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.

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In this study, we provide evidence suggesting that in countries with severe disaster experience (SDE), the response to the coronavirus disease 2019 (COVID-19) pandemic is characterized by a higher level of attention in the population, more timely market responses, and stricter government containment measures. Specifically, we find that during the first COVID-19 outbreak in Wuhan, China, people in countries with SDE searched for related information more frequently on Google than did people in countries with mild disaster experience (MDE). Moreover, we find that a higher level of attention to COVID-19, as measured by Google search index usage, led to greater declines in stock market indexes in countries with SDE than in those with MDE. Finally, we find that compared with countries with MDE, those with SDE implemented more stringent social distancing policies in response to domestic COVID-19 outbreaks, and individuals in the latter group of countries were more likely to follow government-imposed rules of social distancing in both the early outbreak and reopening phases. Our findings suggest that disaster experience increases risk aversion and is an essential mechanism by which individuals, markets, and countries respond to COVID-19 in a timely manner.

1. Introduction

Since early 2020, the coronavirus disease 2019 (COVID-19) pandemic has spread widely and swiftly around the world, causing enormous social unrest and economic loss. According to estimates by the International Monetary Fund, World Health Organization (WHO) Director-General Tedros Adhanom said at a regular briefing on August 13, 2020, that “the COVID-19 pandemic is costing the global economy $375 billion a month and more than $12 trillion in cumulative economic losses over the next two years.” Despite the universal severity of this global crisis, the responses and containment measures taken by the governments and populations of different countries have varied (Erdem, 2020; Morales and Andreossi-O’Callaghan, 2020; Ashraf, 2020b; Ru et al., 2021). For example, on February 23, 2020, Italy reported a total of 157 confirmed cases of COVID-19, which led the government to announce on that day the forced closure of all schools and public places. In contrast, by March 15, 2020, Sweden had reported a cumulative total of more than 1000 confirmed cases. To date, however, the Swedish government has not taken compulsory measures to close schools and public
Studies show that early experiences affect the subsequent economic activities of individual investors in areas such as their careers (Oyer, 2008; Law and Zuo, 2021), corporate decision-making (Malmendier et al., 2011; Schoar and Zuo, 2017), risk aversion (Cain and McKeon, 2016; Bernile et al., 2017), and portfolio choices (Knüpfert et al., 2017; Malmendier et al., 2020). Chernenko et al. (2016) point out that inexperienced investors tend to ignore risks until they experience severe investment losses. Therefore, the main research question of this study is as follows: when faced with the COVID-19 pandemic, do countries react differently due to their previous national disaster experiences? In other words, how has disaster experience affected countries’ responses to the COVID-19 pandemic?

Theoretically, two main effects of disaster experience on countries’ responses to COVID-19 are proposed: the promoting effect and the inhibiting effect. Regarding the promoting effect, individuals who experience disasters may perceive the world as a riskier place (Lerner and Keltner, 2001). Particularly, individuals who experience disasters early in life are more sensitive to the consequences of taking risks and thus are more risk-averse (Callen et al., 2014; Cassar et al., 2017). From this perspective, disaster experience encourages countries or individuals to adopt restrictive measures to address the COVID–19 pandemic in a timelier manner. Regarding the inhibiting effect, individuals who compare current risk events with past disaster experiences may believe that the current events are less salient and be more willing to take risks (Ben-Zur and Zeidner, 2009). In addition, experiencing a disaster may increase one’s confidence in one’s ability to deal with risk events (Aldwin, 2007). Therefore, disaster experience may increase willingness to face the risks associated with COVID-19 at both the individual and national levels, leading to the delayed implementation of restriction measures. However, whether disaster experience promotes or inhibits a country’s response to the COVID-19 pandemic is an empirical question. We discuss this issue from the perspective of its effects on three aspects: people’s attention, market reactions, and national restriction policy. We find that disaster experience affects all of these aspects in the context of responses to the COVID-19 pandemic.

First, we test whether disaster experience determines people’s level of attention to the initial COVID-19 outbreak using Google search data. Specifically, we use Google search indexes for six keywords related to the COVID-19 pandemic as a measure of users’ attention. We select a time window from January 20–30, 2020, which includes the date of confirmation of the first case of human-to-human COVID-19 transmission and subsequent extensive global coverage of the disease. We find that national disaster experience is significantly positively correlated with Google search index values, suggesting that people in nations with more severe disaster experience (SDE) were more likely to search for information about COVID-19 at an earlier stage of the pandemic due to their memories of past disasters. We then limit our sample to 124 non-Asian countries and again find a correlation between a high national SDE and high attention to COVID-19.

Next, we examine the effect of the level of Google search-related attention to COVID-19 on stock market performance. We take January 20, 2020, as the starting point for calculating the cumulative return (CR) and cumulative abnormal return (CAR) during the subsequent 10-day event window. We find that Google search-related attention to COVID-19 is significantly negatively correlated with the CR and CAR of the stock market index during the studied period. Our results indicate that investors in countries with SDE are highly aware of sudden disasters and related responses. This awareness led to a quick and strong stock market response to the early stage of the pandemic. This finding appears to further support the role of disaster experience in combating epidemics, as stock markets in countries with SDE tend to respond more quickly to COVID-19 outbreaks. In addition, our findings complement the research of Da et al. (2015), who show that investors’ attention (based on information search data) can predict stock market returns.

Finally, we examine the role of disaster experience in government responses to the COVID-19 pandemic in domestic settings. With reference to Ru et al. (2021), we conduct a duration analysis of the effects of various government containment measures on the relationship between disaster experience and the number of confirmed COVID-19 cases. We find positive associations between the timeliness of containment measures (i.e., school closures, workplace closures, public event cancellations, gathering restrictions, public transport closures, home requirements, interval movement restrictions, and international travel controls) and the number of confirmed COVID-19 cases, and this effect is significantly more pronounced in countries with SDE. Our results indicate that governments in countries with SDE adopt more rigorous and rapid measures to contain COVID-19 outbreaks. We also investigate the compliance of residents in each country with government-issued social distancing-based containment measures. We find that residents in countries with SDE restricted their daily travel activities to a greater degree in both the early outbreak and reopening stages.

We make several contributions to the field. First, we contribute to the literature on the effects of experiences on subsequent economic activity. Studies in one stream of research show that the imprints of past experience can influence individuals’ careers (Oyer, 2008; Law and Zuo, 2021), corporate decision-making (Malmendier et al., 2011; Schoar and Zuo, 2017), risk aversion (Cain and McKeon, 2016; Bernile et al., 2017), and portfolio choices (Knüpfert et al., 2017; Malmendier et al., 2020). Distinct from these studies, which focus on the social and economic effects of past experience, we evaluate the role of disaster experience in responding to and combating the COVID-19 pandemic. Our findings have important policy implications for the global fight against this pandemic disease, as early responses could save lives.

Second, we add to a growing stream of research on the consequences of experiencing natural disasters. Studies in economics and finance mainly focus on the negative effects of the damage caused by natural disasters on risk-taking activities by banks (Cortes and Strahan, 2017; Schiwer et al., 2019; Nguyen and Wilson, 2020), the tendency of individuals or corporations to seek insurance coverage (Cummins et al., 2002; Benali and Feki, 2017; Biener et al., 2017), large shocks to the labor market (Belasen and Polachek, 2008; Kircherberger, 2017; Kameda et al., 2021), and macroeconomic consequence (Fomby et al., 2011; Klomp and Valckx, 2014; Klomp, 2020). We supplement this literature by documenting the positive effect of previous disaster experience on responses to new disasters.

Third, we supplement the literature on the possible impacts of the COVID-19 outbreaks on financial markets and institutions. Studies in this area focus on the economic consequences (Ashraf, 2020a; Goodell, 2020; Narayan et al., 2020; Goodell and Goutte, 2021a, b), market reactions (Al-Awadhi et al., 2020; Goodell and Huynh, 2020; Ashraf, 2021; Smales, 2021), and policy responses (Zaremba et al., 2020; Ru et al., 2021). In contrast, we provide international evidence from the perspective of past disaster experience.
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Fig. 1. Timeline of COVID-19 outbreak.
This figure presents a timeline from the first confirmed case in Wuhan in December 2019 to the WHO’s declaration of COVID-19 as a global pandemic in March 2020. The graph shows the timing of important events during the initial COVID-19 outbreak.

to explain why different countries have different market responses to the COVID-19 pandemic.

The remainder of this paper is organized as follows. Section 2 contains a review of the literature and the development of our testable hypotheses. Section 3 includes the summary statistics of our data. Section 4 contains our empirical results. Section 5 presents our robustness tests. Section 6 provides our conclusions.

2. Literature review and research hypotheses

Several economics studies show that disaster experience has long-term effects on personal risk attitudes (Callen et al., 2014; Cassar et al., 2017; Chen et al., 2021). Psychologists explain the underlying mechanism from the perspective of risk perception. Specifically, disaster experience causes an individual to perceive the world as a dangerous place (Cameron and Shah, 2015). This perception stems from the assessment of uncertainty and lack of personal control, which are the two main determinants of risk perception (Slovic, 1987). Lerner and Keltner (2001) note that fear-related uncertainty and lack of control can lead individuals to make risk-averse choices. Therefore, disaster experience makes individuals more sensitive to the consequences of taking risks and thus more risk-averse. In addition, some studies provide empirical evidence that disaster experience increases risk aversion. Callen et al. (2014) report that individuals who experienced the war in Afghanistan exhibit a persistently higher level of risk aversion. Kim and Lee (2014) find a lower tendency to make risky choices among individuals who experienced the Korean War as children 50 years earlier. Cameron and Shah (2015) find that individuals in villages affected by floods or earthquakes are more likely to avoid risk. Similarly, Cassar et al. (2017) find an increased appetite for risk among people who experienced the Great East Japan Earthquake in 2011.

One counterargument suggests that disaster experience makes individuals less risk-averse. Specifically, individuals who compare current risk events with past disaster experiences and find the current event to be less concerning may be more willing to take risks (Ben-Zur and Zeidner, 2009), as such a comparison reduces the perception of loss associated with risk-taking (Taylor and Lobel, 1989). Moreover, disaster experience may increase an individual’s confidence in their ability to deal with dangerous situations, leading to risky behavior (Aldwin, 2007). Some studies also provide empirical evidence that disaster experience reduces risk aversion. Eckel et al. (2009) observe a strong appetite for risk among evacuees from areas affected by Hurricane Katrina. Using field experiments, Voors et al. (2012) find that individuals exposed to violent conflicts exhibit more risk-taking behaviors. Page et al. (2014) observe risk-seeking attitudes among homeowners in Australia who were victims of flooding in 2011. Hanaoka et al. (2018) also find an increased appetite for risk among people who experienced the Great East Japan Earthquake in 2011.

In summary, the above theoretical analysis indicates that disaster experience either promotes or reduces risk aversion. From the perspective of the promoting effect, disaster experience should promote risk aversion. In this context, countries or individuals with SDE are more likely to take restrictive measures in a timely manner to avoid the risk associated with COVID-19 outbreaks. From the perspective of the inhibiting effect, however, disaster experience should reduce the level of risk aversion. In this context, countries or individuals with SDE are more willing to accept the risks associated with COVID-19 outbreaks and to implement restrictive measures after a delay. Empirical research is needed to determine the dominant effect. We propose the following competing hypotheses addressing three aspects: people’s attention, market response, and national restriction policy.

H1a. Disaster experience increases people’s attention to the first known COVID-19 outbreak.

H1b. Disaster experience reduces people’s attention to the first known COVID-19 outbreak.

H2a. Online search attention to COVID-19 is associated with greater market declines in countries with SDE relative to those with mild disaster experience (MDE).

H2b. Online search attention to COVID-19 is associated with smaller market declines in countries with SDE relative to those with MDE.
H3a. Disaster experience causes governments to implement containment measures rapidly.

H3b. Disaster experience causes governments to delay the implementation of containment measures.

3. Window period selection and data source

3.1. Window period selection

In December 2019, the first case of novel coronavirus pneumonia was recorded in Wuhan, China. In early January 2020, the Chinese media and the public began to pay attention to the emerging COVID-19 epidemic. On January 20, 2020, academician Zhong Nanshan delivered a national speech on CCTV, confirming the human-to-human transmission of the virus for the first time. Since then,
Fig. 3. Disaster experience (measured by ND) for different countries. This figure shows the early disaster experience, measured by ND, in different countries. The shade of the color represents the degree of disaster exposure; i.e., countries in dark red are those with high exposure to disasters.

Table 2
Summary statistics.

Panel A: Country cross-sectional data

| Variables     | N   | Mean  | S.D.  | 25 % | 50 % | 75 % |
|---------------|-----|-------|-------|------|------|------|
| Search        | 168 | 18.48 | 27.89 | 0.00 | 10.44| 35.25|
| DD            | 168 | 7.15  | 11.07 | 1.40 | 3.49 | 7.40 |
| ND            | 168 | 32.82 | 84.48 | 3.00 | 9.00 | 23.25|
| Log(GDP)      | 168 | 6.30  | 2.14  | 4.91 | 6.27 | 7.93 |
| Log(Pop)      | 168 | 6.76  | 1.83  | 5.76 | 6.89 | 8.02 |
| Log(AveCovid) | 168 | 0.24  | 0.91  | 0.00 | 0.00 | 0.00 |
| EXIM          | 168 | 12.80 | 2.18  | 11.33| 12.88| 14.38|
| LifeExpectancy| 168 | 72.01 | 6.59  | 67.19| 71.88| 80.66|
| Debt          | 168 | 51.81 | 37.53 | 31.35| 45.75| 64.04|
| SARSDummy     | 168 | 0.17  | 0.38  | 0.00 | 0.00 | 0.00 |
| AsiaDummy     | 168 | 0.26  | 0.44  | 0.00 | 0.00 | 1.00 |
| CoastalDummy  | 168 | 0.79  | 0.41  | 1.00 | 1.00 | 1.00 |

Panel B: Stock market returns

| Variables | N | Mean  | S.D.  | 25 % | 50 % | 75 % |
|-----------|---|-------|-------|------|------|------|
| CR        | 65| -0.03 | 0.02  | -0.04| -0.03| -0.01|
| CAR       | 65| -0.01 | 0.03  | -0.02| 0.00 | 0.01 |

Panel C: Social distancing

| Variables            | N   | Mean   | S.D.  | 25 % | 50 % | 75 % |
|----------------------|-----|--------|-------|------|------|------|
| School               | 34,790| 0.63   | 0.48  | 0.00 | 1.00 | 1.00 |
| Workplace            | 34,790| 0.58   | 0.49  | 0.00 | 1.00 | 1.00 |
| PublicEvent          | 34,790| 0.65   | 0.48  | 0.00 | 1.00 | 1.00 |
| Gathering            | 34,790| 0.61   | 0.49  | 0.00 | 1.00 | 1.00 |
| PublicTransport      | 34,790| 0.39   | 0.49  | 0.00 | 1.00 | 1.00 |
| StayHome             | 34,790| 0.52   | 0.50  | 0.00 | 1.00 | 1.00 |
| InternalMovement     | 34,790| 0.51   | 0.50  | 0.00 | 1.00 | 1.00 |
| InternationalTravel  | 34,790| 0.77   | 0.42  | 1.00 | 1.00 | 1.00 |
| Log(CovidCases)      | 34,790| 6.82   | 3.48  | 4.52 | 7.19 | 9.39 |

This table shows the summary statistics for all variables. Panel A reports the summary statistics for the variables across 165 countries. Panel B reports the summary statistics of stock market returns across 65 countries. Panel C presents the summary statistics for country-date panel data on government social distancing policies and domestic COVID-19 development across 142 countries from January 1 to August 30, 2020. The variables are defined in Table A1.
the Chinese government has taken effective containment measures to handle COVID-19 outbreaks. On January 23, 2020, the Chinese government implemented a complete lockdown policy in Wuhan after 571 local COVID-19 cases were confirmed. This blockade has been confirmed as an important measure that effectively curbed the spread of the epidemic. However, on January 30, 2020, the WHO declared COVID-19 to be a global public health emergency. Beginning in late February 2020, outbreaks of COVID-19 emerged in South Korea, Italy, and the United States, and on March 11, 2020, the WHO declared COVID-19 to be a global pandemic. Fig. 1 shows the timeline of the COVID-19 outbreak.

Referring to Ru et al. (2021), we use the 2-week window period from January 20–30, 2020, which covers the first widespread media reports and government restriction measures related to COVID-19. To ensure the robustness of the results, we apply other alternative window periods, as discussed in Section 5.

3.2. Data source

The disaster data are derived from a sigma report issued by the Swiss Re-insurance Company (hereinafter referred to as SwissRe) during the 1999–2017 period. Each year, SwissRe publishes several forms of disaster events, including storms, droughts, floods, earthquakes, freezing rain, hail, fires/explosions, traffic, mines, and other types of incidents. The summary statistics for these disasters are shown in Table 1. The total number of disasters (ND) is 5,697, and the mean (standard deviation of) disaster duration (DD) is 6.04 (21.78) days. During the 1999 to 2017 period, an average of 67.61 disasters per country was recorded, and the average DD was 5.21 days. Figs. 2 and 3 present graphic maps of standardized DD and ND data by country, respectively. Countries labeled in dark red are those with SDE.

Both natural and man-made disasters are included in this study because the COVID-19 outbreak is attributed to both natural and man-made factors. In fact, COVID-19 is classified into different disaster categories under different classification systems. According to the 2020 World Risk Report issued by the World Economic Forum, infectious diseases are classified into the social risk category, whereas risks related to natural disasters are generally classified into the environmental risk category. According to the 2012 Natural Disaster Classification and Code of China, infectious diseases are classified as natural disasters, along with storms, droughts, floods, earthquakes, freezing rain, and hail, which are caused by natural forces. In contrast, fires/explosions, traffic accidents, and mine accidents are classified as man-made disasters, which are mainly triggered by human activities; this category also includes incidents caused by building or bridge collapses and terrorist activities. According to Elnahas et al. (2018), we use the average DD and average ND over the past two decades to measure early disaster experience.

We use the Google Search Index as a measure of people’s attention. Six keywords are selected: virus, flu, pandemic, epidemic, coronavirus, and disaster. The Google Search Index yields values between 0 (no searches on the keyword) and 100 (keyword with peak popularity). We obtain cross-sectional data for 168 countries using the Interest by Region option in Google Trends. We use a weighted average of searches for these six keywords in each country to compare the relative search intensity between countries. The results are shown in Panel A of Table 2. From January 20–30, 2020, the average Google search index value for the six keywords is 18.48.

The stock market index data for the 65 sample countries/territories are obtained from the website www.investing.com. The 65 sample countries are selected because they have developed financial markets. According to data from the World Bank, the GDP of these 65 countries/territories accounted for more than 98 % of the total global GDP in 2019. The most representative index in each market is selected. The list of markets and indexes is provided in Table A2. Following Ru et al. (2021), we select the MSCI World Price Index as the world market index. We calculate CR and CAR to measure the responses of stock markets to the COVID-19 outbreak in Wuhan, using the time interval from January 20–30, 2020. The results are shown in Panel B of Table 2. The average CR and CAR of the 65 countries within the sample time interval are -0.04 % and -0.43 %, respectively.

We also obtain social distancing policy data from Oxford University’s COVID-19 Government Response Tracking System. This system provides information about school closures, workplace closures, public event cancellations, gathering restrictions, public transportation closures, home requirements, interval movement restrictions, and international travel controls (Hale et al., 2020). The results are shown in Panel C of Table 2. International travel control and public event cancellation are the most frequently implemented government policies, whereas public transportation closure is the least frequently implemented policy.

3.3. Controls

Cavallo et al. (2013) observe that a higher national disaster risk level is related to factors such as national development, population size, and geographic location; consequently, these countries may be more strongly affected by COVID-19 outbreaks. To mitigate this concern, we control for the natural logarithm of GDP (Log(GDP)) and the natural logarithm of the population (Log(Population)). To control for geographic proximity to the sea, we also apply CoastalDummy, a dummy variable that is equal to 1 if the country is geographically coastal and 0 otherwise. According to data from the WHO, Japan, South Korea, and Thailand first reported confirmed COVID-19 cases on January 20, 2020, becoming the first countries with confirmed cases outside of China. To further mitigate the concern of geographic proximity to China, we also control for the continent fixed effect (Continent FE).

Ru et al. (2021) also find that previous experience with outbreaks of similar epidemic viral diseases (e.g., severe acute respiratory syndrome [SARS]) affects stock market responses to the COVID-19 pandemic. Therefore, we control for the previous experience with SARS outbreaks to eliminate this concern by using SARSDummy, a dummy variable that is equal to 1 if the country had SARS cases and 0 otherwise. We also control for a series of country-level characteristics that may affect a country’s ability to combat the epidemic. In this category, Life expectancy represents the average life expectancy in the population and is used to measure the robustness of a country’s health system. Debt represents the ratio of government debt to the country’s GDP and is used to measure the government’s...
fiscal capacity to combat COVID-19 (Sun et al., 2019). EXIM represents the ratio between an index country’s trade volume with China and the total trade volume and is used to measure the intensity of trade between the index country and China. Finally, according to Zaremba et al. (2020), we control for the natural logarithm of average daily confirmed cases of COVID-19 (\(\text{Ln(COVID-19)}\)) to decouple

This table reports the results of the univariate analysis. Based on the severity of the disaster as measured by \(DD\) (ND), the samples are divided into the low, median, and high \(DD\) (ND) groups. Differences in the mean values of variables between the high and low \(DD\) (ND) groups are calculated. The t-statistics are shown in Columns (5) and (10). ** and * indicate statistical significance at the 1%, and 5% levels, respectively.

This table shows the results of a cross-sectional OLS regression of Google search index values during the initial COVID-19 outbreak in Wuhan on disaster experience. In Columns (1) to (6), we include all sample countries. In Columns (7) and (8), we limit the sample to non-Asian countries. The dependent variable, Search, represents the Google search indexes for the keywords virus, influenza, pandemic, epidemic, coronavirus, and disaster with weighted averages on a percentile scale, from January 20–30, 2020. The main independent variable, \(DD\) (ND), denotes the average duration (number) of disasters for each sample country. \(\text{Log(AveCovid)}\), \(\text{Log(GDP)}\), \(\text{Log(Pop)}\), \(\text{Debt}\), \(\text{EXIM}\), LifeExpectancy, SARSDummy, and CoastalDummy are controlled. Mainland China is excluded. The variables are defined in Table A1. Continent, a dummy variable is also included to control for Continent FE. The independent and dependent variables are standardized to allow comparisons across variables and across specifications. The associated t-statistics reported in parentheses are based on robust standard errors. ** and * indicate statistical significance at the 1%, and 5% levels, respectively.
early disaster experience from the COVID-19 pandemic.

Data on SARS and COVID-19 cases in each country are collected from the WHO website. Data on each country’s trade volume with China, life expectancy, and government debt are obtained from the Wind database. GDP and population data are obtained from the World Bank. Geographic location data are collected from Google Maps. The descriptive statistics of the above control variables are shown in Panel A of Table 2.

4. Empirical results

4.1. Imprint of disaster experience

4.1.1. Univariate analysis

Table 3 reports the results of a univariate analysis of the main variables. Based on the severity of the disaster experience measured by DD (ND), the samples are divided into low, medium, and high DD (ND) groups. Differences in the mean values of variables between the high and low DD (ND) groups are calculated, and the t-statistics are shown in Columns (5) and (10). The high DD (ND) group has a larger Google search index value than that of the low DD (ND) group, and this difference is significant at the 1% level. The unconditional model shows that people in countries with SDE pay more attention to information related to COVID-19 than people in countries with MDE. This result is consistent with H1a. As other factors that affect people’s attention also differ between the groups, regression analysis is needed to further control these factors and obtain more reliable conclusions.

4.1.2. Regression analysis

Next, we begin our analysis by examining the role of disaster experience in responses to the initial COVID-19 outbreak in Wuhan. Specifically, we conduct an ordinary least squares (OLS) regression of Google search indexes (Search) from January 20–30, 2020, on disaster experience (D or ND), corresponding to the dates when human-to-human virus transmission was confirmed and when the WHO declared COVID-19 to be a global public health emergency, respectively. This time window covers the first broad response of the Chinese government to the COVID-19 outbreak and the extensive related media coverage. To determine the robustness of our results, we apply alternative window periods as described in Section 5. The regression model is expressed as follows:

\[
\text{Search}_i = \alpha + \beta_i \text{DisasterExperience}_i + \sum_j \beta_j \text{Control}_j + \text{Continent} + \varepsilon_i
\]  

(1)

Where Search\(_i\) represents the Google search indexes for the keywords virus, influenza, pandemic, epidemic, coronavirus, and disaster in country \(i\) during the initial COVID-19 outbreak in Wuhan. The primary independent variable, DisasterExperience\(_i\), is proxied by DD and ND. We add a series of control variables that may affect people’s attention to the initial COVID-19 outbreak. The variable \(\log(AveCovid)\) is defined as the natural logarithm of 1 plus the average daily number of new confirmed COVID-19 cases during the studied period. \(\log(GDP)\), \(\log(Pop)\), Debt, EXIM, LifeExpectancy, SARSDummy, CoastalDummy, and Continent FE are used as indicated in Section 3.3. The associated t-statistics reported in parentheses are based on robust standard errors.

The results of the regression analysis are shown in Table 4. In Column (1), DD is used to measure the disaster experience. When only Continent FE is controlled, DD is significantly positive at the 1% level, indicating a more intensive search for information about the initial COVID-19 outbreak by people in countries with SDE. This result suggests that people holding strong memories of disaster experiences were more motivated to search for information related to the epidemic during the initial COVID-19 outbreak. In Columns (2) and (3), a series of factors that affect the Google search index are added, and DD remains significantly positive at the 1% level. In terms of economic significance, when DD increases from the mean (7.15) to the mean plus 1 standard deviation (18.22) and all other variables are held at their means, the Google search index increases by 0.91. Of the control variables, \(\log(AveCovid)\) is significantly positive, indicating a link between the increase in the number of confirmed COVID-19 cases and the likelihood of searching for information related to the epidemic. In addition, SARSDummy is significantly positive at the 1% level, which indicates increased attention to the initial outbreak among people with previous SARS experiences. Such results are consistent with the findings of Ru et al. (2021). In Columns (4), (5), and (6), DD is replaced by ND, and the conclusion remains unchanged.

We further exclude Asian countries and limit the sample to 124 countries in Europe, Africa, the Americas, and Oceania. The regression results are shown in Columns (7) and (8). After controlling for other variables, the regression coefficients of DD and ND are both significantly positive. These findings strongly prove that even in non-Asian countries, disaster experience is associated with an increase in people’s attention to the first known COVID-19 outbreak. Such results support H1a and, consequently, the promoting effect.

4.2. Search attention and stock return

We further study the relationship between attention (Google search index) and stock market performance at the beginning of the COVID-19 pandemic. Referring to Da et al. (2015) and Xu et al. (2021), we estimate the correlation between Google search indexes and stock market index returns during the initial COVID-19 outbreak period in Wuhan. Taking January 20, 2020, as the starting point and using MSCI World Price Index data, we calculate the CR and CAR during the subsequent 10-day event window. Specifically, the abnormal return (AR) is calculated based on the following conventional Capital Asset Pricing Model (CAPM) model:

\[
AR_{it} = r_{it} - \hat{\alpha} - \hat{\beta}_i r_{M,t}
\]  

(2)
### Table 5
Search attention and stock return.

| Variables          | (1)   | (2)   | (3)   | (4)   | (5)   | (6)   |
|--------------------|-------|-------|-------|-------|-------|-------|
| Search             | -0.33** | -0.50** | -0.31** | -0.38** | -0.39** |       |
| Search \(\hat{D}D\) |       |       |       | -0.50** | -0.53** | -0.51** |
| Search \(\hat{CR}\) |       |       |       |       |       |       |
| \(\log{\text{AveCovid}}\) | -0.31* | -0.75** | -0.49** | -0.53** | -0.51** |       |
| \(\log{\text{GDP}}\) | 0.26*  | 0.30*  | 0.24*  | 0.27*  | 0.26*  |       |
| \(\log{\text{Pop}}\) | 0.06   | 0.60   | 0.44   | 0.73   | 0.70   |       |
| Debt               | 0.05   | 0.32   | 0.01   | 0.32*  | 0.32*  |       |
| EXIM               | (0.42) | (1.74) | (1.78) | (2.13) | (2.09) |       |
| LifeExpectancy     | -0.21  | -0.16  | -0.14  | -0.43* | -0.37  | -0.41*
| SARSDummy          | -0.56* | -0.61* | -0.51* | -0.50  | -0.49  |       |
| CoastalDummy       | 0.11   | 0.07   | 0.04   | 0.01   | 0.01   |       |
| Constant           | 0.00   | 0.00   | 0.00   | 0.00   | 0.00   |       |
| Observations       | Yes    | Yes    | Yes    | Yes    | Yes    |       |
| R-squared (%)      | 34.06  | 38.03  | 38.15  | 45.98  | 51.55  | 51.15 |

This table shows the results of a cross-sectional OLS regression of stock market returns during the initial COVID-19 outbreak in Wuhan on search attention in 65 markets. The dependent variables are CR and CAR, which are calculated from January 20–30, 2020. \(\text{Search}_{\hat{ND}}\) (\(\text{Search}_{\hat{D}D}\)) is the predicted Google search index using DD (ND). \(\log{\text{AveCovid}}\), \(\log{\text{GDP}}\), \(\log{\text{Pop}}\), Debt, EXIM, LifeExpectancy, SARSDummy, and CoastalDummy are controlled in all columns. Mainland China is excluded. The variables are defined in Table A1. Continent, a dummy variable, is also included to control for Continent FE. The independent and dependent variables are standardized to allow comparisons across variables and across specifications. The associated t-statistics reported in parentheses are based on robust standard errors. ** and * indicate statistical significance at the 1%, and 5% levels, respectively.

Where \(r_i, t\) is the individual index return for country \(i\) on day \(t\) and \(r_M, t\) is the world market index return on day. \(\alpha_i\) and \(\beta_i\) are estimated during the window period corresponding to 6 months before the event.

Then, we conduct a cross-sectional regression of CR (CAR) from January 20–30, 2020, on Search while controlling for country-specific characteristics. The regression model is as follows:

\[
R_i = \alpha + \beta_1 \text{Search}_i + \sum_j \beta_j \text{Control}_j + \text{Continent} + \varepsilon_i
\]

Where \(R_i\), the dependent variable, is measured using either the CR or CAR; \(\text{Search}_i\) represents the Google search indexes of country \(i\) during the initial COVID-19 outbreak in Wuhan; \(\text{Control}_j\) is a series of country-level characteristics; and \(\varepsilon_i\) is the error term. Continent is a dummy value included to control for Continent FE. Detailed definitions of the variables are provided in Table A1.

The regression results are shown in Table 5. In Column (1), the coefficient of Search is significantly negative at the 1% level, indicating a correlation between an increase in search attention and a decline in the stock market. Investors in countries with SDE are highly aware of the need to address sudden disasters, resulting in a quick and strong stock market response to the early stage of the epidemic in China. In terms of economic significance, when the value of Search is increased from the mean (18.48) to the mean plus 1 standard deviation (46.37) and all other variables are held at their means, CR decreases by 15.30. In Column (4), similar results are obtained with CAR as the dependent variable.

Next, we explore whether disaster experience explains the relationship between attention (i.e., Google search index values) and stock market returns. For the 65 sample countries, we repeat Model (1) and calculate the predicted Search. Then, we perform a regression of CR (CAR) on predicted Search. In Column (2), the main independent variable is the Google search indexes predicted by DD, namely \(\text{Search}_{\hat{D}D}\); the dependent variable is CR. The coefficient of \(\text{Search}_{\hat{D}D}\) is -0.50, which is significantly negative at the 1% level. In Column (3), we use ND to predict Search and find that the coefficient of \(\text{Search}_{\hat{ND}}\) is -0.50, which is significant at the 1% level. In
Table 6

Government actions to combat COVID-19.

Panel A: DD

| Variables                         | School | Workplace | Public Event | Gathering | Public Transport | Home | Internal Movement | International Travel |
|-----------------------------------|--------|-----------|--------------|-----------|------------------|------|-------------------|---------------------|
|                                   | (1)    | (2)       | (3)          | (4)       | (5)              | (6)  | (7)               | (8)                 |
| Log(CovidCases)                   | 0.35** | 0.31**    | 0.42**       | 0.27**    | 0.13             | 0.35**| 0.24**            | 0.16*               |
|                                   | (4.25) | (3.86)    | (3.51)       | (2.84)    | (1.45)           | (3.72)| (2.80)            | (2.03)              |
| Log(CovidCases) × DD              | 0.62** | 0.77**    | 0.53**       | 0.67**    | 0.46**           | 0.78**| 0.65**           | 0.35**              |
|                                   | (6.37) | (8.70)    | (7.31)       | (7.38)    | (5.63)           | (8.90)| (7.62)            | (3.25)              |
| DD                                | 0.21** | 0.16**    | 0.18**       | 0.20**    | 0.19**           | 0.25**| 0.22**           | 0.24*               |
|                                   | (3.25) | (2.75)    | (3.15)       | (3.11)    | (2.73)           | (4.06)| (3.17)           | (2.51)              |
| Controls                          | Yes    | Yes       | Yes          | Yes       | Yes              | Yes  | Yes               | Yes                 |
| Continent FE                      | Yes    | Yes       | Yes          | Yes       | Yes              | Yes  | Yes               | Yes                 |
| Observations                      | 8096   | 9717      | 8046         | 9600      | 13,933           | 10,565| 9877             | 5490                |
| Chi-Squared                       | 113.23 | 124.78    | 118.52       | 114.28    | 83.16            | 103.25| 100.85          | 62.17               |

Panel B: ND

| Variables                         | School | Workplace | Public Event | Gathering | Public Transport | Home | Internal Movement | International Travel |
|-----------------------------------|--------|-----------|--------------|-----------|------------------|------|-------------------|---------------------|
|                                   | (1)    | (2)       | (3)          | (4)       | (5)              | (6)  | (7)               | (8)                 |
| Log(CovidCases)                   | 0.32** | 0.35**    | 0.45**       | 0.33**    | 0.09             | 0.32**| 0.33**           | 0.18*               |
|                                   | (4.02) | (3.04)    | (3.64)       | (3.24)    | (0.94)           | (3.51)| (3.24)           | (2.25)              |
| Log(CovidCases) × ND              | 0.58** | 0.79**    | 0.50**       | 0.74**    | 0.32**           | 0.62**| 0.73**           | 0.40**              |
|                                   | (6.04) | (8.54)    | (6.84)       | (8.71)    | (3.24)           | (7.43)| (6.59)           | (3.76)              |
| ND                                | 0.18** | 0.15**    | 0.14**       | 0.22**    | 0.17*            | 0.22**| 0.26**           | 0.22*               |
|                                   | (2.64) | (2.73)    | (2.66)       | (3.37)    | (2.42)           | (3.62)| (3.84)           | (2.46)              |
| Controls                          | Yes    | Yes       | Yes          | Yes       | Yes              | Yes  | Yes               | Yes                 |
| Continent FE                      | Yes    | Yes       | Yes          | Yes       | Yes              | Yes  | Yes               | Yes                 |
| Observations                      | 8096   | 9717      | 8046         | 9600      | 13,933           | 10,565| 9877             | 5490                |
| Chi-Squared                       | 100.38 | 118.59    | 104.33       | 132.85    | 67.82            | 90.36| 103.52           | 89.27               |

This table presents the results of a Cox proportional hazard regression of government actions taken to combat the COVID-19 pandemic across different countries. The original date is the date when the country reported its first case of COVID-19. The expiration date is the date when the corresponding policy took effect. Observations before the original date or after the expiration date are deleted. In Panel A (B), the independent variable, DD (ND), denotes the average duration (number) of disasters for each sample country. Log(CovidCases) is the natural logarithm of 1 plus the cumulative number of confirmed COVID-19 cases in each sample country. Log(GDP), Log(Pop), Debt, EXIM, LifeExpectancy, SARSDummy, and CoastalDummy are controlled in all columns. For the sake of brevity, control variables are not shown in the table. Mainland China is excluded. The variables are defined in Table A1. Continent, a dummy variable, is also included to control for Continent FE. The independent and dependent variables are standardized to allow comparisons across variables and across specifications. The associated t-statistics reported in parentheses are based on robust standard errors. ** and * indicate statistical significance at the 1%, and 5% levels, respectively.

Columns (5) and (6), the dependent variable is CAR, and the conclusion remains unchanged. Our findings suggest that increased attention to COVID-19 via Google searches is correlated with greater declines in the markets of countries with SDE. Such results support H2a but not H2b.

4.3. Government containment measures

4.3.1. Government actions to combat COVID-19

In this section, we aim to examine the effect of disaster experience on governments’ responses to domestic COVID-19 pandemic situations. We use the Cox proportional hazards regression model to explore the effect of disaster experience on the time when the government takes various containment measures (i.e., response time). Traditional regression methods (e.g., logistic regression) can only correlate the observed influencing factors with the dependent variables without considering the time factor. The Cox proportional hazards regression model can solve this problem, as follows:

\[
h(t, X) = h_0(t) \exp(\beta_1 \times \text{Log(CovidCases)}_{1,t} + \beta_2 \times \text{Log(CovidCases)}_{2,t} \times \text{DisasterExperience}_{i,t} + \beta_3 \times \text{DisasterExperience}_{i,t} + \text{Control}_{i,t} + \text{Continent})
\]
Where \( X \) represents predictors that may affect the government’s response time, which are also known as covariates; \( t \) represents the response time; \( h(t, X) \) is the risk function of an individual with covariate \( X \) at time \( t \) and represents the probability that a government will take corresponding containment measures at time \( t \); and \( h_0(t) \) is the baseline risk function at time \( t \) and represents the probability that a government will take corresponding containment measures when all of the predictors are equal to 0.

\[
\log(\text{CovidCases}_i) = \log(1 + \text{cumulative number of confirmed COVID-19 cases for country } i \text{ at date } t; \text{DisasterExperience}_i \text{ is measured by either } DD \text{ or } ND; \text{Control}_i \text{ represents a series of country-level variables, including } \log(\text{GDP}_i), \log(\text{Pop}_i), \text{EXIM}, \text{LifeExpectancy}, \text{Debt}, \text{SARSDummy}, \text{and CoastalDummy}. \text{Continent FE} \text{ is also controlled. Each country enters hazard regression on the day of its first confirmed domestic COVID-19 case and exits hazard regression after taking the corresponding containment measures.}
\]

Our sample contains government behavior data from 142 countries worldwide. We estimate the hazard probabilities of the implementation of eight different containment measures. The results are shown in Table 6. In Panel A, \( DD \) is used to measure disaster experience. In Column (1) of Panel A, the coefficient of \( \log(\text{CovidCases}) \) is significantly positive, which indicates that when more COVID-19 cases are confirmed, the government is more likely to take measures to contain the outbreak by closing schools. In terms of economic significance, a 100% increase in the number of COVID-19 cases leads to a 27.46% increase in the probability of school closure (\( \exp(0.35 \times \ln(2)) - 1 = 27.46\% \)). Meanwhile, the coefficient of \( DD \) is significantly positive, indicating that the longer the durations of previously experienced disasters are, the greater the possibility that the government will take measures to close schools is. More importantly, the coefficient of \( \log(\text{CovidCases}) \times DD \) is significantly positive, indicating that there is a stronger positive correlation between the number of COVID-19 cases and the possibility of measures involving school closures in countries with SDE relative to those with MDE. In other words, the governments of countries with SDE respond to domestic epidemics more rapidly than those of countries with MDE.

In Columns (2) to (8) of Panel A, the coefficients of \( DD \) are all positive, indicating that the longer the durations of previously experienced disasters are, the greater the possibility that the government will take corresponding containment measures is, including workplace closures, public event cancellations, gathering restrictions, public transportation closures, home requirements, interval movement restrictions, and international travel controls. Moreover, the coefficients on \( \log(\text{CovidCases}) \times DD \) are all significantly positive, suggesting that the positive association between the COVID-19 case number and the likelihood of containment measures is stronger in countries with SDE relative to those with MDE. In Panel B, we use \( ND \) to proxy for early disaster experience and find similar results. These results are consistent with the expectations of H3a.

In summary, we identify the important role of disaster experience in responding to emerging new crises. Specifically, we find more rapid implementation of containment measures, such as the closure of schools, workplaces, and public transportation routes, the cancellation of public events, the restriction of gatherings and internal movements, home requirements, and controls on travel, by governments in countries with SDE relative to those with MDE at the beginning of the COVID-19 outbreak.
### Table 7
Robustness tests.

#### Panel A: DD

| Variables | (1)          | (2)          | (3)          | (4)          | (5)          | (6)          |
|-----------|--------------|--------------|--------------|--------------|--------------|--------------|
| DD        | 0.12**       | 0.09**       | 0.11**       | 0.09**       | 0.13**       | 0.10**       |
|           | (4.38)       | (3.05)       | (4.32)       | (2.97)       | (4.28)       | (2.93)       |
| Log(AveCovid) | 4.25*         | 4.22*         | (2.14)       | (2.08)       | (2.02)       |              |
| Log(GDP)  | 5.83**       | 5.87**       | (2.95)       | (2.92)       | (2.84)       |              |
| Log(Pop)  | 1.94*        | 1.98*        | (2.36)       | (2.52)       | (2.51)       |              |
| Debt      | –0.11        | –0.12        | (-1.88)      | (-1.93)      | (-1.86)      |              |
| EXIM      | 2.62*        | 2.72*        | (2.10)       | (2.52)       | (2.67)       |              |
| LifeExpectancy | –1.00        | –0.91        | (-1.24)      | (-1.04)      | (-0.96)      |              |
| SARSDummy | 16.38**      | 16.46*       | (2.53)       | (2.66)       | (2.59)       |              |
| CoastalDummy | 3.95         | 3.92         | (0.82)       | (0.80)       | (1.25)       |              |
| Constant  | 18.26**      | 16.43**      | 17.42**      | 15.15**      | 17.03**      | 15.36**      |
|           | (7.02)       | (5.51)       | (6.95)       | (5.44)       | (6.84)       | (5.49)       |
| Continent FE | Yes          | Yes          | Yes          | Yes          | Yes          |              |
| Observations | 168          | 168          | 168          | 168          | 168          | 168          |
| R-squared (%) | 11.83        | 11.67        | 39.63        | 11.59        | 37.28        |              |
| Time window | [Jan 07, Jan 30] | [Jan 07, Jan 30] | [Jan 20, Feb 28] | [Jan 20, Feb 28] | [Jan 07, Feb 28] | [Jan 07, Feb 28] |

#### Panel B: ND

| Variables | (1)          | (2)          | (3)          | (4)          | (5)          | (6)          |
|-----------|--------------|--------------|--------------|--------------|--------------|--------------|
| ND        | 0.18**       | 0.14**       | 0.16**       | 0.13**       | 0.16*        | 0.14**       |
|           | (4.37)       | (3.28)       | (4.41)       | (3.24)       | (4.39)       | (3.26)       |
| Log(AveCovid) | 5.42*         | 5.83**       | (2.11)       | (2.04)       | (2.24)       |              |
| Log(GDP)  | 6.21**       | 5.92**       | (2.83)       | (2.62)       | (2.72)       |              |
| Log(Pop)  | 2.70*        | 2.72*        | (2.20)       | (2.27)       | (2.21)       |              |
| Debt      | –0.15*       | –0.13**      | (-2.75)      | (-2.68)      | (-2.50)      |              |
| EXIM      | 3.44*        | 3.24*        | (2.20)       | (2.09)       | (2.25)       |              |
| LifeExpectancy | –1.25        | –1.20        | (-1.18)      | (-1.13)      | (-0.87)      |              |
| SARSDummy | 16.38**      | 18.20**      | (2.54)       | (2.48)       | (2.36)       |              |
| CoastalDummy | 4.02         | 4.13         | (0.93)       | (1.07)       | (0.97)       |              |
| Constant  | 15.29**      | 14.53**      | 15.16**      | 15.30        | 11.53**      |              |
|           | (6.83)       | (6.72)       | (5.08)       | (6.82)       | (5.14)       |              |
| Continent FE | Yes          | Yes          | Yes          | Yes          | Yes          |              |
| Observations | 168          | 168          | 168          | 168          | 168          | 168          |
| R-squared (%) | 10.96        | 11.32        | 39.38        | 11.27        | 41.54        |              |
| Time window | [Jan 07, Jan 30] | [Jan 07, Jan 30] | [Jan 20, Feb 28] | [Jan 20, Feb 28] | [Jan 07, Feb 28] | [Jan 07, Feb 28] |

This table shows the results of cross-sectional OLS regressions of Google search indexes on disaster experience in three different time windows. The time windows are from January 7–30, 2020, in Columns (1) and (2); from January 20 to February 28, 2020, in Columns (3) and (4); and from January 7 to February 28, 2020, in Columns (5) and (6). These dates were chosen because they correspond to important events. On January 7, 2020, China announced that a novel coronavirus was the causative agent of the reported pneumonia cases, and human-to-human coronavirus transmission was confirmed on January 20, 2020. The WHO declared COVID-19 to be a global public health emergency on January 30, 2020, and raised the global risk of disease spread from high to very high on February 20, 2020. In Panel A (B), the independent variable, DD (ND), denotes the average duration...
China announced that a novel coronavirus was the causative agent of the identified pneumonia cases on January 7, 2020, and human-to-human coronavirus transmission was confirmed on January 20, 2020. The WHO declared COVID-19 to be a global public health outbreak in three different time windows, namely January 7

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### Table A1

| Variable names          | Variable definitions                                                                 |
|-------------------------|--------------------------------------------------------------------------------------|
| Search                  | Google search index for the keywords virus, influenza, pandemic, epidemic, coronavirus, and disaster with weighted averages on a percentile scale from January 20-30, 2020. |
| CR                      | Cumulative return in the respective event window for each sample country.             |
| CAR                     | Cumulative abnormal return in the respective event window for each sample country. Abnormal return is calculated based on the following model for each country \( t \): \( AR_{it} = r_{it} - \bar{a}_i - \beta_i r_M, \) where \( r_{it} \) is the individual index return for country \( i \) on day \( t \), and \( r_M \) is the world market index return on day \( t \). \( \bar{a}_i \) and \( \beta_i \) are estimated during the window corresponding to 6 months before the event. |
| DD                      | Average duration of disasters between 1999 and 2017 for each sample country.        |
| ND                      | Natural logarithm of GDP for each sample country in 2019.                            |
| Log(GDP)                | Natural logarithm of the population for each sample country in 2019.                 |
| Log(ND)                 | Average number of disasters between 1999 and 2017 for each sample country.          |
| Log(AveCovid)           | Natural logarithm of 1 plus the average daily number of new COVID-19 confirmed cases from January 20-30, 2020. |
| EXIM                    | Ratio between the country’s trade volume with China and its total trade volume in 2019, where trade volume equals the total import and export volumes. |
| LifeExpectancy          | Average life expectancy of an individual in the sample country.                     |
| Debt                    | Ratio of government debt to the country’s GDP.                                      |
| SARSDummy               | A dummy variable equal to 1 if the country had SARS cases, and 0 otherwise.          |
| CoastalDummy            | A dummy variable equal to 1 if the country is geographically coastal, and 0 otherwise. |
| School                  | A dummy variable equal to 1 when the school closure policy is implemented, and 0 before the policy takes effect. |
| Workplace               | A dummy variable equal to 1 when the workplace closure policy is implemented, and 0 before the policy takes effect. |
| PublicEvent             | A dummy variable equal to 1 when the public event cancellation policy is implemented, and 0 before the policy takes effect. |
| Gathering               | A dummy variable equal to 1 when the gathering restriction policy is implemented, and 0 before the policy takes effect. |
| PublicTransport         | A dummy variable equal to 1 when the public transport closure policy is implemented, and 0 before the policy takes effect. |
| StayHome                | A dummy variable equal to 1 when the stay-at-home requirement policy is implemented, and 0 before the policy takes effect. |
| InternalMovement        | A dummy variable equal to 1 when the internal movement restriction policy is implemented, and 0 before the policy takes effect. |
| InternationalTravel     | A dummy variable equal to 1 when the international travel control policy is implemented, and 0 before the policy takes effect. |
| Log(CovidCases)         | Natural logarithm of 1 plus the cumulative number of confirmed COVID-19 cases for each sample country on day \( t \). |

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5. Robustness tests

To ensure the robustness of our empirical results, we examine the role of disaster experience in responses to the initial COVID-19 outbreak in three different time windows, namely January 7–30, 2020, in Columns (1) and (2); January 20 to February 28, 2020, in Columns (3) and (4); and January 7 to February 28, 2020, in Columns (5) and (6). These dates are chosen for the following reasons. China announced that a novel coronavirus was the causative agent of the identified pneumonia cases on January 7, 2020, and human-to-human coronavirus transmission was confirmed on January 20, 2020. The WHO declared COVID-19 to be a global public health...
emergency on January 30, 2020, and raised the global risk of COVID-19 spread from high to very high on February 28, 2020.

In Panel A of Table 7, $DD$ is used to measure disaster experience. We find a significant positive correlation between disaster experiences and Google search indexes related to COVID-19, regardless of the selected time window. In other words, the empirical evidence suggesting that disaster experience promotes Google searches for pandemic information is robust and not affected by the time window. In Panel B of Table 7, $DD$ is replaced by $ND$, and the conclusion remains unchanged. In summary, people retain deep memories of disaster experiences, which encourage them to search for epidemic-related information more quickly.

6. Conclusion

Using disaster data released by SwissRe to cover the 1999–2017 period, we examine the effect of disaster experience on responses to the initial COVID-19 outbreak. Our results indicate a higher level of attention to COVID-19 among residents, more timely market responses, and stricter government-imposed containment measures in response to the COVID-19 pandemic in countries with SDE relative to countries with MDE. Specifically, we observe more frequent Google searches for COVID-19-related information among people in countries with SDE during the initial COVID-19 outbreak in Wuhan, China, in late January 2020. Moreover, this increase in Google search activity is correlated with greater stock market decreases in countries with SDE relative to those with MDE. Finally, governments in countries with SDE tend to implement stricter social distancing policies to combat domestic COVID-19 outbreaks, and residents in countries with SDE are more likely than their counterparts in countries with MDE to follow these government containment measures in both the initial outbreak and reopening phases. Our results suggest that disaster experience increases risk aversion and is an essential mechanism underlying timely national responses to COVID-19 outbreaks.

The COVID-19 pandemic remains a major global crisis at the time of writing. Despite the efforts of many countries to combat outbreaks, COVID-19 continues to spread rapidly in many parts of the world, with adverse effects on human life and well-being. The accepted wisdom suggests that public healthcare systems should respond to outbreaks as early as possible. We show for the first time the role of past disaster experience in responses to the COVID-19 pandemic. We demonstrate that in the early stages of the pandemic, countries with SDE responded in a timely and powerful manner. The significance of this study extends beyond financial markets. Policymakers should be made aware of the role of disaster experience as a factor contributing to delayed responses to the COVID-19 pandemic.

Subject to the timing of COVID-19 occurrence, we only discuss disaster experiences and COVID-19 short-term outcomes. As Zhang et al. (2020) pointed out, government measures during the pandemic can prevent investor panic in the short term. In the long run,
however, these policies may change investors’ expectations and have a completely different impact. Exploring the long-term outcomes of disaster experiences on COVID-19 is one of our future research directions. In addition, without distinguishing the types of disasters, we explore the overall role of past natural disaster experiences in combating the pandemic. The degree of imprint caused by different types of natural disasters may be different. For example, the difference between earthquakes and other natural disasters, such as floods and droughts, is that earthquakes not only cause property damage, but also bring greater death threats (Filipski et al., 2019). Different types of disaster experiences may play different roles in combating the pandemic. Exploring the role of different types of disaster experiences in combating COVID-19 is another future research direction for us.

Author statement

Jie Li: Conceptualization, Methodology, Data curation, Visualization.
Yahui An: Software, Investigation, Funding acquisition.
Lidan Wang: Formal analysis, Writing- Original draft preparation, Writing - Review & Editing.
Yongjie Zhang: Supervision, Project administration, Validation.

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Appendix A

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