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Government disclosure in influencing people's behaviors during a public health emergency

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We shed light on the importance of government disclosure in public emergency management. During the outbreak of COVID-19, provinces in China entered a government disclosure regime, which mandated the disclosure of the number of people infected with the virus on a daily basis. Each province also voluntarily disclosed its own virus situation. We find that various forms of province-level government disclosure generally reduced the number of trips made by the infected and sped up their diagnosis. They also raised attention paid to the virus and self-protection awareness as well as reduced mobility among the susceptible. Finally, government voluntary disclosure helped to reduce the duration of local epidemics. We conclude that government disclosure can be effective in instilling the correct human behaviors that are conducive to fighting the pandemic.

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Introduction

The COVID-19 pandemic which started in late 2019 has spread to almost all countries/territories in the world (WHO, 2020). China, being the first to be severely stricken by COVID-19, has implemented aggressive public health emergency measures on an unprecedented scale and effectively controlled nationwide transmissions (Cyranoski, 2020; Chinazzi et al., 2020; Tian et al., 2020) in 2020. In the absence of effective cures or large-scale implementations of vaccination for COVID-19 during the early stage of the pandemic, state interventions, including government-instituted emergency measures and coordinated information disclosure were important in deterring the spread of the pandemic. We present evidence that government disclosure, in addition to the entry into a public health emergency regime, can favorably shape the outcome of the fight against COVID-19.

Specifically, we focus on the role of government disclosure in influencing people's behaviors that are conducive to fighting COVID-19 in China, a country where strong state interventions permeate people's civic and economic life. The prior literature predominantly examines government disclosure from the perspective of western-style institutions, such as media independence, transparency, and electoral participation. Mixed results are found in the economic, social, and political consequences of government disclosure. While government disclosure can enhance productivity by improving resource allocation efficiency and curtailing rent-seeking, it also induces adverse selection and limits government executive power due to divergent individual interests. We study the role of government disclosure in a pandemic setting where the very basic human right of living was being threatened by COVID-19 and the state's interventions in protecting life assumed paramount importance. The COVID-19 pandemic setting provides us with a unique opportunity to determine whether the effect of government disclosure is of significant importance to the outcome of a state's role in public health emergency management.

We construct a sample comprising 30 of mainland China's provinces (excluding Hubei province) during January 1 to February 29, 2020 and analyze the impact of government information disclosure on the behaviors of the infected and the susceptible. Our sample period covers the pandemic's initial outbreak and subsequent dissipation in China in the presence of strong government administrative interventions (Fig. 1). Starting from March 5, local cases in provinces other than Hubei have largely died down. Hubei province, whose capital city is Wuhan, the epicenter of China's outbreak, is examined in a separate analysis due to its large scale, extreme government interventions, and being potentially China's source of infection the impact of which we control for in our main analysis.

To capture government information disclosure, we record provincial governments' daily mandatory disclosure of the number of newly confirmed cases in addition to the timing of these provinces' entry into a government disclosure regime. We also track the number of voluntary disclosures made by provincial Center for Disease Control (CDCs) on information about progress in virus control, prevention knowhow, announcements, and notifications about infections. While our focus is on the effects of three forms of province-level government disclosure, we also consider a form of national level disclosure on January 20, 2020 by *Zhong Nanshan*, head of the COVID-19 expert panel of China's National Center for Disease Control, that the virus could be transmitted from human to human.

To measure the behaviors of the infected population, we extract reported travel routes of the infected from the Internet. We construct variables that record the number of trips made by the infected and their speed of confirmed diagnosis (the number of days between the first appearance of symptoms and the confirmation of infection) on a daily basis for each province. These variables on the behaviors of the infected are inputs used in examining the impact of government information disclosure on containing the source of infection.

To measure the attention and self-prevention awareness of the susceptible population, we extract province-level daily Internet searches for key words related to the COVID-19 epidemic ("pneumonia") and prevention methods ("mask"). Relying on the Baidu migration index, we capture immigration/emigration/city activity patterns of the susceptible. These variables on the behaviors of the susceptible are inputs used in examining the impact of government information disclosure on severing paths of transmissions among the susceptible.

We obtain the following findings. First, the entry into a government disclosure regime and voluntary disclosure are effective in containing the source of infection. They reduce trips made by the infected and accelerate confirmed diagnosis of the infected. Second, the entry into a government disclosure regime, mandatory and voluntary disclosures are effective in severing paths of transmissions among the susceptible. They increase public attention paid to the epidemic/pandemic and self-prevention awareness and reduce the number of people moving across provinces and within cities. An approximate regression discontinuity design based on a short 11-day [−5, 5] window around the entry into a government disclosure regime produces similar results, with disclosure regime, mandatory and voluntary disclosures significantly inducing the correct behaviors among the infected and the susceptible. These empirical patterns also largely survive when we further device ways to tease out the interfering effect of public health emergency measures. Finally, government voluntary

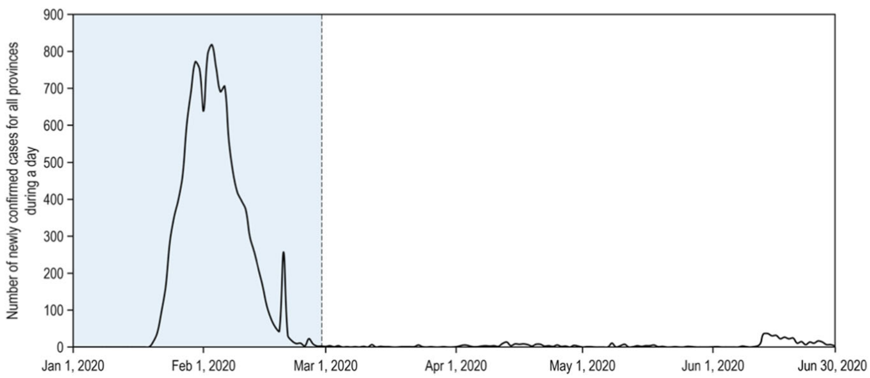

Fig. 1 Daily newly confirmed cases of infection. The number of daily newly confirmed cases of infection in thirty provinces (excluding Hubei province where the city of Wuhan is located) of mainland China during January–June 2020.

disclosure appears to shorten the duration of a province's local epidemic.

We make an important contribution to the literature on how government disclosure and transparency affect public behaviors. The prior literature on government disclosure and transparency focuses on government influence of the media and its consequences (Enikolopov et al., 2011; Piotroski et al., 2017; Qin et al., 2018), how it handles civil disputes (Acemoglu et al., 2020) as well as government accounting/finance disclosures (Zimmerman, 1977; Laswad et al., 2005; Cuny, 2016). We document evidence on the positive role of government disclosure in combating public health emergencies, such as the COVID-19, through instilling the "correct" behaviors from both the infected and the susceptible. Our results are also consistent with the benefits associated with government transparency in people's civic life (Stiglitz, 2002). We point to desirable human behavioral consequences associated with government disclosure in a public health emergency setting.

Literature and research questions

Government disclosure and transparency. There are a few strands of the literature on government information disclosure and transparency. One utilizes an indirect approach, such as the extent of government interventions of the independence of the news media or the press, to assess the impact of government's control over information disclosure and dissemination. Enikolopov et al. (2011), examining Russian parliamentary elections, find that independent media coverage reduces the ruling party's chance of election and increases the opposition party's chance of election, indirectly showing governments' control over media can impact political election outcomes. Piotroski et al. (2017) and Qin et al. (2018) analyze the tonality of Chinese news media and find that the government shapes the political inclinations of the media through controlled media outlets. Piotroski et al. (2015) find that during periods before China holds important political conferences, negative news related to listed firms is temporarily suppressed, consequently increasing their stock price crash risk. This pattern provides evidence of government control and intervention of media disclosure for political purposes such as shaping election outcomes and framing public opinions.

Another strand directly investigates the incentives of government financial disclosure and its consequences. This literature, largely oriented from an agency framework, argues that self-interested politicians make disclosure decisions to maximize their pecuniary and non-pecuniary wealth (Zimmerman, 1977; Banker and Patton, 1987; Baber, 1983). In this framework, good institutions featuring counter-checking and balance-of-power can be fundamental to sustaining the transparency of government disclosure and curtailing private rent seeking. Zimmerman (1977) shows that poor disclosure of municipal accounting information arises from a lack of monitoring from the public as well as from government officials possessing superior resources and power which help them reach agreement with specific interest groups in political lobbying, reducing their willingness to disclose government accounting information. Further, economic incentives such as debt financing need and capital market scrutiny can also discipline government disclosure transparency and enhance financial accountability (Ingram and DeJong, 1987; Evans and Patton, 1987). Examining Internet financial information disclosures, Laswad et al. (2005) find that local authorities having a higher debt ratio or creating relatively more municipal wealth than other authorities are more likely to disclose financial information. Cuny (2016) finds that after the bankruptcy of the US municipal bond insurance group Ambac, municipal bond issuers of insured debt increase disclosure relative to issuers of uninsured debt.

The third strand of the literature takes the perspective from the very nature and responsibility of the government and examines the impact of government disclosure on public behavior and social welfare. Government information disclosure reduces information asymmetry between the government and social entities (Akerlof, 1970), allowing social entities to feedback on the information and make decisions in production and resource allocation more accurately and efficiently, ultimately promoting public welfare (Jin and Leslie, 2003; Shambaugh and Shen, 2018). During public health emergencies, timely government disclosure and authoritative guidance can promote self-protection in the society (Malley et al., 2009). During economic crises, timely disseminations of credible macroeconomic information contribute to shortening the durations of inflation and currency crises (Shambaugh and Shen, 2018). Further, government information disclosure and information transparency enhance social monitoring, thus improving administrative efficiency and reducing rent-seeking. Besley and Burgess (2002) show that in India, state governments are more responsive to falls in food production and crop flood damage via public food distribution and calamity relief expenditure where newspaper circulation is high and electoral accountability is great. Jin and Leslie (2003) show that San Francisco's information disclosure on restaurants hygiene ratings led to an improvement in the general restaurant hygiene condition, enhanced sensitivity to restaurant hygiene conditions and a reduction in cases of food poisoning. Eiji and Haruo (2013) show that in Japan, the enacted Information Disclosure Ordinances reduced the rate of government construction expenditure, leading to reduced losses from official rent-seeking. In a more recent research on social dispute management, Acemoglu et al. (2020) show that information about reduced delays in state courts in rural Pakistan leads to citizens reporting a higher likelihood of using them. These studies suggest that governments can enhance their efficacy and build public trust by credibly disclosing and transmitting information, ultimately improving social welfare.

Of course, the effect of government disclosure and transparency on public behaviors does not have to be positive. Public disclosure can induce market panic and adverse selections, reducing efficiency in resource allocation (Jasanoff, 2016; Yan et al., 2017) and limit the executive power (Hollyer et al., 2015). For example, Dranove et al. (2003) find that the disclosure of hospital medical information causes patients to run on high-quality medical resources, reducing the efficiency of matching between hospitals and patients and consequently damaging the overall interest of patients.

To sum, increasing government transparency can be a double-edged sword for various different forms of governments (Stiglitz, 2002), the handling of which requires sound judgements. In line with this literature, our research uses a pandemic setting, where the state is in a good position to synchronize the collective behaviors of the public and coordinate the fight against the pandemic. In particular, we highlight the role of government disclosure in containing the virus through inducing the correct human behaviors.

China setting for government disclosure. We believe that China is a good setting for examining the effect of government disclosure on human behaviors during the COVID-19 pandemic. First, the world's first serious outbreak of COVID-19 occurred in China. Second, after the 2003 SARS epidemic, many procedures and laws were installed to deal with public health emergencies. On January 8, 2006, the state department passed the "Draft on Measures for Handling Emergencies at the National Level". This document categorizes emergent situations into four categories:

natural disasters, accidents, public health and social securities. It also ranks these situations based on severity into four categories: Category I (extremely grave), Category II (grave); Category III (relatively grave), and Category IV (common). The COVID-19 outbreak trigged Category I public health emergency measures. In terms of organizational structure, on March 17, 2018, the 13th national people's congress passed "Organizational Reforms of the State Department" and the state department established an emergency response office to coordinate the handling of emergency situations. There are reasons to believe that the Chinese government wanted to handle COVID-19 correctly. Proper disclosure could help it achieve this goal.

Third, and on a state governance dimension, China's leadership, or even the mass, knows only too well, from China's long history, that cataclysmic regime changes and social unrests can topple the ruling group, depriving their legitimacy to rule, different from western-style electoral institutions where a political party can come back after a streak of electoral defeats. Therefore, China's state governance and polity emphasize long-term objectives such as economic revival, welfare of the people, social harmony and international prestige. Effective handling of a public health emergency is crucial to strengthening the government's prestige and help it garner support from the mass.

Finally, while many think of China as a centrally governed country, it is actually regionally decentralized (Xu, 2011; Qian et al., 2006), with each province preserving a degree of autonomy in its governance. That is, central control and local decentralization coexist in China, allowing the government to pursue political as well as economic goals (Huang et al., 2017). This dualism is also reflected in the heterogeneity in media bias in China (Piotroski et al., 2017; Qin et al., 2018) where the potential conflict between politics and business is mitigated, enabling the government to manage public opinions as well as pursuing economic welfare. Along this line, we focus on disclosure practices of provincial governments during China's COVID-19 epidemic. Variation in the content of province-level disclosure allows us to establish a link between government disclosure and human behaviors.

Research questions. We pose the following research questions. First, we examine how government disclosure affects the behaviors of the infected in the absence of effective cures or vaccines for COVID-19. We focus on infected people's frequency of trips and speed of diagnosis. For government disclosure to be successful in containing the source of infection, it needs to reduce the frequency of trips made by the infected and increase their speed of diagnosis. Second, we examine how government disclosure affects the behaviors of the susceptible. We focus on public attention paid to the virus and self-protection awareness induced by government disclosure as well as cross-province migration by the susceptible. For government disclosure to be effective in severing paths of transmissions, it needs to increase public attention paid to and self-protection awareness related to the virus as well as reducing cross-province migration among the susceptible. Finally, we examine the duration of the local epidemic and government disclosure. If government disclosure is effective in combating the COVID-19, it will help a locality reduce the duration of its epidemic.

Analyses

Data. We focus on government disclosure and its human behavior consequences in 30 provinces (excluding Hubei province where epicenter Wuhan is located) in mainland China from January 1 to February 29, 2020. We focus on this period because it covers the most intense period of COVID-19 development in China and government emergency measures and interventions for these provinces (Fig. 1). Since the end of February, most cases have been imported and local flare-ups have been small and sporadic.

Our data are obtained from the following sources:

a. Migration data are from Baidu migration index.
b. Public attention (Internet searches for "pneumonia") and self-protection awareness (Internet searches for "mask") data are obtained using a web crawler on Baidu.
c. Infected people's activities are obtained using a web crawler on infected people's activities disclosed by the People's Daily, China Central TV, and local media.
d. Daily numbers of confirmed cases of infection are obtained from the Real Time COVID-19 Database (http://projects.thepaper.cn/thepaper-cases/839studio/feiyan/) which consolidates all provincial CDC data.
e. Provinces' entries into a government disclosure regime and entries into the Category I public health emergency regime as well as their information disclosures are compiled from provincial CDC websites.
f. Province-level population, GDP, medical resources and other macroeconomic data are obtained from China National Bureau of Statistics.

During our sample period, Wuhan, the capital city of Hubei province was China's epi-center containing the super-majority of its cases. It was also subject to the most stringent lockdown and received the most financial and medical support from the central government. This makes Hubei province very different from other provinces in terms of the epidemic's trajectory and the level of government intervention. Further, in all our regressions, we control for daily cumulative emigration from Wuhan as it can be an important factor affecting the behaviors of the infected and the susceptible. Therefore, in our main analysis, we do not include Hubei province. It is, however, considered in a supplemental analysis.

Effect of government disclosure on the infected. We first determine how government disclosure influences the behaviors of those infected with the virus using a negative binomial model. Studies on the COVID-19 pandemic, notably in the medical field, predominantly use the susceptible–exposed–infectious–recovered (SEIR) model to predict patterns of outbreaks and suggest possible means to interfere with the course of the pandemic (Chinazzi et al., 2020; Wu et al., 2020; Gilbert et al., 2020; Yang et al., 2020). To predict the impact of various measures on the prevention and control of an epidemic/pandemic, the SEIR model relies on manipulating the initial parameters such as the degree of contact and the infection rate. However, these parameters cannot be accurately estimated under the joint effect of multiple factors. The negative binomial model enables us to incorporate real event data in assessing the aggregate impact of multiple factors simultaneously. It is regularly adopted in the evaluation of intervention measures for infectious diseases such as H1N1 and HIV (Fraser et al., 2009; Lipsitch et al., 2003; McLaughlin et al., 2019; Sousa et al., 2009; Fox et al., 2012; Ortega et al., 2014; Mayer-Davis et al., 2017). We follow these studies in line with ex post program evaluations (Fraser et al., 2009; Lipsitch et al., 2003; McLaughlin et al., 2019) and use the negative binomial model to gauge the effect of government information disclosure on the behaviors of the infected and the susceptible, while controlling for pre-existing conditions such as local economic development, population, fiscal conditions and medical resources. Specifically, we consider two behavioral variables of the infected population: (1) the number of trips made by these people; and (2) the speed of their confirmed diagnosis.

Table 1 Descriptive statistics of main variables.

	Obs	Mean	Median	STD	1st percentile	99th percentile
$\text{Trip}_{i,t}$	1800	1.287	0.000	3.202	0.000	15.000
$\text{Speed\_Diagnosis}_{i,t}$	573	17.354	16.615	7.185	3.000	42.000
$\text{Search\_Pneumonia}_{i,t}$	1800	6925.538	3274.000	9367.259	80.000	44,013.000
$\text{Search\_Mask}_{i,t}$	1800	1523.401	1047.000	1901.196	0.000	9693.000
$\text{Emigration}_{i,t}$	1800	3.586	2.050	4.700	0.030	28.090
$\text{Immigration}_{i,t}$	1800	3.597	1.975	4.095	0.050	18.350
$\text{City\_Activity}_{i,t}$	1800	3.220	2.590	1.704	0.490	6.550
$\text{Post}_{i,t-1}$	1800	0.641	1.000	0.480	0.000	1.000
$\text{Mandatory\_New}_{i,t-1}$	1800	7.174	0.000	16.015	0.000	74.000
$\text{Voluntary\_Dis}_{i,t-1}$	1800	4.349	3.000	5.457	0.000	23.000
$\text{ZhongNS\_Post}_{i,t-1}$	1800	0.667	1.000	0.472	0.000	1.000
$\text{Speed\_Response}_{i}$	1800	−2.000	−2.000	1.733	−4.000	5.000
$\text{Immigration\_from\_WH}_{i,t-1}$	1800	1.376	0.908	1.666	0.000	8.943
lnGDP_Capita_{i}	1800	11.003	10.868	0.389	10.353	11.851
lnPop_{i}	1800	8.128	8.248	0.841	5.841	9.337
Fiscal_{i}	1800	0.112	0.107	0.032	0.078	0.218
lnBeds_Capita_{i}	1800	4.079	4.101	0.138	3.778	4.279
Peak_Period_{i}	1800	30.333	30.000	8.505	7.000	55.000
$\text{Cases\_Cumulative}_{i,t}$	1800	183.196	39.000	306.636	0.000	1271.500

Trips. To determine the impact of disclosure on the number of trips made by the infected, we estimate the following negative binomial regression:

$$\begin{aligned}\log(\text{Trip}_{i,t}) =\ & \beta_0 + \beta_1\text{Post}_{i,t-1} \text{ or Mandatory\_New}_{i,t-1} \text{ or Voluntary\_Dis}_{i,t-1} \\ & \text{or ZhongNS\_Post}_{i,t-1} + \beta_2\text{Speed\_Response}_i \\ & + \beta_3\text{Immigration\_from\_WH}_{i,t-1} + \beta_4\text{lnGDP\_Capita}_i \\ & + \beta_5\text{lnPop}_i + \beta_6\text{Fiscal}_i + \beta_7\text{lnBeds\_Capita}_i + \varepsilon_{i,t}.\end{aligned} \tag{1}$$

where the dependent variable Trip is the number of trips made by infected people (before being diagnosed) for a province during a day. This information comes from ex post interviews of infected people by the local government virus-prevention authority. Trips obtained through these interviews were verified and enhanced with big data information on transportation, credit and ID card scans and usages as well as cell phone locations. A trip can be a local shopping trip, or a cross-city or cross-province trip. Information on trajectories of these trips was supplied by provincial governments.

We consider three province-level disclosure measures. Post is an indicator that equals 1 after a province entered a government disclosure regime which started when it disclosed the number of cases for the first time, and 0 before. This entry into a disclosure regime was triggered by the confirmation on January 20, 2020 by Zhong Nanshan, head of the COVID-19 expert panel of China's National Center for Disease Control, that the virus could be transmitted from human to human and that each province should start disclosing the number of people infected. The entry into the Category I public health emergency regime trailed the entry into a government disclosure regime by 0–3 days (with the exception of Gansu and Qinghai provinces) (see Appendix A). As Category I public health emergency regime brought about testing, lockdowns and other mobility restrictions, Post can to a certain extent capture the interfering effect of emergency measures. Later in the manuscript, we devise ways to tease out the interfering effect.

We use two additional province-level disclosure variables. Mandatory disclosure Mandatory_New is the number of newly confirmed cases for a province during a day. Voluntary disclosure Voluntary_Dis is the number of independent voluntary disclosures made by a province's Center for Disease Control (CDC) on information about virus control dynamics, prevention knowhow, announcements, and notifications on infection. When included in the regression model together with Post, Mandatory_New and Voluntary_Dis capture the effect of province-level government disclosure, mandatory or voluntary, on the behaviors of the infected population, in addition to the entry into a disclosure regime.

While we focus on province-level disclosure in our research, we also consider a form of national level disclose based on the timing of the statement by Zhong Nanshan, head of the COVID-19 expert panel, that the virus could be transmitted from human to human. We form an indicator, ZhongNS_Post, which equals 1 for observations after January 20, 2020 and 0 otherwise.

We consider the following control variables. Two controls are related to the local epidemic. Speed_Response captures the speed of a province's activation of Category I public health emergency measures. It is the number of days between the first confirmed case in a province and its activation of Category I public health emergency measures. Immigration_from_WH is the cumulative daily Baidu immigration index from Wuhan since January 1, 2020. We track immigration index from Wuhan as it was the epicenter of China's COVID-19 outbreak during January and February of 2020, our sample period.

Other controls are related to provinces' characteristics. lnGDP_Capita is the extent of economic development for a province computed as the logarithm of per capita GDP for a province. lnPop measures the population of a province computed as the logarithm of population for a province. Fiscal measures the fiscal condition for a province computed as fiscal revenue divided by GDP for a province. lnBeds_Capita measures medical resources for a province computed as the logarithm of the number of hospital beds per 10,000 people for a province. All variable definitions are consolidated in Appendix B and their descriptive statistics are presented in Table 1.

We carry out the maximum-likelihood estimation for the negative binomial model, with standard errors clustered by provinces. All variables in Eq. (1) have exactly 1800 observations (30 provinces times 60 days) (Table 1). Note that using the negative binomial model, we observe that the correlation between the predicted travel pattern of the infected population and its actual travel pattern is as high as 0.9997, highlighting the appropriateness of using this model (Fig. 2).

As shown in Appendix A, provinces' entries into a disclosure regime and their entries into the Category I public health

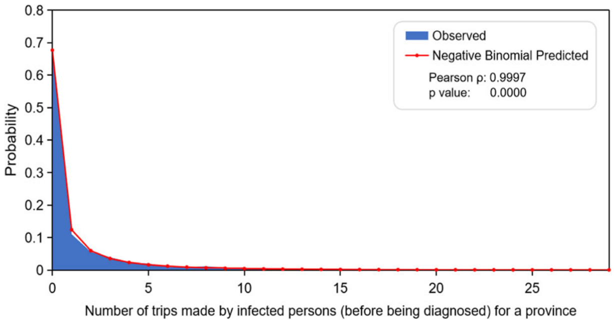

Fig. 2 Predicted number of trips made by the infected. Negative binomial model predicted number of trips made by infected people and its actual value.

emergency regimes clustered very closely to each other. The entry into the Category I public health emergency regime normally trailed the entry into a government disclosure regime by 0–3 days (with the exception of Gansu and Qinghai provinces). The public health emergency regime brings about testing, lockdown and other forms of mobility restriction. These measures can interfere with our analysis of the effect of government disclosure on behaviors of the infected and the susceptible. To deal with this issue, we use an intuitive and approximate regression discontinuity design by including only observations during the 5 days before and 5 days [−5, 5] after the entry into a disclosure regime. A short window around the entry into a disclosure regime would diminish the interfering effect of public health emergency measures on people's behaviors. We present the [−5, 5] window subsample results parallel to the full sample results for all related analyses. We find similar results using [−4, 4] and [−3, 3] windows. Of course, our approach is not a typical regression discontinuity design which often requires plenty of scatter diagrams to present the jump of status at the discontinuity point. Further, the discontinuity windows under our observation, during the five days before and five days after the entry of a disclosure regime, may not be very proper as the entry dates of most provinces were only 1, 2 or 3 days before the entry into the Category I Public Health Emergency Regime.

Full sample results for estimating regression Eq. (1) are presented in Columns (1)–(5) of Panel A, Table 2. We first enter Post, Mandatory_New, Voluntary_Dis and ZhongNS_Post individually and sequentially and then simultaneously. Control variables are always included. In Column (1) where we just have Post, its coefficient is negative and significant (−0.469, $z = -2.84$). Therefore, the entry into a disclosure regime reduces mobility among the infected. In Column (2) where we just include Mandatory_New, its coefficient is negative but insignificant (−0.004, $z = -1.07$). Thus, there is no evidence that governments' mandatory disclosure of the number of newly confirmed cases would discourage trips made by the infected. As discussed earlier, provincial CDCs also voluntarily disclose information about virus situations, we enter voluntary disclosure Voluntary_Dis in Column (3). Its coefficient is negative and significant (−0.076, $z = -3.90$). This suggests that government voluntary disclosure of the virus situation curtails trips made by the infected. In Column (4), the coefficient on ZhongNS_Post is not significant. Finally, in Column (5) where all four are included simultaneously, the coefficients on Post (−1.657, $z = -6.22$) and Voluntary_Dis (−0.085, $z = -4.34$) continue to be negative and significant, consistent with our expectations. However, the coefficient on Mandatory_New becomes positive and significant (0.009, $z = 2.10$), inconsistent with our expectation, potentially due to high correlations among the four variables. For example, ZhongNS_Post is highly correlated with Post (Corr. = 0.940), Mandatory_New (Corr. = 0.315) and Voluntary_Dis (Corr. = 0.563). The coefficient on ZhongNS_Post is positive and significant (1.793, $z = 7.64$). Results using the [−5, 5] window subsample presented in Columns (6–10) are generally stronger. Daily effects are visualized in Fig. 3.

It is tempting to attribute this positive coefficient on ZhongNS_Post, which is based on calendar time, to Chinese Spring Festival travel. Note that the infected population is tiny compared with the susceptible population. If a positive coefficient on ZhongNS_Post for the infected reflects Spring Festival travel, it should be more so for the susceptible which is vastly greater than the infected. However, In Panel B, Table 3, for all the three migration statistics, the coefficients on ZhongNS_Post are never significantly positive and in fact are often significantly negative, not reflecting Spring Festival travel. We conjecture that the positive coefficient on ZhongNS_Post can potentially indicate that people who felt that they had virus symptoms during the early stage of the pandemic had a greater urge to reach their hometowns before lockdowns were officially imposed.

Speed of diagnosis. We next examine the second dependent variable, Speed_Diagnosis, by estimating the following negative binomial regression:

$$\begin{aligned}\log\left(\text{Speed\_Diagnosis}_{i,t}\right) = {} & \beta_0 + \beta_1 \text{Post}_{i,t-1} \text{ or Mandatory\_New}_{i,t-1} \text{ or Voluntary\_Dis}_{i,t-1} \\ & \text{or ZhongNS\_Post}_{i,t-1} + \beta_2 \text{Speed\_Response}_i \\ & + \beta_3 \text{Immigration\_from\_WH}_{i,t-1} + \beta_4 \text{lnGDP\_Capita}_i \\ & + \beta_5 \text{lnPop}_i + \beta_6 \text{Fiscal}_i + \beta_7 \text{lnBeds\_Capita}_i + \varepsilon_{i,t}.\end{aligned} \tag{2}$$

where the dependent variable is the speed of a confirmed diagnosis, Speed_Diagnosis. It is the average number of days between the first appearance of symptoms and the confirmation of infection for people confirmed during a day. It has 573 observations (Table 1). All other variables are as defined earlier.

We again first enter Post, Mandatory_New, Voluntary_Dis and ZhongNS_Post individually and then simultaneously. Control variables are always included. Full sample results are reported in Columns (1–5) of Panel B, Table 2. In Column (1) where we have just Post, its coefficient is negative and significant (−0.399, $z = -10.30$). Therefore, the entry into a disclosure regime speeds up the diagnosis of infection by reducing the number of days between the first appearance of symptoms and the diagnosis of infection. In Column (2), the coefficient on Mandatory_New is negative and significant (−0.005, $z = -3.31$), meaning that government mandatory disclosure on the daily newly confirmed number of people infected speeds up diagnosis of infection. Similarly, in Column (3), the coefficient on Voluntary_Dis is negative and significant (−0.026, $z = -4.79$), suggesting that voluntary disclosure of virus situation also speeds up diagnosis of infection. In Column (4), the coefficient on ZhongNS_Post is negative and significant (−0.421, $z = -11.53$), meaning Zhong Nanshan's statement speeds up diagnosis. When all four variables are included simultaneously in Column (5), while coefficient on Voluntary_Dis continues to be negative and significant (−0.009, $z = -1.66$), the coefficients on Post and Mandatory_New become insignificant. Results using the [−5, 5] window subsample presented in Columns (6)–(10) are similar. Daily effects are visualized in Fig. 3.

Overall, results in Table 2 indicate that, in terms of inducing the "correct" behaviors from the infected population, government disclosure generally reduces trips made by the infected and speeds up diagnosis, with the exception of the effect of mandatory disclosure on the number of trips made by the infected when all

Table 2 Government disclosure on behaviors of the infected.

Panel A: Trips

Variables	Trip$_{i,t}$									
	Full sample					[−5, 5] Window				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post$_{i,t-1}$	−0.469*** (−2.84)				−1.657*** (−6.22)	−0.077 (−0.48)				−0.422*** (−2.58)
Mandatory_New$_{i,t-1}$		−0.004 (−1.07)			0.009** (2.10)		−0.022** (−2.50)			−0.012 (−1.05)
Voluntary_Dis$_{i,t-1}$			−0.076*** (−3.90)		−0.085*** (−4.34)			−0.092*** (−4.08)		−0.108*** (−4.20)
ZhongNS_Post$_{i,t-1}$				0.049 (0.48)	1.793*** (7.64)				0.329*** (2.78)	0.979*** (7.66)
Speed_Response$_i$	−0.276*** (−3.77)	−0.246*** (−3.50)	−0.252*** (−2.98)	−0.247*** (−3.61)	−0.327*** (−3.75)	−0.361*** (−4.44)	−0.349*** (−4.01)	−0.307*** (−3.33)	−0.369*** (−4.60)	−0.352*** (−4.20)
Immigration_from_WH$_{i,t-1}$	0.121 (0.95)	0.088 (0.80)	0.150 (1.04)	0.058 (0.61)	0.110 (0.75)	−0.063 (−0.98)	−0.028 (−0.37)	−0.037 (−0.55)	−0.087 (−1.49)	−0.029 (−0.39)
lnGDP_Capita$_i$	0.310 (1.25)	0.345 (1.43)	0.459* (1.84)	0.335 (1.38)	0.477* (1.87)	0.183 (0.70)	0.237 (0.92)	0.133 (0.53)	0.224 (0.87)	0.203 (0.92)
lnPop$_i$	0.234 (1.04)	0.284 (1.37)	0.193 (0.77)	0.294 (1.42)	0.237 (0.92)	0.453** (2.54)	0.438** (2.34)	0.427** (2.53)	0.502*** (2.79)	0.499*** (2.87)
Fiscal$_i$	−7.304** (−1.98)	−7.253** (−1.97)	−7.039* (−1.84)	−7.248** (−1.99)	−6.511* (−1.71)	−7.661** (−2.09)	−7.586** (−1.99)	−6.581* (−1.82)	−7.253* (−1.95)	−5.338 (−1.46)
lnBeds_Capita$_i$	2.355*** (3.14)	2.363*** (3.16)	2.262** (2.56)	2.358*** (3.19)	2.119** (2.35)	2.324*** (3.31)	2.414*** (3.39)	2.306*** (3.34)	2.300*** (3.26)	2.248*** (3.15)
Constant	−14.511*** (−3.01)	−15.489*** (−3.28)	−15.492*** (−3.14)	−15.469*** (−3.22)	−15.865*** (−3.13)	−13.630*** (−2.99)	−14.463*** (−3.20)	−12.706*** (−2.96)	−14.657*** (−3.17)	−14.446*** (−3.51)
N	1800	1800	1800	1800	1800	330	330	330	330	330
Pseudo-R^2	0.030	0.028	0.038	0.027	0.050	0.076	0.079	0.087	0.080	0.106

Panel B: Speed of diagnosis

Variables	Speed_Diagnosis$_{i,t}$									
	Full sample					[−5, 5] Window				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post$_{i,t-1}$	−0.399*** (−10.30)				−0.083 (−1.22)	−0.122*** (−3.43)				0.023 (0.41)
Mandatory_New$_{i,t-1}$		−0.005*** (−3.31)			0.001 (1.17)		−0.003 (−1.20)			0.003 (0.95)
Voluntary_Dis$_{i,t-1}$			−0.026*** (−4.79)		−0.009* (−1.66)			−0.020*** (−2.88)		−0.011 (−1.34)
ZhongNS_Post$_{i,t-1}$				−0.421*** (−11.53)	−0.322*** (−5.46)				−0.160*** (−4.44)	−0.171*** (−3.29)
Speed_Response$_i$	−0.045*** (−2.66)	−0.026 (−1.22)	−0.035* (−1.75)	−0.026* (−1.65)	−0.033** (−2.14)	−0.043** (−2.20)	−0.037* (−1.76)	−0.034* (−1.70)	−0.027 (−1.41)	−0.025(−1.23)
Immigration_from_WH$_{i,t-1}$	-0.032*** (−2.59)	−0.051*** (−2.59)	−0.057*** (−4.03)	−0.031*** (−2.75)	−0.032*** (−2.85)	−0.017 (−1.32)	−0.019 (−1.42)	−0.019 (−1.63)	−0.015 (−1.22)	−0.019 (−1.50)
lnGDP_Capita$_i$	0.036 (0.85)	0.028 (0.51)	0.029 (0.50)	0.027 (0.71)	0.032 (0.79)	0.005 (0.08)	0.007 (0.10)	−0.011 (−0.17)	0.005 (0.09)	−0.010 (−0.15)
lnPop$_i$	−0.001 (−0.05)	0.059* (1.72)	0.036 (1.00)	−0.019 (−0.76)	−0.021 (−0.85)	−0.079* (−1.74)	−0.072 (−1.58)	−0.076 (−1.64)	−0.094** (−2.10)	−0.095** (−2.08)

Table 2 (continued)

Panel B: Speed of diagnosis

Variables	$Speed\_Diagnosis_{i,t}$									
	Full sample					[−5, 5] Window				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Fiscal_i$	−0.780 (−1.41)	−0.758 (−1.30)	−0.466 (−0.78)	−0.887* (−1.68)	−0.750 (−1.43)	−0.746 (−0.90)	−0.694 (−0.86)	−0.574 (−0.71)	−0.892 (−1.12)	−0.840 (−1.06)
$lnBeds\_Capita_i$	−0.024 (−0.17)	−0.043 (−0.26)	−0.019 (−0.10)	−0.011 (−0.08)	−0.009 (−0.06)	−0.107 (−0.57)	−0.090 (−0.47)	−0.107 (−0.56)	−0.091 (−0.50)	−0.098 (−0.54)
Constant	2.812*** (3.29)	2.385** (2.35)	2.440** (2.50)	3.085*** (3.84)	3.015*** (3.88)	3.962*** (3.83)	3.788*** (3.71)	4.096*** (3.78)	4.105*** (4.03)	4.308*** (4.08)
N	573	573	573	573	573	256	256	256	256	256
Pseudo-R^2	0.049	0.018	0.027	0.054	0.057	0.022	0.014	0.019	0.028	0.029

***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

four measures are entered simultaneously in the full sample analysis.

As the regression discontinuity design to an extent tease out the interfering effect of public health emergency measures, we use results during the [−5, 5] window to estimate economic significance, using coefficients when the three province-level disclosure measures are considered separately. For an indicator independent variable, its economic significance is computed as the change in the dependent variable when it switches from 0 to 1 (while all other variables are kept at their sample means) divided by the mean of the dependent variable. For a continuous independent variable, its economic significance is computed as the change in the dependent variable when it switches from its mean to its mean plus a standard deviation (while all other variables are kept at their sample means) divided by the mean of the dependent variable. The effect of government disclosure on the behaviors of the infected is visualized in Fig. 4. We can see that the entry into a disclosure regime, the mandatory disclosure of daily newly confirmed number of cases and the number of voluntary disclosures all individually significantly reduce trips made by the infected (7.37%, 14.05% and 28.56%, respectively) and speed up their diagnosis (11.5%, 2.22% and 7.17%, respectively).

Effect of government disclosure on the susceptible. We now move to an analysis of the effect government disclosure on the behaviors of another important, and much larger, population, the susceptible. We focus on three types of behaviors, public attention paid to the virus, self-protection awareness, and cross-province migration/city activities among the susceptible.

Public attention and self-protection awareness. We first examine public attention and self-protection awareness, the measures of which are both Internet-search-based. To capture public attention, we employ a web crawler to extract province-level daily Internet searches for "pneumonia" (using "novel coronavirus" produces similar results) which represent public attention paid to the virus. To capture self-protection awareness, we employ a web crawler to extract province-level daily Internet searches for "mask" (using "disinfection" and "alcohol" which the Chinese often use to refer to "sanitizers" produces similar results).[1]

We estimate the following negative binomial regression:

$$\begin{aligned}&\log(\mathrm{Search\_Pneumonia})\ \text{or}\ \log(\mathrm{Search\_Mask})\\&\quad=\beta_0+\beta_1 Post_{i,t-1}\ \text{or Mandatory\_New}_{i,t-1}\\&\qquad\text{or Voluntary\_Dis}_{i,t-1}\text{or ZhongNS\_Post}_{i,t-1}+\beta_2\mathrm{Speed\_Response}_i\\&\qquad+\beta_3\mathrm{Immigration\_from\_WH}_{i,t-1}+\beta_4\mathrm{lnGDP\_Capita}_i\\&\qquad+\beta_5\mathrm{lnPop}_i+\beta_6\mathrm{Fiscal}_i+\beta_7\mathrm{lnBeds\_Capita}_i+\varepsilon_{i,t}.\end{aligned}\tag{3}$$

where Search_Pneumonia is the number of Internet searches for "pneumonia" for a province during a day and Search_Mask is the number of Internet searches for "mask" for a province during a day. All other variables are as defined earlier.

Full sample regression results for public attention paid to the virus, Search_Pneumonia, are presented in Columns (1)–(5) of Panel A1, Table 3. In Column (1) where we just have Post, its coefficient is positive and significant (1.913, $z = 15.41$). Therefore, the entry into a disclosure regime increases people's attention paid to the virus and Internet search intensity for "pneumonia" increases. In Column (2) where we just include Mandatory_New, its coefficient is positive and significant (0.028, $z = 5.26$). This is evidence that mandatory government disclosure of daily number of new cases trigger Internet searches for "pneumonia". Thus, government mandatory disclosure raises people's attention paid to the virus. In Column (3) where we just include Voluntary_Dis, its coefficient is positive and significant (0.068, $z = 5.23$), similar

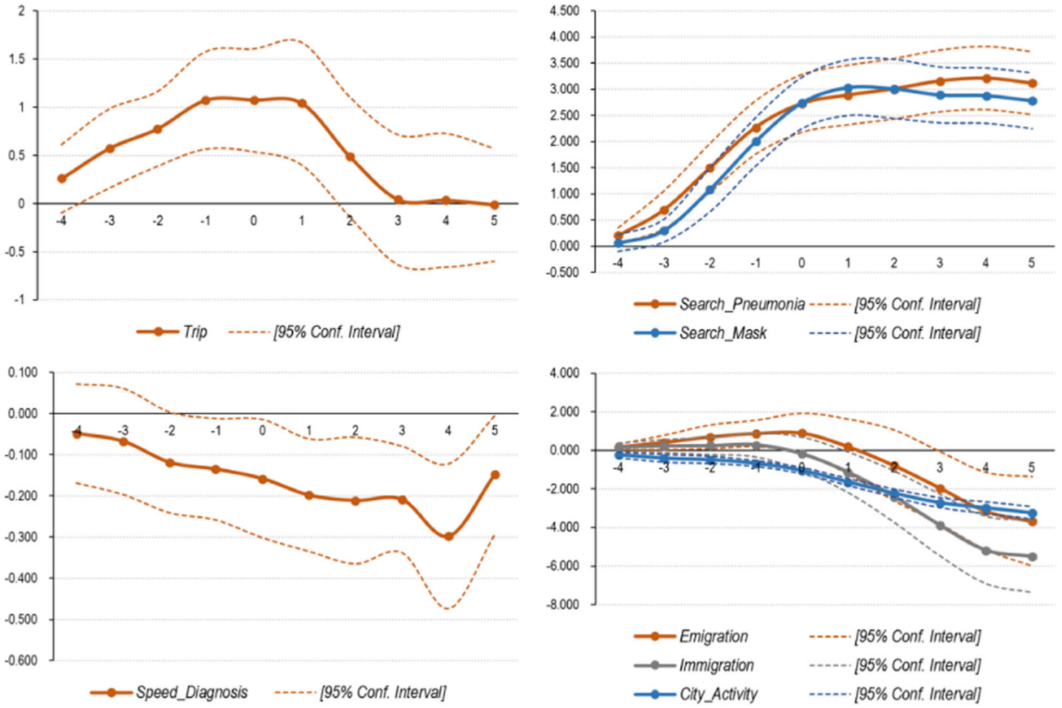

Fig. 3 Behaviors of the infected and the susceptible around the entry into a government disclosure regime. In a 11-day window [−5, 5] around the entry into a government disclosure regime, we estimate regression Eqs. (1–4) replacing Post with indicators Day −4, Day −3, ..., Day 4 and Day 5 indicating days relative to the entry into the disclosure regime. The coefficients and confidence intervals for these indicators are plotted here.

to mandatory disclosure. Therefore, voluntary disclosure also raises people's attention paid to the virus. Column (4) shows that Zhong Nanshan's statement also increase the search for "pneumonia" (2.242, $z = 38.84$). In Column (5) where we enter all four simultaneously, the coefficient on Voluntary_Dis becomes negative and significant, inconsistent with our expectation, potentially due to high correlations among the four variables. Results using the [−5, 5] window subsample presented in Columns (6–10) are similar and less ambiguous. Daily effects are visualized in Fig. 3.

Full sample regression results for self-protection awareness, Search_Mask, are presented in Columns (1–5) of Panel A2, Table 3. Similar to results in Panel A1 on people's attention paid to the virus, when Post, Mandatory_New, Voluntary_Dis and ZhongNS_Post enter regression Equation (3) separately, their respective coefficients are positive and significant (2.061, $z = 15.60$ for *Post*; 0.018, $z = 5.37$ for Mandatory_New; 0.069, $z = 6.01$ for Voluntary_Dis; 2.650, $z = 55.18$ for ZhongNS_Post). Therefore, mandatory and voluntary disclosures, as well as the entry into a disclosure regime, help raise self-protection awareness among the susceptible. In Column (5) where all four enter the regression simultaneously, the coefficient on Voluntary_Dis becomes negative and significant, inconsistent with our expectation, again potentially due to high correlations among the four variables. Results using the [−5, 5] window subsample presented in Columns (6)–(10) are similar and less ambiguous. Daily effects are visualized in Fig. 3.

Evidence here again suggests that province-level government disclosure instills the "correct" behaviors among the susceptible during the epidemic. Figure 5 shows that the entry into a disclosure regime, the mandatory disclosure of daily newly confirmed number of cases and the number of voluntary disclosures all individually significantly increase attention paid to the virus (413.47%, 66.71% and 52.33%, respectively) and raise self-protection awareness (501.69%, 55.88% and 43.97%, respectively) among the susceptible.

Cross-province emigrations, immigrations and city activities. We next examine how government disclosure affects mobility patterns among the susceptible. We consider cross-province emigrations, immigrations, as well as city activities. We estimate the following OLS regression:

$$\begin{aligned}\text{Emigration}_{i,t}&\text{or Immigration}_{i,t}\text{or City\_Activity}_{i,t}\\ &= \beta_0 + \beta_1\text{Post}_{i,t-1}\text{or Mandatory\_New}_{i,t-1}\text{or Voluntary\_Dis}_{i,t-1}\text{or ZhongNS\_Post}_{i,t-1}\\ &\quad + \beta_2\text{Speed\_Response}_i + \beta_3\text{Immigration\_from\_WH}_{i,t-1} + \beta_4\text{lnGDP\_Capita}_i\\ &\quad + \beta_5\text{lnPop}_i + \beta_6\text{Fiscal}_i + \beta_7\text{lnBeds\_Capita}_i + \varepsilon_{i,t}.\end{aligned} \tag{4}$$

where Emigration is Baidu emigration index for a province during a day, Immigration is Baidu immigration index for a province during a day, and City_Activity is Baidu provincial city activity index for a province during a day. All other variables are as defined earlier. As Emigration, Immigration and City_Activity are continuous variables based on Baidu population index, we estimate an OLS Equation (4). Standard errors are clustered by provinces.

Full sample results for cross-province emigrations are reported in Columns (1–5) of Panel B1, Table 3. When Post, Mandatory_New, Voluntary_Dis and ZhongNS_Post enter the regression equation separately, their coefficients are negative and significant (−3.918, $t = -4.72$ for Post; −0.074, $t = -4.84$ for Mandatory_New; −0.292, $t = -4.88$ for Voluntary_Dis; −3.904, $t = -4.61$), suggesting that the entry into a disclosure regime and government mandatory and voluntary disclosures individually reduce cross-province emigrations during the epidemic. In Column (5) where we enter the four variables of interest simultaneously, their coefficients are negative and significant for Mandatory_New (−0.045, $t = -3.82$) and Voluntary_Dis (−0.139, $t = -3.39$). The coefficients on Post and ZhongNS_Post are negative but insignificant. Results using the [−5, 5] window subsample presented in Columns (6–10) are similar. Daily effects are visualized in Fig. 3. Therefore, both government mandatory and voluntary disclosures have an incremental effect of reducing

Table 3 Government disclosure on behaviors of the susceptible. A: . B: Migrations.

Panel A: Public attention and self-protection awareness

Panel A1: Internet Searches for "Pneumonia"

Variables	$Search\_Pneumonia_{i,t}$									
	Full sample					[−5, 5] Window				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Post_{i,t-1}$	1.913*** (15.41)				0.079 (0.37)	1.636*** (10.89)				0.410** (2.43)
$Mandatory\_New_{i,t-1}$		0.028*** (5.26)			0.010*** (5.25)		0.074*** (7.76)			0.018*** (3.44)
$Voluntary\_Dis_{i,t-1}$			0.068*** (5.23)		−0.013** (−2.27)			0.116*** (4.60)		0.005 (0.47)
$ZhongNS\_Post_{i,t-1}$				2.424*** (38.84)	2.358*** (11.89)				2.294*** (41.15)	1.825*** (13.56)
$Speed\_Response_i$	0.111*** (4.22)	0.001 (0.04)	−0.004 (−0.11)	0.006 (0.34)	0.005 (0.32)	0.169*** (3.62)	0.047 (1.45)	−0.001 (−0.03)	0.011 (0.52)	0.032 (1.45)
$Immigration\_from\_WH_{i,t-1}$	0.101*** (2.71)	0.097 (1.38)	0.186** (1.99)	0.056** (2.45)	0.014 (0.73)	0.043 (1.49)	−0.006 (−0.15)	0.072** (2.04)	0.040* (1.70)	0.006 (0.26)
$lnGDP\_Capita_i$	0.728*** (6.58)	0.714*** (4.45)	0.629*** (4.57)	0.820*** (7.70)	0.824*** (7.31)	0.683*** (4.32)	0.525*** (3.54)	0.787*** (4.94)	0.903*** (7.44)	0.829*** (7.06)
$lnPop_i$	0.816*** (11.56)	0.746*** (5.65)	0.842*** (6.47)	0.922*** (17.59)	0.895*** (15.19)	0.884*** (8.42)	0.866*** (6.99)	0.936*** (7.34)	1.046*** (13.68)	1.004*** (11.52)
$Fiscal_i$	4.355** (2.41)	3.419 (1.54)	3.895 (1.60)	4.886*** (3.17)	4.657*** (2.93)	3.949 (1.59)	3.366 (1.63)	2.688 (1.07)	6.060*** (3.58)	5.442*** (2.87)
$lnBeds\_Capita_i$	−0.001 (−0.00)	0.191 (0.38)	0.346 (0.62)	−0.055 (−0.19)	−0.041 (−0.14)	0.038 (0.08)	−0.099 (−0.20)	0.063 (0.11)	−0.080 (−0.24)	−0.052 (−0.14)
Constant	−8.068*** (−4.33)	−6.962** (−2.35)	−7.728*** (−2.92)	−0.461*** (−5.96)	−0.297*** (−5.50)	−7.129*** (−2.91)	−3.995 (−1.57)	−8.215*** (−2.84)	−11.683*** (−5.20)	−0.492*** (−4.79)
N	1800	1800	1800	1800	1800	330	330	330	330	330
Pseudo-R^2	0.063	0.032	0.032	0.093	0.095	0.052	0.030	0.028	0.077	0.081

Panel A2: Internet Searches for "Mask"

Variables	$Search\_Mask_{i,t}$									
	Full sample					[−5, 5] Window				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Post_{i,t-1}$	2.061*** (15.60)				0.117 (0.66)	1.795*** (9.21)				0.505*** (3.17)
$Mandatory\_New_{i,t-1}$		0.018*** (5.37)			0.005*** (3.46)		0.064*** (7.10)			0.007* (1.72)
$Voluntary\_Dis_{i,t-1}$			0.069*** (6.01)		−0.013*** (−3.68)			0.100*** (3.92)		−0.011 (−1.49)
$ZhongNS\_Post_{i,t-1}$				2.650*** (55.18)	2.591*** (15.23)				2.674*** (43.63)	2.241*** (18.11)
$Speed\_Response_i$	0.116*** (4.38)	0.002 (0.07)	−0.001 (−0.03)	−0.002 (−0.10)	−0.000 (−0.02)	0.169*** (3.64)	0.024 (1.20)	−0.015 (−0.45)	−0.018 (−0.90)	0.019 (1.00)
$Immigration\_from\_WH_{i,t-1}$	0.101** (2.18)	0.173 (1.57)	0.224* (1.72)	0.031 (1.37)	0.014 (0.75)	0.057* (1.75)	0.055 (1.52)	0.117** (1.96)	0.055 (1.55)	0.038 (1.35)
$lnGDP\_Capita_i$	0.654*** (8.28)	0.627*** (4.96)	0.496*** (3.54)	0.691*** (7.65)	0.711*** (7.56)	0.653*** (4.08)	0.487*** (4.97)	0.733*** (5.54)	0.840*** (8.82)	0.790*** (8.95)
$lnPop_i$	0.674*** (12.10)	0.586*** (4.60)	0.671*** (4.93)	0.831*** (15.44)	0.809*** (14.03)	0.659*** (8.65)	0.649*** (10.40)	0.712*** (8.07)	0.821*** (11.85)	0.784*** (12.34)
$Fiscal_i$	3.643*** (2.84)	3.092 (1.63)	3.959* (1.84)	4.326*** (3.99)	4.016*** (3.60)	2.125 (1.18)	2.500** (2.11)	1.927 (1.07)	4.647*** (4.23)	4.133*** (3.56)
$lnBeds\_Capita_i$	0.012 (0.04)	0.206 (0.50)	0.371 (0.78)	−0.089 (−0.35)	−0.089 (−0.36)	0.440 (1.44)	0.374 (1.53)	0.467 (1.27)	0.190 (0.68)	0.237 (0.92)
Constant	−7.669*** (−5.55)	−6.211** (−2.48)	−6.513** (−2.48)	−9.750*** (−5.33)	−9.748*** (−5.24)	−8.131*** (−4.15)	−0.305*** (−3.59)	−8.983*** (−4.19)	−12.134*** (−6.40)	−11.316*** (−6.53)
N	1800	1800	1800	1800	1800	330	330	330	330	330
Pseudo-R^2	0.075	0.030	0.033	0.122	0.124	0.061	0.027	0.026	0.115	0.121

Panel B: Migrations

Panel B1: Emigrations

Variables	$Emigration_{i,t}$									
	Full sample					[−5, 5] Window				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Post_{i,t-1}$	−3.918*** (−4.72)				−1.738 (−1.67)	−1.826** (−2.70)				−0.199 (−0.25)
$Mandatory\_New_{i,t-1}$		−0.074*** (−4.84)			−0.045*** (−3.82)		−0.224*** (−3.09)			−0.190** (−2.68)
$Voluntary\_Dis_{i,t-1}$			−0.292*** (−4.88)		−0.139*** (−3.39)			−0.266*** (−3.22)		−0.125 (−1.57)
$ZhongNS\_Post_{i,t-1}$				−3.904*** (−4.61)	−1.038 (−1.14)				−1.734** (−2.51)	−0.130 (−0.17)
$Speed\_Response_i$	0.354** (2.32)	0.424** (2.20)	0.394** (2.61)	0.415** (2.68)	0.399** (2.56)	1.037** (2.67)	1.114** (2.73)	1.255*** (2.94)	1.123*** (2.82)	1.213*** (2.77)
$Immigration\_from\_WH_{i,t-1}$	0.246*** (2.84)	0.102 (0.79)	−0.005 (−0.03)	0.250*** (3.09)	0.417*** (5.23)	0.225 (0.96)	0.553* (1.94)	0.188 (0.75)	0.201 (0.84)	0.550* (1.91)
$lnGDP\_Capita_i$	2.940*** (4.17)	3.036*** (3.53)	3.662*** (6.12)	2.888*** (4.02)	3.403*** (5.31)	8.717*** (5.69)	9.248*** (5.45)	8.580*** (5.96)	8.611*** (5.63)	9.099*** (5.55)
$lnPop_i$	2.742*** (5.11)	3.247*** (4.69)	2.754*** (5.47)	2.676*** (5.12)	2.708*** (5.08)	5.473*** (3.90)	5.578*** (3.87)	5.499*** (3.84)	5.402*** (3.92)	5.500*** (3.85)
$Fiscal_i$	26.410** (2.64)	26.672** (2.20)	21.382** (2.49)	26.305** (2.62)	24.200** (2.49)	87.991*** (3.67)	88.199*** (3.52)	90.495*** (3.80)	87.219*** (3.65)	89.270*** (3.60)
$lnBeds\_Capita_i$	−3.491* (−2.01)	−4.236* (−1.92)	−4.383** (−2.17)	−3.497* (−2.01)	−4.116** (−2.15)	−6.386 (−1.25)	−6.269 (−1.20)	−6.333 (−1.23)	−6.299 (−1.25)	−6.218 (−1.19)
Constant	−36.881*** (−3.98)	−40.680*** (−3.49)	−41.539*** (−4.54)	−35.528*** (−3.70)	−38.829*** (−4.25)	−115.119*** (−5.14)	−122.809*** (−5.01)	−114.208*** (−5.28)	−113.288*** (−5.04)	−120.309*** (−5.10)
N	1800	1800	1800	1800	1800	330	330	330	330	330
Adjusted R^2	0.409	0.317	0.376	0.403	0.446	0.662	0.686	0.662	0.659	0.687

Panel B2: Immigrations

Variables	$Immigration_{i,t}$									
	Full sample					[−5, 5] Window				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Post_{i,t-1}$	−4.125*** (−7.38)				−3.579*** (−4.11)	−3.197*** (−5.55)				−0.748* (−1.80)
$Mandatory\_New_{i,t-1}$		−0.071*** (−4.82)			−0.043*** (−3.92)		−0.343*** (−6.08)			−0.274*** (−5.19)
$Voluntary\_Dis_{i,t-1}$			−0.254*** (−6.06)		−0.072*** (−3.03)			−0.419*** (−3.88)		−0.173*** (−2.82)
$ZhongNS\_Post_{i,t-1}$				−3.921*** (−7.40)	0.242 (0.44)				−3.052*** (−5.39)	−0.367 (−0.80)
$Speed\_Response_i$	0.174 (1.22)	0.245 (1.31)	0.217 (1.26)	0.238* (1.70)	0.196 (1.33)	−0.150 (−0.56)	−0.034 (−0.14)	0.192 (0.69)	0.001 (0.01)	0.106 (0.44)
$Immigration\_from\_WH_{i,t-1}$	0.269** (2.15)	0.088 (1.05)	−0.036 (−0.37)	0.250** (2.18)	0.420*** (3.20)	1.344*** (4.14)	1.818*** (4.57)	1.263*** (4.18)	1.303*** (4.21)	1.812*** (4.69)
$lnGDP\_Capita_i$	1.121* (1.77)	1.206 (1.53)	1.733*** (2.85)	1.065 (1.63)	1.418** (2.37)	−1.161 (−0.90)	−0.347 (−0.28)	−1.378 (−1.02)	−1.347 (−1.02)	−0.617 (−0.50)
$lnPop_i$	2.599*** (6.67)	3.122*** (6.41)	2.685*** (7.18)	2.553*** (6.64)	2.639*** (6.42)	2.773*** (3.30)	2.964*** (3.48)	2.837*** (3.50)	2.646*** (3.15)	2.801*** (3.36)
$Fiscal_i$	19.616** (2.35)	19.864* (1.86)	15.229* (1.86)	19.508** (2.32)	18.568** (2.22)	−2.459 (−0.18)	−2.132 (−0.16)	1.492 (0.11)	−3.818 (−0.28)	−0.763 (−0.06)
$lnBeds\_Capita_i$	−3.037* (−1.91)	−3.785* (−1.88)	−3.873* (−2.00)	−3.059* (−1.91)	−3.488* (−2.04)	−2.908 (−0.69)	−2.745 (−0.63)	−2.839 (−0.68)	−2.755 (−0.65)	−2.657 (−0.62)
Constant	−17.048* (−1.99)	−20.959* (−1.89)	−21.614** (−2.15)	−15.825* (−1.77)	−18.733** (−2.18)	8.207 (0.37)	−3.925 (−0.18)	9.369 (0.41)	11.441 (0.50)	0.935 (0.04)
N	1800	1800	1800	1800	1800	330	330	330	330	330
Adjusted R^2	0.469	0.324	0.372	0.443	0.496	0.566	0.637	0.547	0.547	0.656

Panel B3: City activities

Variables	$City\_Activity_{i,t}$									
	Full sample					[−5, 5] Window				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Post_{i,t-1}$	−3.033*** (−26.14)				−1.662*** (−7.55)	−1.928*** (−21.00)				−0.935*** (−7.34)
$Mandatory\_New_{i,t-1}$		−0.037*** (−7.97)			−0.016*** (−6.91)		−0.121*** (−7.40)			−0.055*** (−5.70)
$Voluntary\_Dis_{i,t-1}$			−0.172*** (−10.57)		−0.031*** (−3.42)			−0.210*** (−7.76)		−0.077*** (−6.10)
$ZhongNS\_Post_{i,t-1}$				−3.043*** (−30.12)	−1.155*** (−7.01)				−1.902*** (−26.58)	−0.572*** (−4.54)
$Speed\_Response_i$	−0.096** (−2.62)	−0.049 (−0.71)	−0.064 (−0.85)	−0.048 (−1.48)	−0.069* (−1.86)	−0.356*** (−6.66)	−0.317*** (−6.08)	−0.186** (−2.51)	−0.262*** (−6.78)	−0.245*** (−4.69)
$Immigration\_from\_WH_{i,t-1}$	−0.102*** (−3.36)	−0.301*** (−3.15)	−0.338*** (−4.35)	−0.097*** (−3.59)	−0.032 (−0.97)	−0.112*** (−3.16)	−0.003 (−0.05)	−0.176*** (−3.52)	−0.133*** (-4.08)	−0.008 (−0.17)
$lnGDP\_Capita_i$	0.415*** (3.37)	0.439* (2.01)	0.821*** (2.81)	0.375*** (3.28)	0.521*** (3.54)	0.394* (1.85)	0.677*** (3.02)	0.284 (0.95)	0.278 (1.59)	0.453** (2.16)
$lnPop_i$	0.026 (0.25)	0.392*** (3.02)	0.110 (0.87)	−0.028 (−0.32)	0.006 (0.06)	−0.063 (−0.47)	0.064 (0.46)	−0.006 (−0.04)	−0.147 (−1.24)	−0.097 (−0.71)
$Fiscal_i$	−4.233* (−1.72)	−4.117 (−1.22)	−7.198* (−2.03)	−4.315* (−1.79)	−4.718* (−1.92)	−6.243** (−2.16)	−6.113** (−2.36)	−4.258 (−1.21)	−7.091** (−2.66)	−5.732** (−2.18)
$lnBeds\_Capita_i$	0.433 (0.70)	−0.032 (−0.04)	−0.151 (−0.18)	0.430 (0.71)	0.262 (0.44)	0.976 (1.28)	1.001 (1.17)	0.998 (1.29)	1.074 (1.48)	1.073 (1.42)
Constant	−0.948 (−0.34)	−3.623 (−1.06)	−4.207 (−0.85)	0.122 (0.05)	−1.109 (−0.39)	−2.847 (−0.68)	−7.795* (−1.76)	−2.544 (−0.47)	−0.776 (−0.23)	−3.378 (−0.79)
N	1800	1800	1800	1800	1800	330	330	330	330	330
Adjusted R^2	0.792	0.250	0.436	0.773	0.828	0.654	0.483	0.441	0.574	0.750

***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

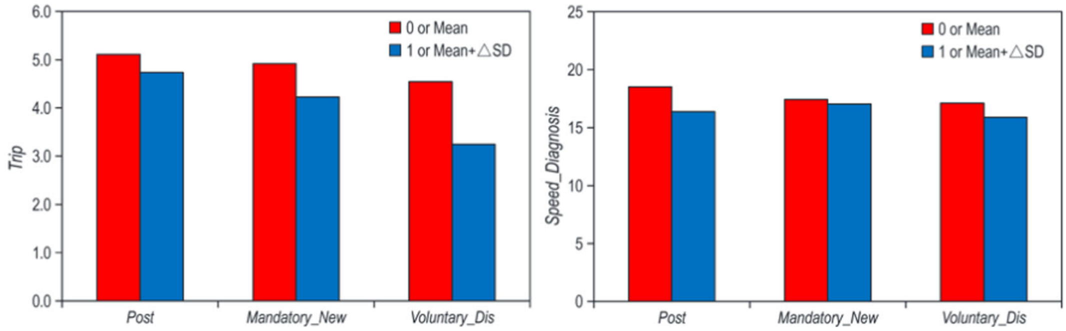

Fig. 4 Impact of government disclosure on behaviors of the infected. Post is an indicator that equals 1 after a province entered the Category I public health emergency regime and 0 before. Mandatory_New is the daily new confirmed cases for a province. Voluntary_Dis is the number of independent disclosures by a province's Center for Disease Control (CDC). For indicator Post, the red column represents value for the number of trips (speed of diagnosis) when Post is 0 and the blue column represents value for the number of trips (speed of diagnosis) when Post is 1. For continuous variables Mandatory_New and Voluntary_Dis, the red column represents value for the number of trips (speed of diagnosis) when they are at their mean and the blue column represents value for the number of trips (speed of diagnosis) when they are at their mean plus one standard deviation.

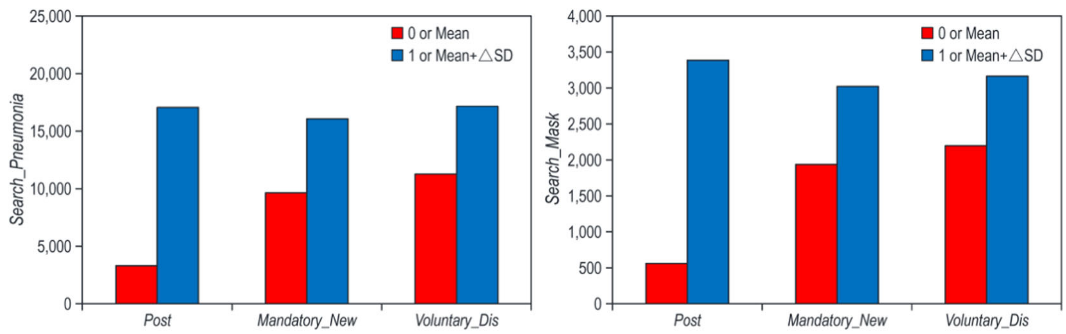

Fig. 5 Impact of government disclosure on behaviors of the susceptible—Internet searches for "pneumonia" and "mask" by the susceptible. Post is an indicator that equals 1 after a province entered the Category I public health emergency regime and 0 before. Mandatory_New is the daily new confirmed cases for a province. Voluntary_Dis is the number of independent disclosures by a province's Center for Disease Control (CDC). For indicator Post, the red column represents Internet searches for "pneumonia" ("mask") when Post is 0 and the blue column represents Internet searches for "pneumonia" ("mask") when Post is 1. For continuous variables Mandatory_New and Voluntary_Dis, the red column represents Internet searches for "pneumonia" ("mask") when they are at their mean and the blue column represents Internet searches for "pneumonia" ("mask") when they are at their mean plus one standard deviation.

cross-province emigrations beyond that of the entry into a disclosure regime. Reduced cross-province travels should contribute to containing the spread of the virus.

Columns (1–5) of Panel B2, Table 3 report full sample results on cross-province immigrations. Columns (1–4) show that each of Post (−4.125, $t=-7.38$), Mandatory_New (−0.071, $t=-4.82$), Voluntary_Dis (−0.254, $t=-6.06$) and ZhongNS_Post (−3.921, $t=-7.40$) individually reduces cross-province immigrations. When the four variables of interest are entered simultaneously in Column (5), only ZhongNS_Post becomes insignificant. Therefore, government mandatory and voluntary disclosures have an incremental effect on reducing cross-province immigrations among the susceptible in addition to the entry into a disclosure regime. Results using the [−5, 5] window subsample presented in Columns (6–10) are similar. Daily effects are visualized in Fig. 3.

Columns (1–5) of Panel B3, Table 3 report full sample results on city travel activities. Columns (1–4) show that Post (−3.033, $t=-26.14$), Mandatory_New (−0.037, $t=-7.97$), Voluntary_Dis (−0.172, $t=-10.57$) and ZhongNS_Post (−3.043, $t=30.12$) individually reduce city travel activities. When the four variables of interest are entered simultaneously in Column (5), they continue to be negative and significant. Results using the [−5, 5] window subsample presented in Columns (6–10) are similar. Daily effects are visualized in Fig. 3. Again, government mandatory and voluntary disclosures have an incremental effect on reducing city activities among the susceptible in addition to the entry into a disclosure regime.

Figure 6 illustrates that all the three forms of province-level disclosure significantly reduce cross-province emigration (24.88%, 24.36%, and 15.28% respectively), immigration (39.52%, 37.36%, and 24.06% respectively) and city activities (40.11%, 22.18%, and 20.35% respectively) among the susceptible.

Results including Hubei province and results excluding Gansu and Qinghai provinces. As we have discussed earlier, during our sample period, Wuhan, the capital city of Hubei province was China's epi-center, containing the super-majority of China's cases during January and February. It was also subject to the most stringent lockdown and received the most support from the central government. This makes Hubei province very different from other provinces. Further, in all our regressions, we control for daily cumulative emigrations from Wuhan as it can be an important factor affecting the behaviors of the infected and the susceptible. Therefore, in our main analysis, we do not include Hubei province.

Here, we repeat all analyses with Hubei province included. As Wuhan is the capital city of Hubei, we no long can control for immigrations from Wuhan. All other control variables are the

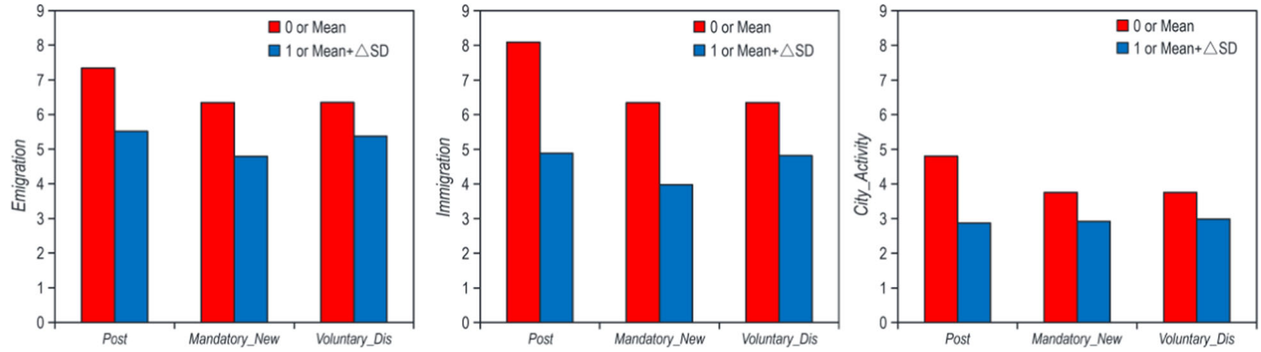

Fig. 6 Impact of government disclosure on behaviors of the susceptible—mobility among the susceptible. Post is an indicator that equals 1 after a province entered the Category I public health emergency regime and 0 before. Mandatory_New is the daily new confirmed cases for a province. Voluntary_Dis is the number of independent disclosures by a province's Center for Disease Control (CDC). For indicator Post, the red column represents values for emigration/immigration/city activity when Post is 0 and the blue column represents values for emigration/immigration/city activity when Post is 1. For continuous variables Mandatory_New and Voluntary_Dis, the red column represents values for emigration/immigration/city activity when they are at their mean and the blue column represents values for emigration/immigration/city activity when they are at their mean plus one standard deviation.

same. Table S1 reports the results for the infected and the susceptible. Overall, results are consistent with government disclosure instilling the "correct" human behaviors.

As shown in Appendix A, Gansu and Qinghai provinces are different from other provinces as they entered a government disclosure regime after the entry into the Category I Public Health Emergency Regime. When we omit Gansu and Qinghai and re-estimate all our regressions, we obtain qualitatively similar results (Table S2).

Teasing out the effect of public health emergency measures on people's behaviors

Subsample analysis within the Category I public health emergency regime. A way of separating out the interfering effect of public health emergency measures is to focus entirely on observations during the public health emergency regime so that cross-sectional and time-series variation in these emergency measures is minimized. We therefore use only observations where all provinces were in the Category I public health emergency regime. We repeat all analysis in this subsample. As the entries into a disclosure regime and the entries into a Category I public health emergency regime are very closely clustered, we no long use Post. Results are reported in Table S3. With the exception that the effects of mandatory disclosure on infected people's trip and speed of diagnosis are opposite to our expectation, all other results all consistent with our expectation.

Controlling for the effect of public health emergency measures in the full sample. Another way of teasing out the effect of public emergency measures is actually controlling for it. We tabulate the daily numbers of local CDCs' disclosures on virus-fighting policy measures, Measure. Specifically, it is the number of disclosures that are related to physical mobility restrictions and virus-fighting policies for a province. To the extent that Measure is well correlated with actual emergency policy measures, it will help us reduce the interfering effect of emergency measures. We perform the analysis on the full sample. Results are reported in Table S4. With the exception of the effect of mandatory disclosure on trips made by the infected (when all four disclosure measures are considered simultaneously), all other results are consistent with our expectation.

Virus duration and government disclosure. To determine how government disclosure affects the trajectory of the virus, we examine its effect on the duration of provinces' local epidemic.

Table 4 Duration of local epidemic and government disclosure.

Variables	Hazard
Voluntary_Dis$_{i,t}$	0.056*** (6.60)
Cases_Cumulative$_{i,t}$	0.003*** (13.07)
Speed_Response$_i$	0.824*** (10.88)
Immigration_from_WH$_{i,t}$	−0.440*** (−5.22)
lnGDP_Capita$_i$	−1.560*** (−4.94)
lnPop$_i$	−1.388*** (−13.57)
Fiscal$_i$	1.180 (0.34)
lnBeds_Capita$_i$	0.746 (1.40)
N	1800
Pseudo-R^2	0.154

***, ** and * indicate significance levels at 1, 5 and 10% respectively.

We estimate the following Cox hazard model:

$$h(t)_i = h(0) \cdot \exp\begin{pmatrix} \beta_1 \text{Voluntary\_Dis}_{i,t} + \beta_2 \text{Cases\_Cumulative}_{i,t} \\ +\beta_3 \text{Speed\_Response}_i + \beta_4 \text{Immigration\_from\_WH}_{i,t} \\ +\beta_5 \text{lnGDP\_Capita}_i + \beta_6 \text{lnPop}_i + \beta_7 \text{Fiscal}_i \\ +\beta_8 \text{lnBeds\_Capita}_i + \varepsilon_{i,t} \end{pmatrix}, \quad (5)$$

where all dependent variables are on Day t as here we are tracking trajectory of the development of the virus and not human behaviors. Cases_Cumulative is the cumulative number of confirmed cases for a province during a day since January 1, 2020. In this model, Post is not added as having it would create multi-collinearity in the Cox hazard model. Peaking period t is the period between a province's first confirmed case and its day of the peak, which is defined as the day followed by 3 days of no newly confirmed cases.

Table 4 reports the result for the Cox hazard analysis. The coefficient on Voluntary_Dis is positive and significant (0.056, $t = 6.60$), suggesting that voluntary disclosure helps end a local epidemic quicker. The coefficient on Cases_Cumulative is positive and significant (0.003, $t = 13.07$), suggesting that a local epidemic tends to exhaust itself when there are more cases. In sum, government disclosure helps end the local epidemic quicker, potentially due to its ability in instilling the "correct" behaviors from both the infected and the susceptible that are conducive to virus containment.

Conclusion

Using the setting of COVID-19 in China, we examine the role played by government disclosure in a public health emergency. We show that government disclosure concerning COVID-19 generally reduces the frequency of trips made by the infected and increase their speed of diagnosis. Further, government disclosure generally increases public attention paid to and self-protection awareness of COVID-19 as well as reduces cross-province migrations among the susceptible. Finally, government disclosure helps provinces shorten the duration of their virus situation. We conclude that government disclosure and transparency, through instilling the correct behaviors from both the infected and the susceptible, can be effective in handling public health emergencies such as the COVID-19.

Data availability

Data used in our research are publicly available as identified in the data sub-section of the paper. They can also be obtained from the corresponding author by request.

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Note

1 While the infected can also be searching for these, the population of the susceptible is vastly larger than that of the infected, we therefore consider these searches to be conducted by the susceptible.

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