence** | **Prevalence** | **Deaths** |
| | **(1)** | **(2)** | **(3)** |
| Auto Regression (*t*-1) | 0·931*** | 0·960*** | 0·888*** |
| | (0·009) | (0·006) | (0·007) |
| Temperature | -0·000 | -0·002* | -0·000 |
| | (0·001) | (0·001) | (0·003) |
| Precipitation | -0·000 | 0·000 | -0·000* |
| | (0·000) | (0·000) | (0·000) |
| Infant Mortality (*t*-1) | 0·012** | 0·001 | 0·093*** |
| | (0·004) | (0·003) | (0·012) |
| Life Expectancy (*t*-1) | 0·031*** | 0·012*** | 0·125*** |
| | (0·005) | (0·003) | (0·014) |
| ln(GDP pc) (*t*-1) | -0·011* | 0·012*** | -0·042** |
| | (0·005) | (0·004) | (0·014) |
| ln(Population Density) (*t*-1) | 0·052*** | 0·024*** | -0·010 |
| | (0·011) | (0·007) | (0·029) |
| Rural Population (*t*-1) | 0·017** | 0·005 | 0·006 |
| | (0·006) | (0·004) | (0·017) |
| Democracy (*t*-1) | -0·001* | 0·000 | -0·000 |
| | (0·000) | (0·000) | (0·001) |
| Gini (*t*-1) | 0·009*** | 0·003 | 0·019** |
| | (0·003) | (0·002) | (0·007) |
| Internet Coverage (*t*-1) | -0·008*** | -0·006*** | -0·004 |
| | (0·002) | (0·001) | (0·005) |
| Disinformation (*t*-1) | 0·009*** | 0·006*** | 0·015** |
| | (0·002) | (0·001) | (0·005) |
| Constant | 0·004 | 0·017 | 0·022 |
| | (0·019) | (0·013) | (0·052) |
| Country Fixed Effect | Yes | Yes | Yes |
| Year Fixed Effect | Yes | Yes | Yes |
| $R^2$ | 0·999 | 0·999 | 0·996 |
| Adjusted $R^2$ | 0·999 | 0·999 | 0·996 |

Note: N = 2,448. Coefficient of linear regression absorbing multiple levels of fixed effects model, standard errors in parentheses, * $p < .05$, ** $p < .01$, *** $p < .001$, two-tailed test.

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# Appendix

## Appendix 1: Government-sponsored disinformation and upper respiratory infections: standardized HDFE regression

| | Upper Respiratory Infections | | |
|---|---|---|---|
| | Incidence | Prevalence | Deaths |
| | (1) | (2) | (3) |
| Auto Regression (*t*-1) | 0·932*** | 0·958*** | 0·898*** |
| | (0·009) | (0·006) | (0·005) |
| Temperature | -0·000 | -0·002* | -0·005 |
| | (0·001) | (0·001) | (0·003) |
| Precipitation | -0·000 | 0·000 | -0·000* |
| | (0·000) | (0·000) | (0·000) |
| Infant Mortality (*t*-1) | 0·011* | 0·001 | 0·048*** |
| | (0·004) | (0·003) | (0·010) |
| Life Expectancy (*t*-1) | 0·032*** | 0·015*** | 0·049*** |
| | (0·005) | (0·003) | (0·012) |
| ln(GDP pc) (*t*-1) | -0·011* | 0·010** | 0·002 |
| | (0·005) | (0·003) | (0·013) |
| ln(Population Density) (*t*-1) | 0·051*** | 0·025*** | -0·016 |
| | (0·010) | (0·007) | (0·025) |
| Rural Population (*t*-1) | 0·018** | 0·007 | 0·006 |
| | (0·006) | (0·004) | (0·015) |
| Democracy (*t*-1) | -0·001* | 0·000 | 0·002* |
| | (0·000) | (0·000) | (0·001) |
| Gini (*t*-1) | 0·009*** | 0·003* | 0·019** |
| | (0·002) | (0·002) | (0·006) |
| Internet Coverage (*t*-1) | -0·008*** | -0·006*** | -0·002 |
| | (0·002) | (0·001) | (0·005) |
| Disinformation (*t*-1) | 0·009*** | 0·006*** | 0·020*** |
| | (0·002) | (0·001) | (0·004) |
| Constant | 0·005 | 0·017 | 0·082 |
| | (0·018) | (0·012) | (0·046) |
| Country Fixed Effect | Yes | Yes | Yes |
| Year Fixed Effect | Yes | Yes | Yes |
| $R^2$ | 0·999 | 0·999 | 0·997 |
| Adjusted $R^2$ | 0·999 | 0·999 | 0·997 |

Note: N = 2,448. Coefficient of linear regression absorbing multiple levels of fixed effects model, standard errors in parentheses, * $p < .05$, ** $p < .01$, *** $p < .001$, two-tailed test.

## Appendix 2: Government-sponsored disinformation and lower respiratory infections: standardized HDFE regression

| | Lower Respiratory Infections | | |
|---|---|---|---|
| | **Incidence** | **Prevalence** | **Deaths** |
| | **(1)** | **(2)** | **(3)** |
| Auto Regression (*t*-1) | 0·930*** | 0·921*** | 0·888*** |
| | (0·005) | (0·004) | (0·007) |
| Temperature | 0·001 | -0·000 | -0·000 |
| | (0·001) | (0·001) | (0·003) |
| Precipitation | -0·000 | 0·000 | -0·000* |
| | (0·000) | (0·000) | (0·000) |
| Infant Mortality (*t*-1) | 0·014*** | 0·016*** | 0·092*** |
| | (0·004) | (0·004) | (0·012) |
| Life Expectancy (*t*-1) | -0·027*** | -0·033*** | 0·125*** |
| | (0·005) | (0·005) | (0·014) |
| ln(GDP pc) (*t*-1) | 0·014** | 0·018*** | -0·042** |
| | (0·005) | (0·005) | (0·014) |
| ln(Population Density) (*t*-1) | -0·017 | -0·020* | -0·010 |
| | (0·010) | (0·010) | (0·029) |
| Rural Population (*t*-1) | -0·014* | -0·018** | 0·005 |
| | (0·006) | (0·006) | (0·017) |
| Democracy (*t*-1) | -0·000 | 0·000 | -0·001 |
| | (0·000) | (0·000) | (0·001) |
| Gini (*t*-1) | -0·001 | -0·003 | 0·019** |
| | (0·002) | (0·002) | (0·007) |
| Internet Coverage (*t*-1) | 0·003 | 0·002 | -0·004 |
| | (0·002) | (0·002) | (0·005) |
| Disinformation (*t*-1) | 0·002 | 0·001 | 0·015** |
| | (0·002) | (0·002) | (0·005) |
| Constant | -0·018 | -0·007 | 0·021 |
| | (0·019) | (0·019) | (0·052) |
| Country Fixed Effect | Yes | Yes | Yes |
| Year Fixed Effect | Yes | Yes | Yes |
| $R^2$ | 0·999 | 0·999 | 0·996 |
| Adjusted $R^2$ | 0·999 | 0·999 | 0·996 |

Note: N = 2,448. Coefficient of linear regression absorbing multiple levels of fixed effects model, standard errors in parentheses, * $p$ < .05, ** $p$ < .01, *** $p$ < .001, two-tailed test.