Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Study on the mechanism of public attention to a major event: The outbreak of COVID-19 in China

Lu Liu*, Yifei Fu

School of Economics, Southwestern University of Finance and Economics, 555 Liutai Avenue, Wenjiang District, Chengdu, Sichuan 611130, China

ARTICLE INFO

Keywords:
Public attention
COVID-19
Chinese medical website
Daily clicks
Sustainable development goals (SDGs)

ABSTRACT

This study focuses on public attention to major events, which has become an important topic in the context of the COVID-19 pandemic. In the background of the global transmission of COVID-19, this study discusses the relationship between information shock and sustainable development, which is rarely mentioned before. By developing an appropriate theoretical model, we discuss how the level of public attention changes over time and with the severity of events. Then we use data on the daily clicks on a popular Chinese medical website to indicate public attention to the pandemic. Our analysis shows that, in the first half of 2020, the level of public attention is closely related to the scale of domestic transmission. The marginal effect of the domestic cases in the first wave is 1% to 0.217%. After the pandemic was largely under control in China, people still followed the latest news, but the scale of public attention to regional transmission diminished. And when the pandemic quickly and severely worsened in other countries, people in China were very attentive, that is, public attention increased. The time interval of social reaction we calculate is fairly stable, with a value of between 0 and 5 most of the time. The average time interval from January 2020 to May 2021 ranges from 1.76 days to 1.94 days, depending on the choice of models and parameters. This study suggests that raising public participation in dealing with the crisis over the long term would be enhanced in China by media encouragement to pay more attention to small-scale regional transmission and the course of the pandemic in other countries. The goal of sustainable development requires dealing with health and economic crises much better in the long term. Thus, the model and method used in the paper serve to enhance general interest.

1. Introduction

1.1. Facts

Public attention is greatly influenced by major events. When an important event happens, public attention is quickly aroused. For events such as natural disasters, diplomatic activity, and sporting events, the media constantly follow the latest news, so people remain informed about them.

These events usually take place over a short period, but public health emergencies occupy a much longer time. In spring 2003, the transmission of SARS was one of the most important news stories in China for months. When the outbreak of COVID-19 occurred, the same thing happened but on a much larger scale. As of August 14, 2021, more than 200 million people around the world have been infected, with around half a million new cases still reported daily. Because the conditions remain extremely challenging, the pandemic continues to be the focus of public attention (Chan, Yuan & Kok, 2020; Hung, Lauren & Hon, 2020; Wang, Horby & Hayden, 2020). Some websites have prominently displayed the number of page views, indicating the extent of public interest. Data provided by Dingxiangyuan, a popular medical website in China, shows that as of January 2022, it had received more than 4.6 billion total page views, more than three times the size of the entire Chinese population.

1.2. Motivation for the research

The COVID-19 pandemic is so serious that every aspect deserves to be studied carefully. Because of its unprecedented scale and severity, it has a tremendous impact on many people, both physically and mentally.

* Corresponding author.
E-mail address: liulu@swufe.edu.cn (L. Liu).
1 Our World in Data. https://ourworldindata.org/covid-vaccinations/
2 Dingxiangyuan. https://ncov.dxy.cn/ncovh5/view/pneumonia/ [in Chinese]
Since the outbreak of the pandemic, scholars have been greatly interested in psychological research regarding COVID-19. Many papers focus on public attention, which is crucial for social governance. In this study, we pose several important questions about public attention. For example, how much time elapses between the event and the moment that people begin to react to it? What differences arise between the outbreak in China and elsewhere in terms of public attention? Considering that more than the initial outbreak of COVID-19 was more than two years ago, are people still as concerned about it as they were earlier?

1.3. Contributions to the literature

Using modeling and data analysis, this study aims to explain how major events affect public attention. The COVID-19 pandemic is just one of many major events happening. If we can reveal the relationship between major events and public awareness in the context of the pandemic, we can apply similar methods to study other events. In this way, we can gain a deeper understanding of the mechanism in people’s reactions to various events, which is meaningful for academic research in this field.

To conduct our study, we employ valuable data collected on the internet. The internet has become one of the main ways to raise people’s awareness, and an increasing number of studies are examining public opinion using data from the internet. However, data on page views are seldom used in academic research as an intuitive indicator of public attention. Perhaps part of the reason for this is the difficulty in collecting this type of data. Furthermore, few models or methods have been developed to analyze page views for new media, such as specialized websites. To fill this research gap, we obtained data on the daily clicks on the website Dingxiangyuan, to determine the relationship between public attention and the transmission of COVID-19.

The article is structured as follows. After reviewing the existing literature in Section 2, we set up a theoretical model in Section 3 to discuss the mechanism of public attention to a certain event. Then, in Section 4, we introduce the data set and determine how much the model reflects reality. In Section 5, we present the results and discussion in Section 6. In Section 7, we offer some policy implications and closing remarks.

2. Literature review

People’s reaction to major events has long been an important aspect in social psychology. The evolving paths of public attention vary dramatically for different types of events (Neuman, 1990). In this section, we first introduce two opinions about how public attention evolves. Then we focus on public sentiment and discuss its characteristics and functions. We also cover some similar phenomena in other fields, to form a complete picture of the latest research related to this issue.

2.1. How does public attention evolve? Two opinions

Over time, the magnitude of people’s perception of various events changes. Some evidence shows that after some time has passed, people tend to be less concerned about an event, regardless of its severity (Ortega & Bernabé-Moreno, 2021). When COVID-19 was first transmitted, the outbreak caused strong sentiments of stress and panic (Bao, Sun & Meng, 2020; Morin, Bjorvatn & Chung, 2021; Xiang, Yang & Li, 2020). Later on, although the virus continued to spread rapidly around the world, the level of media attention has declined since the first wave of pandemic (Buigut & Kapan, 2021; Pearman, Boykoiff & Osborne-Gowey, 2021). People’s sentiments are also changing. Based on the theories of VADER sentiments and Ekman’s emotions, recent research on changes in people’s feelings in Singapore analyzed data on Twitter. In mid-March 2020, fearfulness dominated the public sentiment, but in later months the frequency of happiness expressed on Twitter was much higher. At this time, the country was still in a state of partial lockdown (Ridhwan & Hargreaves, 2021). This reveals that people’s attention and sentiments towards an event are highly changeable over time, which is a basic motivation of our research.

The extent of severity and public attention are also related. Some theories support the view that people’s mental motivation increased only when the situation is serious, and this tendency rapidly dissipated after the situation was under control (Zhao, Ding & Yu, 2020). Since February 2020, public attention to COVID-19 has declined on Sina Weibo, a Chinese microblog platform, and people’s positive feelings have significantly increased. The main reason for this phenomenon is the successful prevention and control of the pandemic in China in the first wave of the outbreak (Cui & Kertész, 2021; Lyu, Chen & Wu, 2020; Zhao, Cheng & Yu, 2020).

2.2. Public attention paid to the internet

Nowadays, most people can remain informed about official statistics and policies online. An increasing number of studies use data from social media to perform analysis, such as on the relationship between banks and customers (Botschway, Jibril & Kwarteng, 2019). For public policy researchers, this kind of information is also valuable for understanding people’s concerns, such as people’s awareness of COVID-19 (Jang, Rempel & Roth, 2021; Medford, Saleh & Somarsono, 2020). The evidence shows that authentic appropriate preventive measures, real-time updates, and confident reports help raise people’s level of happiness (Chandrasekaran, Mehta, & Valkunde et al., 2020; Lu, Nie & Qian, 2020; Rao, Vemprala & Akello, 2020). Keywords and phrases such as "stay safe at home" are connected with positive feelings, reflecting people’s confidence in how the situation is being handled (Ridhwan & Hargreaves, 2021). In contrast, bias, criticism, and fake news on the internet can mislead people and dampen their enthusiasm for overcoming the crisis (Bunker, 2020; Flew, 2021; Ginpel, Heger & Olenberger, 2021; Zhu, Ding & Yu, 2021). Moreover, the pandemic affects people’s views about privacy. People start to consider what kind of information is suitable for sharing to enhance the public good and what is not (Nabby-Grover, Cheung & Thatcher, 2020). These topics are all worthy of further studies and discussion.

Because the severity of the pandemic varies across countries, people’s attitudes about the pandemic in one’s own country and other countries have aroused scholars’ interest. Research shows that the level of public attention is positively related to the existence of COVID-19 confirmed cases, especially domestic cases, which is the term with the largest number of retweets (Aksoy, 2020; Hou, Hou & Cai, 2021; Wang, Zhou & Zhang, 2020). For example, in Croatia, a dramatic rise in public prevention awareness was detected after the first domestic case was confirmed (Korajilija & Jokic-Begic, 2020). Also, by analyzing comments on social media, it is shown that public attention is also related to the policy of the domestic government, such as travel controls (Chandra & Krishna, 2021; Chokshi, DallaPiazza & Zhang, 2021; Sun, Wandelt & Zhang, 2021; Zhang, Zhang & Wang, 2020). This inspires the choice of controlled variables that we use in empirical studies.

2.3. The social value of research on public attention

In general, a high level of public awareness is helpful to control the large-scale transmission of the pandemic. Evidence from Singapore shows that timely communication between the government and the public is effective to increase sentiments of calmness in society (Shorey, Ang & Yamina, 2020). The mobile internet keeps people aware, especially with the system of "digital contact tracing", leading them to take preventive measures against the pandemic and alleviate the crisis (Albouy-Lluty, Martin & Bonamouzig, 2021; Dwivedi, Hughes & Coombs, 2020). Moreover, people’s awareness of safety measures to deal with the pandemic presents an important opportunity for the application of digital technology, because of the popularity of working remotely and online activities (Davison, 2020; Doyle & Conboy, 2020;
Before we continue discussing public attention to COVID-19, it would be better if we take a look at the background of this research. According to statistics from the World Bank, in 2020, more than 56% of the global population was living in cities. Compared to rural areas, economic activities in cities are much denser. As a result, in most countries, the initial outbreak of the pandemic occurred in cities.

Nowadays, cities are playing a crucial role in the emergence of global issues, and the sustainable development of cities has long been an important topic (Niemets, Kravchenko & Kandyba, 2021). Besides economic growth, big cities also have to deal with social and environmental problems, including a large number of public affairs, requiring comprehensive information from various sources. Upon now, topics such as air pollution, climate change, citizen engagement, and smart cities have been widely discussed, and lots of empirical studies have been conducted (Adil & Khan, 2021; Bingöl, 2022; Pee & Pan, 2022; Shulina, Filho & Sommer, 2020; Zhang, Pan & Yu, 2019).

In the background of the COVID-19 pandemic, scholars are also interested in how the pandemic affects the development of cities (Liu, 2020; among others). It has been found that COVID-19 significantly reduced air pollution in many countries due to the lockdown policy, bringing an unexpected positive effect to environmental protection (Aboagye, Attobrah & Effah, 2021; Chelani & Gautam, 2021; Rothengatter, Zhang & Hayashi, 2021). During the pandemic, video surveillance systems are used to monitor social distancing, which help build smart cities (Shorfuzzaman, Hossain & Alhamid, 2021). Lockdowns also impacted international trade, but exports of most cities in China recovered rapidly after lockdowns, suggesting the cost-effectiveness of the policy (Hayakawa & Mukunoki, 2021; Pei, Vries & Zhang, 2021).

Studies on the economic and financial shocks due to the COVID-19 pandemic are emerging rapidly (Wang & Liu, 2022). However, little research mentioned the relationship between information shock (e.g., the COVID-19 pandemic) and the sustainable development of cities. COVID-19 pandemic is just one typical example of information shock to citizens. In the era of information explosion, there is a large amount of news that attracts people’s attention, some of which can cause stress and panic among people. The sustainable development of a city requires the ability to react and keep the whole society in order when facing challenges. Through the application of technology, such as information monitoring and big data analysis, we can form a better understanding of public sentiments from a dynamic perspective (Du, Shan & Zuo, 2013; Ye, Pan & Wang, 2021). This facilitates the government to launch appropriate policies and helps achieve the goal of sustainable development (Ameli et al., 2022).

Inspired by the analysis above, our paper presents a typical example of data analytics using the records of daily page views, to reveal the characteristics of the changes in public attention after an information shock. The COVID-19 pandemic is indeed a major public event that brings substantial shock to our daily life and the entire society. However, there could be so many other types of events (social or not). Each time, a new event would induce the public attention either positively or negatively. And the mechanism demonstrated in this study is still applicable to different events other than the COVID-19 pandemic. In this sense, this study is of very general interest.

2.6. Research gap

Based on existing literature, there remain three aspects worthy of further studies, and they are the main motivations for our research.

First, people have different preferences on social media websites. Instead of analyzing only one website, such as Twitter or Sina Weibo, it would be better to identify other data sources that can better represent the attention more broadly. In China, most people use Baidu as their main search engine, and the medical website Dingshiyoujian works with Baidu to report news about the pandemic on mobile phones. Using data on daily clicks, we provide a complete picture of public attention to the COVID-19 pandemic.

Second, although we use data on daily clicks, our research still has problems. To date, scholars have not paid much attention to this type of data, so there are not many quantitative methods available to measure and analyze them. In this paper, not only do we use this type of data, but we also develop a theoretical model to reveal the general mechanism in people’s reactions to social events.

Third, the differences in public attention to the pandemic between China and other countries have not yet been fully explored. Although existing papers state that the level of public attention is mainly influenced by whether the cases are domestic, we still have no idea about changes in public attention after the virus spread in the country. In this study, we focus on the reaction of Chinese people to the pandemic elsewhere, to provide an answer to this question.

In the next section, we construct a novel theoretical model, to study the mechanism in these phenomena.

3. Model

The goal of this section is to construct a suitable theoretical model for the mechanism of public attention. In the context of the COVID-19 pandemic, we integrate mathematical and economic methods, to show
the mechanism of major events and public attention.

Let $N_t$ denote the number of daily domestic cases of COVID-19 and $N_p$ denote the number of daily clicks on the Dingxiangyuan website. As shown in Fig. 1, the level of people’s attention generally lags behind the scale of the event. If $t$ is the time, $\Delta t$ is the time interval (time or interval) between $N_p$ and $N_t$. For simplification, we assume that $\Delta t$ is constant throughout the pandemic.

What kind of function best reflects the relationship between public attention and new confirmed cases? Inspired by the Cobb-Douglas function in economic theory, which is useful in discussing the trade-off between two influential factors, we propose the following equation:

$$N_p(t) = k(N_t(t))^\alpha (t + \Delta t)^\beta$$  \hspace{1cm} (1)

where $k$ is a constant. As shown in the equation, given $\alpha$ and $\beta$, public attention is determined by the severity of the pandemic and the time duration. In Section 2, we discussed that people’s attention changes over time, so we consider $t$, which here means any particular time, and $\Delta t$ is the time interval after it. Moreover, if we assign different signs and values to $\alpha$ and $\beta$, this Cobb-Douglas function is flexible enough to fit most possible situations, which is helpful in our study. The logarithmic linear form of the function is as follows.

$$\ln N_p(t) = \ln k + \alpha \ln N_t(t) + \beta \ln(t + \Delta t)$$  \hspace{1cm} (2)

The first-order condition with respect to $t$ is:

$$\frac{\dot{N}_p(t)}{N_p(t)} = \frac{\alpha N_t(t) + \beta}{t + \Delta t}$$  \hspace{1cm} (3)

Because we assume that $\Delta t$ is constant, it would be easier for us to express $\Delta t$ under specific conditions. The precise time of the outbreak of the COVID-19 pandemic is still uncertain, so it is impossible for us to calculate the time interval directly. Instead, we use the time that public attention reached its peak to express $\Delta t$. At this point, the first-order condition becomes:

$$\frac{\alpha N_t}{N_p(t)} + \frac{\beta}{t + \Delta t} = 0$$  \hspace{1cm} (4)

The time interval can be expressed as:

$$t + \Delta t = \frac{\beta}{\alpha} \left( \frac{N_p(t)}{N_t(t)} \right)^{-1}$$  \hspace{1cm} (5)

Note that this equation holds only when $N_p(t) < 0$, because public attention lags behind the announcement of new confirmed cases. So, when public attention reaches a peak, the number of new confirmed cases must be declining. The logarithmic form of Eq. (5) is thus:

$$\ln(t + \Delta t) = \ln \left( \frac{\beta}{\alpha} \right) - \ln \left( -\frac{N_p}{N_t} \right)$$  \hspace{1cm} (6)

If we substitute the expression $\ln(t + \Delta t)$ in Eq. (6), the result is:

$$\ln N_p(t) = \ln k + \beta \ln \left( \frac{\beta}{\alpha} \right) + \alpha \ln N_t(t) - \alpha \ln \left( -\frac{N_p}{N_t} \right)$$  \hspace{1cm} (7)

Eq. (7) implies that public attention is directly related to the number of new cases, as well as the trends over time. Based on the model, we collect data to conduct empirical studies in the following sections.

4. Data

The data set we construct in this study comes from two sources.

First, the number of page views of Dingxiangyuan is recorded daily from the website. Since the data set is obtained from the website and maintained manually, some of the data are missing due to errors of the website (sometimes the web page failed to update the number of page views) or the absence of the researcher who records data every day in person. But luckily not very much (less than 8%), so we can interpolate to generate a complete series of data. As a popular medical website in China, Dingxiangyuan’s webpage reporting the data of the COVID-19 pandemic has more than 4.6 billion page views by January 2022. This implies that the number of page views is very unlikely to change drastically overnight. Considering this, we do linear interpolation in all cases when necessary, and we believe this is an acceptable approximation of the real value.

Second, data on the pandemic are downloaded from the website of Our World in Data. We focus on the number of domestic and foreign cases (cases in mainland China are excluded), but we are also concerned about the strictness of regulations that may directly influence public attention to the pandemic. Thanks to the Oxford Coronavirus Government Response Tracker (OxCGRT) project, we have a composite indicator called the Stringency Index, which indicates the extent of social response and stringency of regulations to the pandemic on a scale from 0 to 100 (Hale, Angrist & Goldszmidt, 2021). It is calculated as the mean score of the 9 metrics that are related to public places closures, gathering restrictions, and public information campaigns. A higher score means stricter regulations due to the pandemic.

The period of data covers exactly 16 months, from January 23, 2020, to May 23, 2021 (data on daily page views start on January 26, 2020). Descriptive statistics for all the variables are listed in Table 1. Figs. 2a to 2c show the fluctuation in the number of domestic new cases and daily clicks during this period.

Below, we study public attention to the COVID-19 pandemic in terms of the waves of infection. In China, the massive transmission of COVID-19 started around January 20, 2020, which marks the beginning of the first wave of the pandemic in China. It reached its peak around February 13. Afterward, the rate of infection gradually came under control, and the number of new cases in China dropped sharply until June. At the end of May and the beginning of June, China had nearly no new cases (usually less than 10 per day). As a result, we designate June 4 as the end of the first wave in China. Two waves occurred since the second half of 2020, but they were regional and at a much lower scale, lasting for 156 days and 130 days each, as shown in Fig. 3. The arrows indicate the declining stage of each wave of the pandemic.

5. Empirical results

In this section, we use models in various forms to test how well the models reflect reality. We perform the regressions first with the full sample and then analyze the characteristics of public attention in each wave of the pandemic.

5.1. Results using the full sample

Traditionally, public attention is influenced mainly by the severity of the event (Zhao et al., 2020). In the context of the COVID-19 pandemic, the most obvious indicator of severity is the daily number of new cases. At the first attempt (just a casual illustration, not considering the theoretical model in Section 3), we used the daily page views as the explained variable and the number of new cases as explanatory variables to conduct a simple log-log regression, as shown in Table 2. Models (1) and (2) use the explanatory variables directly, without any special procedures. By contrast, Models (3) and (4) adopt the first-order difference form of both the explained variable and explanatory variables.

According to Model (1), the number of page views is strongly positively related to the number of domestic cases, which is consistent with our intuition. However, beginning with Model (2), the results become quite confusing. The sign of domestic cases becomes negative in Model (2), and it is not significant in Models (3) and (4). The significance levels

4 Our World in Data. https://ourworldindata.org/policy-responses-covid/
of foreign cases in Model (2) are extreme and open to doubt, and so are the R-squared statistics in Models (3) and (4). As a result, we must adjust the settings of the model, to achieve a deeper understanding of this issue.

In fact, one of the weaknesses of this analysis here is that we neglect an important characteristic of the transmission of the pandemic. From the media perspective, the consensus view that public attention to a hot topic usually rises suddenly and then fades quickly, because people have limited attention (Gong et al., 2020). The COVID-19 pandemic has

| Variables | Explanation | Obs. | Mean   | Std. dev. | Min. | Max.      |
|-----------|-------------|------|--------|-----------|------|-----------|
| Clicks    | Daily page views | 484  | 8658.165 | 18.991,366 | 225,793 | 171,104,780 |
| cases_d   | Domestic new cases | 487  | 185.82   | 912.98    | -1.00  | 15,133.00 |
| cases_f   | Foreign new cases  | 487  | 341,487.58 | 251,344.65 | 5.00   | 905,973.00 |
| string_d  | Domestic stringency index | 487  | 71.95    | 10.01     | 44.91  | 81.94     |

Note: Negative number indicates case reduction confirmed by National Health Commission.
already lasted a long time, and most people have become more accustomed to hearing about it. However, because of the global transmission of and variations in the virus, the severity of the pandemic is not stable over the medium to long term. When more new cases are confirmed, especially domestic cases, people’s attention might rise again. The absolute number of new cases does not need to be very large, as seen in China since the second half of 2020. For this reason, we need to analyze the pandemic and public attention in waves, as mentioned in the previous section.

Fig. 2b. Domestic new cases and daily page views (July 1, 2020 - December 31, 2020).

Fig. 2c. Domestic new cases and daily page views (January 1, 2021 - June 30, 2021).
5.2. Results for each wave

The results for Wave 1, using settings similar to those in Models (1) and (2), are in Models (5) and (6) in Table 3. If we add the term for the ratio of reduction in new cases to the equation, the results are Models (7) and (8). As shown in Table 3, the number of daily page views is positively related to domestic new cases, which is significant in all four models. This indicates that public attention to the pandemic is strongly influenced by domestic transmission. In contrast, the sign of foreign new cases is negative, and it is not always significant. This indicates that most people are not very concerned about the pandemic in countries other than their own. In other words, people tend to pay much more attention to events that are nearby or familiar.

Now we focus on the terms of the ratio of reduction in new domestic cases. In Model (7), its sign is significantly negative, indicating that a decrease in new cases might reduce the level of public attention. Actually, this effect is not very strong. In Model (8), its significance level declines, and for new foreign cases, it is even lower. This result is consistent with people’s tendency to prefer the familiar, which is mentioned earlier.

The second wave is from late July to the end of 2020. Beginning in the second half of 2020, people became more used to news about the pandemic, and the characteristics of public attention changed. The models in Table 4 show the change in the signs of the ratio of reduction in new cases. This means the reduction in new cases no longer reduces people’s attention. One explanation is that the absolute number of new cases fell in this period. Even at the peak of Wave 2, the number of daily new domestic cases in China was no more than 200. Despite the fluctuation in the number of new cases, some people were less aware than before, so public attention leveled out.

The same results occur in Wave 3. This wave started when regional transmission in Hebei Province accelerated at the beginning of 2021, with a downward trend in new cases beginning on January 14. In this wave, the case reduction ratio is not significant in either China or other

---

Table 2

| Model | Constant | ln cases_d | ln cases_f | ln cases_reduction_d | ln cases_reduction_f |
|-------|----------|------------|------------|---------------------|---------------------|
| (1)   | 12.897***| 0.569***   | 0.131***   | 0.137*             | 0.016               |
| (2)   | 21.475***| -0.083***  | 0.070      | 0.125              | 0.016               |
| (3)   | -0.005   | 0.032      | 0.101**    | -3.55              | 0.016               |
| (4)   | -0.007   | 0.034      | 0.246**    | 2.06               | 0.016               |

Note: Heteroskedasticity-robust t statistics in parentheses. *** p ≤ 0.01. ** 0.01 < p ≤ 0.05. * 0.05 < p ≤ 0.1.

Table 3

| Model | Constant | ln cases_d | ln cases_f | ln cases_reduction_d | ln cases_reduction_f |
|-------|----------|------------|------------|---------------------|---------------------|
| (5)   | 15.308***| 0.334***   | -0.131***  | 0.062              | 107                 |
| (6)   | 16.999***| 0.217***   | -0.137*    | 0.067              | 107                 |
| (7)   | 15.290***| 0.326***   | -0.125     | 0.069              | 52                  |
| (8)   | 16.206***| 0.246**    | -0.087     | 0.069              | 22                  |

Note: Heteroskedasticity-robust t statistics in parentheses. *** p ≤ 0.01. ** 0.01 < p ≤ 0.05. * 0.05 < p ≤ 0.1.
Second, we have not introduced any control variables in previous models by changing the logarithmic form of the ratio of growth. For growth in foreign cases, there is no significant relationship in Model (17). In contrast, the sign for growth in cases elsewhere is significantly positive in Models (18) and (19). This finding seems to be contradictory to the results in Section 5.2. Actually, it is not the absolute number of foreign cases that absorbs public attention. Instead, it is the drastic change of situation that matters. Chinese people’s attention is still affected by sudden acceleration and serious conditions of the pandemic in other countries, such as the quickly deteriorating situation in the US (mid-2020) and India (spring 2021). It might be true that ordinary people are not aware enough of foreign transmission during the first wave of the pandemic, as the sign for growth in foreign cases is not significant in Model (17). In contrast, after the first wave of the domestic pandemic, most of the new cases in China are imported, so the foreign pandemic aroused more concerns (Zhang, Yang & Wang, 2020). This remains true at the beginning of 2022. As a result, pandemic conditions in other countries also deserve attention.

5.4. Summary of results

Before we make further discussion of the findings, let us summarize the main differences of the models presented in this paper. Models (1)-(2): Simple log-log regressions using the full sample. Models (3)-(4): First-order difference form of both the explained variable and explanatory variables.

Models (1)-(4) are casual illustrations, just to show that using a full sample cannot reach a convincing conclusion. As a result, it’s crucial to divide the samples into parts, according to the waves of the pandemic.

Compared with other pure empirical studies that are commonly seen, this study provides a novel theoretical mechanism to investigate the relationship between the key variables. Inspired by the theoretical model we developed in Section 3, from Model (5) onwards, we add the term of case reduction into the model.

Models (5)-(8): Results of Wave 1 (February 13, 2020 - June 4, 2020); Models (9)-(12): Results of Wave 2 (July 29, 2020 - December 31, 2020); Models (13)-(16): Results of Wave 3 (January 14, 2021 - May 23, 2021).

Models (1)-(4) do not include any control variables. Models (17)-(19) include all of the explanatory variables that appear in Models (5)-(16), as well as the domestic Stringency Index. Also, we improved the previous models by changing the logarithmic form of the ratio of reduction in foreign cases to a linear form of the ratio of growth in foreign cases, so that we can use a larger sample in conducting the regression again. In this way, we reach a convincing result, which shows indicating that the level of public attention remains stable, despite regional small-scale transmission occurring frequently. Actually, from Wave 2 onwards, people are quite used to the new normal, being less sensitive to the numbers of new confirmed cases than before. According to the analysis above, people should pay more attention to the small-scale regional transmission of the virus. Since COVID-19 is a highly contagious disease, people’s negligence may accelerate the transmission and cause a possible new wave of the pandemic on a much larger scale.

We return to the question of public attention towards different countries. Generally speaking, people’s attention is influenced less by cases in other countries than in their own. As we have known from the data, despite the continuous growth in foreign cases, public attention in China decreases over the medium to long term. However, the sign for growth in cases elsewhere is significantly positive in Models (18) and (19).

Before we make further discussion of the findings, let us summarize the main differences of the models presented in this paper. Models (1)-(2): Simple log-log regressions using the full sample. Models (3)-(4): First-order difference form of both the explained variable and explanatory variables.

Models (1)-(4) are casual illustrations, just to show that using a full sample cannot reach a convincing conclusion. As a result, it’s crucial to divide the samples into parts, according to the waves of the pandemic.

Compared with other pure empirical studies that are commonly seen, this study provides a novel theoretical mechanism to investigate the relationship between the key variables. Inspired by the theoretical model we developed in Section 3, from Model (5) onwards, we add the term of case reduction into the model.

Models (5)-(8): Results of Wave 1 (February 13, 2020 - June 4, 2020);
Models (9)-(12): Results of Wave 2 (July 29, 2020 - December 31, 2020);
Models (13)-(16): Results of Wave 3 (January 14, 2021 - May 23, 2021).

Models (5)-(16) do not include any control variables. Models (17)-(19) include all of the explanatory variables that appear in Models (5)-(16), as well as the domestic Stringency Index. Also, we improved the previous models by changing the logarithmic form of the ratio of reduction in foreign cases to a linear form of the ratio of growth in foreign cases, so that we can use a larger sample in conducting the regression again. In this way, we reach a convincing result, which shows

### Table 4

| Model (9)          | Model (10)          | Model (11)          | Model (12)          |
|--------------------|---------------------|---------------------|---------------------|
| Constant           | 13.711***           | 23.358***           | 13.577***           |
|                    | (78.83)             | (31.44)             | (48.43)             |
| In cases$_{d}$     | 0.167***            | 0.165***            | 0.310***            |
|                    | (2.67)              | (3.83)              | (2.62)              |
| In cases$_{f}$     | 0.163***            | 0.164***            | 0.359***            |
|                    | (1.05)              | (1.08)              | (1.05)              |
| In cases$_{reduction,d}$ | 0.157***         | 0.174               |
|                    | (2.14)              | (2.13)              |
| In cases$_{reduction,f}$ | 0.005              |
|                    | (0.07)              |
| Obs.               | 156                 | 156                 |
| R-squared          | 0.522               |
|                    | 0.533               |
|                    | 0.119               |
|                    | 0.641               |

Note: Heteroskedasticity-robust t statistics in parentheses.

*** p ≤ 0.01.
** 0.01 < p ≤ 0.05.
* 0.05 < p ≤ 0.1.

### Table 5

| Model (13)          | Model (14)          | Model (15)          | Model (16)          |
|--------------------|---------------------|---------------------|---------------------|
| Constant           | 12.314***           | 20.825***           | 12.367***           |
|                    | (109.01)            | (24.09)             | (92.11)             |
| In cases$_{d}$     | 0.318***            | 0.357***            | 0.334***            |
|                    | (8.01)              | (9.64)              | (7.42)              |
| In cases$_{f}$     | 0.05                 |
|                    |                     |
| In cases$_{reduction,d}$ | 0.003               |
|                    | (0.05)              | (1.19)              |
| In cases$_{reduction,f}$ | 0.064               |
|                    | (1.40)              |
| Obs.               | 130                 |
| R-squared          | 0.390               |
|                    | 0.598               |
|                    | 0.468               |
|                    | 0.648               |

Note: Heteroskedasticity-robust t statistics in parentheses.

*** p ≤ 0.01.
** 0.01 < p ≤ 0.05.
* 0.05 < p ≤ 0.1.
the characteristics of public attention in different waves of the pandemic.

We show the differences between these models more clearly in Table 7.

6. Discussion

In the model explored in Section 3, we assumed a constant time interval between daily new cases and public attention. Because we have obtained the estimates of parameters \( \alpha \) and \( \beta \), we can now calculate \( \Delta t \) using the data set.

According to Section 3, \( t + \Delta t \) can be expressed as Eq. (5), where \( t \) represents the present time, so it is not necessary to specify a particular value. As a result, we consider \( t + \Delta t \) as a whole to represent the time interval mentioned above. If the time interval we calculate is nearly constant, we can conclude that our assumption is generally correct. Figs. 4a to 4c show the results of our calculation for the three waves of the pandemic.

The figures show that \( t + \Delta t \) remains fairly stable, with a value of between 0 and 5 most of the time. The 16-month average is 1.76 days to 1.94 days, depending on the choice of models and parameters. This result tells us some important facts. First, our assumption of a constant time interval is credible and realistic. Second, although the number of people being aware of regional transmission is smaller, as we concluded in Section 5, it’s reassuring to find out that the time interval of social reaction is not lengthening at all. This reflects the long-term public concern for the pandemic conditions. In 2021 an obvious decline in the time interval has occurred, demonstrating the rapid reaction of the Chinese government to the emergence of new domestic cases.

7. Conclusions

The theoretical model and empirical studies described here have led us to reach some important conclusions. When the pandemic conditions in China were serious, for example, in the first half of 2020 (especially in February 2020), people’s level of attention closely paralleled the severity of the pandemic. But after the pandemic came under control, with a low number of new cases in China, the public there became accustomed to a new normal, with less concern about small-scale regional transmission. In contrast, when the pandemic quickly became severe in other countries, such as in the US (mid-2020) and India (spring 2021), public attention in China rose, concerning the news about the situation.

Given the possible cyclical pattern of the COVID-19 pandemic (Liu, 2022) as well as the complex interaction with human feces and other environmental factors (Wang & Liu, 2021), it would cause a great challenge to the sustainability of human cities and society if it keeps coming wave by wave. And every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves and every time a new wave of epidemic breaks out in the local region or other regions, it would induce public attention to increasing waves of waves.

Finally, our research has some policy implications. Although it is good that people have consistently been concerned about the pandemic conditions, it would be better if more people were more alert to the small-scale regional transmission of the virus, as it could be a sign of an impending outbreak at a larger scale. In addition, at a time when the global economy is important in our daily lives, the pandemic conditions in other countries also deserve attention. Our empirical results indicate that some Chinese people did not pay enough attention to the evolution of the pandemic outside China, especially in the first half of 2020. The
government and the media should consider encouraging public attention in various ways, such as news reports, headlines in newspapers and on web pages, and regulations on gathering and traveling. The public interest would feed public participation, which would help the world deal with health and economic crises much better in the long term, and achieve the goal of sustainable development.

Moreover, it is hoped that this study will inspire future research in other fields, as work on the characteristics of public attention is only just beginning. Using similar methods, many other phenomena could be explained, contributing to knowledge on social psychology and public policy.
Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Aboagye, E., Attobrah, J., Efiah, N., et al. (2021). Fortune amidst misfortune: The impact of Covid-19 city lockdowns on air quality. Sustainable Environment, 7, Article 1685185. Article.

Adil, M., & Khan, M. K. (2021). Emerging IoT applications in sustainable smart cities for COVID-19: Network security and data preservation challenges with future directions. Sustainable Cities and Society, 75, Article 103111. Article.

Ajčević, M., Furlanis, G., Nacciarito, M., et al. (2021). E-Health solution for home patient telemonitoring in early post-acute TIA/Minor stroke during COVID-19 pandemic. International Journal of Medical Informatics, 152, Article 104442. Article.

Aksoy, C. G. (2020). Public attention and policy responses to COVID-19 pandemic. IZA Discussion Paper No. 13427. Available at SSRN: Https://ssrn.com/abstract=3643191.

Albouy-llaty, M., Martin, C., Benamouzig, D., et al. (2021). Positioning digital tracing applications in the management of the COVID-19 pandemic in France. Journal of Medical Internet Research, 23(10), e27301. Article.

Ameli, M., Esfandabadi, Z. S., Sadeghi, S., et al. (2022). COVID-19 and sustainable development goals (SDGs): Scenario analysis through fuzzy cognitive map modeling. In Gondwana Research, doi: https://doi.org/10.1016/j.gr.2021.12.014

Ban, Y., Sun, Y., Meng, S., et al. (2020). 2019-nCoV epidemic: Address mental health care to empower society. The Lancet, 395, e37–e38.

Bioglio, S. E. (2022). Citizen participation in smart sustainable cities. doi: 10.4018/978-1-6684-3706-3.ch052.

Botchway, R. K., Jibril, A. B., Kwarteng, M. A., et al. (2019). A review of social media posts from UniCredit Bank in Europe: A sentiment analysis approach. In Proceedings of the 3rd International Conference on Business and Information Management (pp. 74–79).

Buigut, S., & Kapar, R. (2021). COVID-19 cases, media attention and social mood. International Journal of Economics and Financial Issues, 11, 66–72.

Bunker, D. (2020). Who do you trust? The digital destruction of shared situational awareness and the COVID-19 infodemic. International Journal of Information Management, 55, Article 102201. Article.

Chan, J., Yuan, S., Kok, K. H., et al. (2020). A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: A study of a family cluster. The Lancet, 395(10223), 514–523.

Chandra, R., & Krishna, A. (2021). COVID-19 sentiment analysis via deep learning during the rise of novel cases. PloS one, 16, Article E0255615. Article.

Chandrasekaran, R., Mehta, V., Valkunde, T., et al. (2020). Topics, trends, and sentiments of tweets about the covid-19 pandemic: Temporal infolovewatch study. Journal of Medical Internet Research, 22(10), e2624. Article.

Chelani, A., & Gautam, S. (2021). Lockdown during COVID-19 pandemic: A case study from Indian cities shows significant effects on persistent property of urban air quality. Geoscience Frontiers, Article 101284. Article.

Cheng, J., & Liu, Y. (2018). The effects of public attention on the environmental performance of high-polluting firms: Based on big data from web search in China. Journal of Cleaner Production, 186, 335–341.

Chokshi, A., DallaPiazza, M., Zhang, W. W., et al. (2021). Proximity to international airports and early transmission of COVID-19 in the United States—An epidemiological assessment of the geographic distribution of 490,000 cases. Travel Medicine and Infectious Disease, 40, Article 102004. Article.

Cui, H., & Keterez, J. (2021). Attention dynamics on the Chinese social media Sina Weibo during the COVID-19 pandemic. EPJ Data Science, 10. https://doi.org/10.1140/epjds/s13688-021-00263-0

Davison, R. M. (2020). The transformative potential of disruptions: A viewpoint. International Journal of Information Management, 55, Article 102149. Article.

Doyle, R., & Conboy, K. (2020). The role of IS in the Covid-19 pandemic: A liquid-modern perspective. International Journal of Information Management, 55, Article 102184. Article.

Du, W., Shan, L. P., & Zuo, M. (2013). How to balance sustainability and profitability in technology organizations: An ambidextrous perspective. International Journal of Information Management, 66(2), 366–365.

Dwivedi, Y. K., Hughes, D. L., Coombs, C., et al. (2020). Impact of COVID-19 on information management research and practice: Transforming education, work and life. International Journal of Information Management, 55, Article 102211. Article.

Ezh, J. (2021). Attention dynamics on the Chinese social media Sina Weibo during the COVID-19 pandemic. EPJ Data Science, 10. https://doi.org/10.1140/epjds/s13688-021-00263-0

Flew, T. (2021). The global trust deficit disorder: A communications perspective on trust in the time of global pandemics. Journal of Communication, 71(2), 163–186.

French, K. R., & Poterba, J. M. (1991). Investor diversification and international equity stockholdings and trades. Journal of International Economics, 30, 1–18.

Ginpel, H., Heger, S., Olenberger, C., et al. (2021). The effectiveness of social norms in fighting fake news on social media. International Journal of Information Management, 55, Article 102211. Article.

Gong, X., Han, Y., Hou, M., et al. (2020). Online public attention during the early days of the COVID-19 pandemic. JMIR Public Health and Surveillance, 6(4). https://doi.org/10.2196/23098. Article.

Grinbatt, M., & Keloharju, G. M. (2001). How distance, language, and culture influence personality and individual differences. Journal of the Japanese and International Economies, 60, Article 101284. Article.

Hale, T., Angrist, N., & Goldszmidt, R. et al. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). Nature Human Behaviour. doi: https://doi.org/10.1038/s41562-021-01079-8

Hayakawa, K., & Mokuno, H. (2021). The impact of COVID-19 on international trade: Evidence from the first shock. Journal of the Japanese and International Economies, 60, Article 101135. Article.

Hou, K., Hou, T., & Cai, L. (2021). Public attention about COVID-19 on social media: An investigation based on data mining and text analysis. Personality and Individual Differences, 175. doi: 10.1016/j.paid.2021.110701.
