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.
The correlations among COVID-19, the effect of public opinion, and the systemic risks of China’s financial industries

Zisheng Ouyang a, Shili Chen b, Yongzeng Lai c,*, Xite Yang d

a School of Business, Hunan Normal University, Changsha, 410081, China
b School of Finance, Hunan University of Technology and Business, Changsha, 410205, China
c Department of Mathematics, Wilfrid Laurier University, Waterloo, Ontario, Canada, N2L 3C5
d Business School, Sichuan University, Chengdu, 610064, China

ARTICLE INFO

Article history:
Received 17 January 2022
Received in revised form 15 April 2022
Available online 12 May 2022

JEL classification:
C25
C35
C45
D53
G21
G22
G24

Keywords:
Event study method
COVID-19
Horizontal effect
Trend effect
Public opinion effect

ABSTRACT

In this paper, we use the improved event study method to analyze the changes in the systemic risk trends of various financial sectors after the outbreak of COVID-19. The analysis is based on the daily return data of 45 Chinese financial institutions from January 2, 2019, to November 30, 2020. The improved event study method is also used to explore the horizontal, trend, and public opinion effects of the systemic risk. The empirical analysis results show that: (1) the occurrence of COVID-19 will increase the level and volatility of systemic risk in the financial industry. (2) After the outbreak of COVID-19, there is no horizontal effect in all financial industries. The banking and securities industries have significant and longer-lasting positive trend effects, and from the perspective of trend effects, in the face of external shocks, the banking industry is more stable than the securities industry. (3) After the outbreak of COVID-19, the banking and securities industries have a public opinion effect, which is gradually weakened; but there is no public opinion effect in the insurance industry.

© 2022 Elsevier B.V. All rights reserved.

1. Introduction

On March 11, 2020, the World Health Organization (WHO) classified COVID-19 as “a large-scale pandemic”, and a series of emergency response measures were adopted across the world. The outbreak of the pandemic has undoubtedly brought new challenges to China’s economic development. The Chinese government has also made overall plans and has taken a series of strategic deployments in response to the pandemic to prevent and control the epidemic. Judging from experience, the occurrence of an emergency is a major obstacle to the stability of financial operations. For example, the SARS epidemic in 2003 caused a significant decline in China’s actual GDP growth rate and a cliff-like decline in the total amount of consumer goods; the 2008 snowstorm had a significant negative impact on industrial production. In 2020, the COVID-19 caused the Chinese stock markets to crash on March 2, 2020, and the US stock markets were crashed four times. The impact of emergencies on the economy will eventually be transmitted to the financial markets through the supply chain, capital chain, etc., resulting in drastic changes in financial market volatilities, and may even induce systemic financial risks. Alfaro et al. [1] point out in the study that changes in the COVID-19 epidemic can predict the return of

* Corresponding author.
E-mail addresses: ouyang_zs@hunnu.edu.cn (Z. Ouyang), 2118720832@qq.com (S. Chen), ylai@wlu.ca (Y. Lai), yxt@stu.scu.edu.cn (X. Yang).

https://doi.org/10.1016/j.physa.2022.127518
0378-4371/© 2022 Elsevier B.V. All rights reserved.
US stocks in real-time, and predict that when the number of infections doubles, the return of US stocks will drop by 4% to 11%. Rizwan et al. [2] used catastrophe risk financial indicators to measure the changes in systemic risks in eight countries including Canada during the global financial crisis and the COVID-19 epidemic. During the COVID-19 pandemic, the systemic risk values of all countries rose sharply in March and reached a peak in mid-to-late March. Therefore, the impact of emergencies on systemic risks in the financial industries needs further analysis. In theory, emergencies can usually be regarded as external shocks, which can be divided into positive external shocks and negative external shocks. The final result of external shocks will increase the level of systemic risks among financial institutions [3]. In addition, with the rapid development of information technology, people gradually tend to obtain information from online platforms. Due to information asymmetry, online platforms are gradually becoming the origin of network public opinion. This, in turn, will gradually impact the financial markets, causing systemic risks in severe cases.

After the outbreak of the COVID-19 epidemic in early 2020, various localities introduced epidemic prevention and control policies and home isolation. Therefore, investors will use the Internet to obtain information about the epidemic, increase their attention to the epidemic and the stock market, and adjust their psychological expectations by integrating online information. They will make corresponding investment decisions, thereby causing price changes in the financial market. On the other hand, investors are irrational [4]. When the negative external shock of the COVID-19 epidemic occurs, investors’ excessive attention to the COVID-19 epidemic and the inability to better distinguish between true and false online information will cause investors to panic and gradually spread, leading to decreasing in investors’ willingness to hold stocks and thus selling a large number of stocks. Furthermore, under these extreme circumstances, many investors are irrational usually. They will follow the trend blindly, leading to violent turbulence in the stock market and systemic financial risks in severe cases.

In addition, the occurrence of systemic financial risks usually does not happen overnight. It takes a certain amount of time to accumulate and break out after a certain point in time, and each industry is not completely affected by the epidemic. As an important part of the financial industry, it is necessary to analyze the systemic risks of the banking, securities, and insurance industries. Therefore, based on the impact of COVID-19 on the systemic risks of the financial industries, this paper further analyzes the horizontal effect, trend effect, and public opinion effect of the COVID-19 pandemic on the systemic risks of the financial industries. This has very important theoretical and practical significance for maintaining the stability of the financial system.

The main contributions of this paper are as follows: first, the choice of window period is estimated by constructing dummy variables of the event instead of the event study method to avoid the subjectivity of window period selection; second, this paper links public opinion with systemic risks in the context of emergencies, to provide new ideas for the study of systemic risks in the context of emergencies; third, COVID-19 is linked to the systemic risks of the financial industries through an improved event study method, providing new ideas for regulatory authorities.

The rest of this article is structured as follows: the literature review is given in Section 2. The empirical design, the calculation methods of systemic risk indicators, and the setting of basic regression models are described in Section 3. Section 4 is devoted to the empirical analysis of the level of systemic risks for various financial industries after the outbreak of COVID-19 and the horizontal effect, trend effect, and public opinion effect of systemic risks, and conduct robustness test. The conclusion is delineated in Section 5.

2. Literature review

After the outbreak of the COVID-19, scholars had heated discussions and carried out a wealth of research on this, extended it to relevant research on health emergencies such as the COVID-19, and gradually became a hot issue in academic research. At present, the relevant research mainly focuses on the following aspects.

First, study the impact of the COVID-19 on the real economy and financial markets. Specifically, some scholars believe that the COVID-19-related health incidents will affect the real economy by affecting supply and demand [5] and [6]. In addition, the impact on the real economy is eventually transmitted to the financial market through the industrial chain and supply chain, causing changes in financial market returns and financial market fluctuations. In general, after the outbreak of the COVID-19, financial market returns will fall rapidly [1,7], but as time evolves, the negative impact of the epidemic on financial returns will gradually weaken [8], however, the outbreak of the COVID-19 will cause severe fluctuations in the financial market. Baker et al. [9] measured the changes in the stock market during the COVID-19 epidemic based on the newspaper's stock market volatility tracker and the volatility index itself. The study found that the stock market fluctuates sharply during the epidemic, and the news about the COVID-19 epidemic during this period is irrelevant. Whether it is positive or negative is the main driving force behind the sharp volatility of the US stock market.

Second, study the COVID-19 and systemic risks. Since the 2008 financial crisis, systemic risk has been a research hotspot among scholars, including the definition, measurement, and contagion of systemic risk. Systemic risk is generally considered to be the risk of interruption of financial services due to damage to all or part of the financial system. At present, the commonly used methods for systemic risk measurement include MES (Marginal Expected Shortfall), SRISK (Systemic Risk Measure), VaR (Value at Risk), CoVaR (Conditional Value at Risk), etc. The financial market is facing the huge impact of the COVID-19, and it is very easy to overreact in the short term [10], which magnifies the vulnerability of the financial market and increases the risk spillover effect between stock markets [11]. Scholars’ research on the COVID-19 and systemic risks in existing studies can be divided into three aspects: First, starting from the financial risk itself,
research has found that the COVID-19 will lead to an increase in financial risks. Rizwan et al. [2] used catastrophe risk financial indicators to measure the changes in systemic risks in eight countries including Canada during the global financial crisis and the new crown pneumonia epidemic and concluded that the CATFIN values of all countries peaked during the financial crisis. During the COVID-19 pandemic, the systemic risk values of all countries were relatively stable before March, and thereafter rose sharply and peaked in mid-to-late March. Duan et al. [12] considered that the COVID-19 will increase the vulnerability of the banking system and cause systemic risks. Therefore, using more than a thousand listed banks in 64 countries as a sample to calculate its ∆CoVaR, the study found that the occurrence of the COVID-19 has systemic risks. This has had an adverse effect, and it has also been found that banks with the characteristics of large scale, high leverage, and insufficient capital exhibit higher systemic risks. Second, it is believed that the occurrence of the COVID-19 will cause financial market volatility, which in turn will trigger financial risks. Investors’ panic selling behavior increased significantly after the outbreak, leading to depreciation of companies or insolvency, and even some financial institutions facing bankruptcy, which led to an increase in systemic financial risks. Guo et al. [13] observed financial market fluctuations during the epidemic based on a dynamic financial network and found that after the outbreak, the tail risk contagion in the financial market increased. Third, from the perspective of spillover, some scholars believe that the COVID-19 will exacerbate the spillover of systemic risks. Zhang et al. [14] find that the COVID-19 has a significant impact on the spillover effect of the stock market, and the overall spillover index after the outbreak has increased significantly compared to before the epidemic. Based on the DCC-GARCH model, Abuzayed et al. [15] calculate ∆CoVaR between the stock market index and individual stock index of 14 countries most affected by the epidemic and find that during the epidemic, the risk spillover between the global market and individual stock markets has significantly increased and the two-way contagion. Wang et al. [16] also point out that the occurrence of the COVID-19 has increased the spillover effect between international financial markets by establishing a dynamic network model. Lai and Hu [17] took the G20 as the research object and established a complex network based on Granger causality to identify financial risks, to analyze the network correlation between countries in the context of the COVID-19. The study finds that the Granger Causality complex network can be used to measure systemic risk, and COVID-19 will increase the network correlation between countries and increase the speed of risk transmission.

Third, study the COVID-19 and online public opinion. Zhang et al. [18] believe that investor sentiment played an important role during the COVID-19 pandemic. The possible reason is that after the outbreak of the COVID-19, due to mandatory quarantine measures in various places, investors can only obtain relevant information from the Internet, and the stock market fell sharply on the first trading day after the epidemic, and the U.S. stock market was broken four times in March. The stock markets of Germany, Italy, France, and other countries also saw sharp declines. The stock markets were facing sharp volatility and investor panic increased. In addition, from the perspective of behavioral finance, it can be found that the COVID-19 will affect investors’ risk perception, vague aversion, and irrational expectations, leading to online public opinion. The first is the risk perception mechanism. The occurrence of the COVID-19 will increase the risk assessment of financial assets by investors, which will lead to an increase in risk perception. Reasonable expectations for the future economy of the financial market will become difficult to control and will show a more cautious state. Thereby increasing public opinion on the Internet [19]. The second is the fuzzy aversion mechanism. Investors usually show aversion to uncertain or fuzzy things, which affects online public opinion under the lack of information. Therefore, investors will make investment decisions when the information is sufficient. The third is the irrational expectation mechanism. When faced with the impact of the COVID-19, investors are prone to collective panic, which leads to violent fluctuations in the stock prices of financial institutions. When a crisis occurs in a single market, investors will redistribute their portfolio of assets based on rational expectations. Eventually leading to the continued expansion of public opinion, and even systemic risks in financial institutions, which may be contagious among various financial departments and institutions.

It can be found from the above literature that there are more studies on the COVID-19, but less research on the impact of the COVID-19 on systemic risks. Therefore, this article draws on the methods of Gourinchas and Obstfeld [20] and Schularick and Taylor [21] and uses an improved events study method to analyze the impact of the COVID-19 on the systemic risks of financial institutions. Compared with the traditional event research method, the improved event research method does not need to calculate the expected benefits and avoids the subjectivity of determining the event window period. In addition, a consensus has been reached on the strong correlation between online public opinion and financial risks. De Long et al. [22] also pointed out in their research that in an environment of limited arbitrage, if the mispricing caused by the irrational behavior of investors cannot be eliminated, investors' emotions may become a systemic risk that affects the equilibrium price of financial assets. The occurrence of the COVID-19 has spread investor panic and increased irrational behavior. Therefore, in the context of the epidemic, whether there is public opinion in financial institutions is worthy of further discussion. In the study of systemic risk, although there are many measurement methods, each method has its advantages and disadvantages. For example, the risk described by VaR is the independent risk of a single financial institution, and MES only measures the risk contribution of the institution. The ∆CoVaR proposed by Adrian and Brunnermeier [23] is used to measure the systemic risk in the financial industry. This is because it can measure the tail dependence between financial institutions and the financial system, and then the level effect on systemic risk. Analysis of trend effect and public opinion effect.
3. Methodology

This section contains two parts. The first part seeks to explain the basic regression model to analyze the horizontal effect, trend effect, and public opinion effect of COVID–19 on the systemic risk of the financial industry. The second part is dedicated to explaining the measurement of systemic risk in the financial industry and the construction of the network public opinion index.

3.1. Regression model

The regression model constructed in this section not only includes the impact of COVID–19 on the level of systemic risk in the financial industry but also includes the impact on the trend of systemic risk in the financial industry. That is, it includes the horizontal, trend, and public opinion effects. The horizontal effect refers to the degree to which the systemic risk of each financial institution is higher than the average level during the entire sample period after the outbreak of the COVID–19. The trend effect means that after the outbreak of the COVID–19 pandemic, the trend of systemic risk in a financial industry over time is greater than the level before the outbreak of the COVID–19 pandemic. The public opinion effect means that after the outbreak of the COVID–19 pandemic, the systemic risk of the financial industry is more affected by the network public opinion index than it was before the outbreak.

The regression models for the three types of effects are given by the following equations:

\[
\Delta \text{CoVaR}^{\text{sys}}_{i,t} = \eta_i + \phi_i \cdot D_{-s} + \varphi_i \cdot D_s + \epsilon_i, \tag{1}
\]

\[
\Delta \text{CoVaR}^{\text{sys}}_{i,t} = \psi_j + \delta_j \cdot \text{time} + \zeta_j \cdot D_{-s} + \tau_j \cdot D_s + \rho_j \cdot \text{time} \cdot D_{-s} + \theta_j \cdot \text{time} \cdot D_s + \epsilon_i, \tag{2}
\]

\[
\Delta \text{CoVaR}^{\text{sys}}_{i,t} = \sigma_j + \theta_j \cdot \text{NPO}_{i,t} \cdot D_{-s} + \kappa_j \cdot \text{NPO}_{i,t} \cdot D_s + \epsilon_i, \tag{3}
\]

respectively, where \(\Delta \text{CoVaR}^{\text{sys}}_{i,t}\) is the same as given in (3). \(D_{-s}\) and \(D_s\) are the dummy variables \(s\) days before and after the occurrence of the COVID–19 epidemic, respectively. They are defined by

\[
D_{-s} = \begin{cases} 1, & t' - s \leq t \leq t' - 1, \\ 0, & \text{other time}, \end{cases} \tag{4}
\]

and

\[
D_s = \begin{cases} 1, & t' \leq t \leq t' + s - 1, \\ 0, & \text{other time}, \end{cases} \tag{5}
\]

respectively. In Eqs. (4) and (5), \(t'\) represents the time when COVID–19 occurred. In this paper, the time of the first day of lockdown in Wuhan was counted as the occurrence time of COVID–19. The selection of \(s\) is based on the actual research of this paper, and the value is \(s \in [6, 46]\). The 46-day selection is because Wuhan’s lockdown lasted 46 days (excluding weekends and holidays). Meanwhile, we choose one week after Wuhan’s lockdown as the digestion period, that is, we choose the 6th day after the incident as the shortest time for the study (excluding weekends and holidays).\(^1\) With the change of the value of \(s\), the dynamic impact of the pandemic on the horizontal and trend effects of the systemic risk can be obtained.

From the beginning to the end of the sample period, the initial value of date \(t = 1\), and the value of \(t\) increases by 1 for each additional day. In Eq. (1), if \(\phi_i\) is significantly greater than 0, then it means that COVID–19 has a horizontal effect on a systemic risk, and the magnitude is \(\varphi_i\). In Eq. (2), if \(\delta_j\) is significantly greater than \(\rho_j\), then this means that COVID–19 has a trend effect on a systemic risk, and the size is \((\delta_j - \rho_j)\). In (3), if \(\kappa_j\) is significantly greater than \(\theta_j\), then it means that after the outbreak of the COVID–19 pandemic, the systemic risk of a financial industry has public opinion effect. The size of the effect is represented by \((\kappa_j - \theta_j)\).

3.2. Construction of statistical index

3.2.1. Measurement of systemic risk in the financial industry

In this paper, the measurement of the systemic risk in a financial industry proposed by Adrian and Brunnermeier [23] is used, and the selection of state variables refers to Ouyang et al. [24], etc. We calculate the \(\text{VaR}^i_{q,t}\) and \(\text{CoVaR}^{\text{sys}}_{i,t}\) of each financial institution, and we then use the market value of each financial institution to calculate the systemic risk of each financial industry.

First, we use quantile regression to calculate the dynamic value at risk \(\text{VaR}^i_{0.05,t}\) and \(\text{VaR}^i_{0.5,t}\) of each financial institution at 95% and 50% confidence levels, respectively.

\[
R^i_t = \alpha^i_t + \beta^i_t \cdot M_t + \epsilon^i_{q,t}, \tag{6}
\]

\(^1\) In order to make the results more accurate, we have also done an empirical study of \(s \in [2, 46]\), and the results obtained are consistent with those for \(s \in [6, 46]\).
\[ \text{VaR}_{i,t}^R = \hat{\alpha}_q^i + \hat{\beta}_q^i \cdot R_t, \] 

(7)

where \( R_t^i = \ln(P_t^i) - \ln(P_{t-1}^i) \) represents the return of the \( i \)th financial institution at time \( t \), and \( M_t \) represents the state variable, which includes market risk, credit risk and liquidity risk. The market risk consists of two parts: stock market volatility and stock market return. Here, the CSI 300 index is used to measure the volatility and the return of the stock market. The volatility is obtained by using the GARCH (1,1) model. Credit risk is measured by the credit spread, which is the difference between the 1-year yield to maturity of AAA corporate bond and the 1-year yield to maturity of the treasury bond. Liquidity risk is reflected by two indicators: the change in the month-on-month change in the yield to maturity of the three-month treasury bond and the change in the month-on-month spread of the maturity spread. The difference in the rates of returns is used to measure the term spread.

Second, we use the quantile regression to calculate the VaR of financial system \( i \) under stress (at the 95% confidence level) and normal (at the 50% confidence level) situations, namely \( \text{CoVaR}_{i}^{\text{sys|VaR}_{0.05}} \) and \( \text{CoVaR}_{i}^{\text{sys|VaR}_{0.5}} \). That is,

\[ \text{CoVaR}_{i}^{\text{sys|VaR}_{0.05}} = \alpha_0^{\text{sys|i}} + \beta_0^{\text{sys|i}} \cdot \text{VaR}_{0.05,i,t} + \gamma_0^{\text{sys|i}} \cdot M_t, \] 

(9)

and

\[ \text{CoVaR}_{i}^{\text{sys|VaR}_{0.5}} = \alpha_0^{\text{sys|i}} + \beta_0^{\text{sys|i}} \cdot \text{VaR}_{0.5,i,t} + \gamma_0^{\text{sys|i}} \cdot M_t, \] 

(10)

respectively. According to formulas (9) and (10), it can be further concluded that the systemic risk of the \( i \)th financial institution is:

\[ \Delta\text{CoVaR}_{i}^{\text{sys|i}} = \text{CoVaR}_{i}^{\text{sys|VaR}_{0.05}} - \text{CoVaR}_{i}^{\text{sys|VaR}_{0.5}}, \] 

(11)

Finally, the systemic risk of the \( j \)th sub-industry in the financial industry can be calculated according to the weight of the market value of each financial institution in the industry as follows:

\[ \Delta\text{CoVaR}_{i}^{\text{sys|i}} = \sum_{j=1}^{N_j} \frac{m_{ij,t}}{\sum_{j=1}^{N_j} m_{ij,t}} \cdot \Delta\text{CoVaR}_{i}^{\text{sys|i}}, \] 

(12)

where \( j \in \{1, 2, 3\} \) corresponds to the banking, securities, and insurance industries, respectively; \( N_j \) is the total number of financial institutions in the \( j \)th financial industry; \( m_{ij,t} \) represents the market value on date \( t \) of the \( i \)th financial institution in the \( j \)th financial industry, and \( \Delta\text{CoVaR}_{i}^{\text{sys|i}} \) is the systemic risk of the \( j \)th financial industry at date \( t \).

3.2.2. Construction of network public opinion index

Recently, scholars mainly use crawler technology to crawl information from related websites (such as Weibo, Stock Bar, Twitter, etc.) to build a network public opinion index. This article mainly constructs the public opinion index by crawling the comment data of the stock bar\(^2\) through the web crawler technology, mainly for the following reasons: First, the research object selected by the author is the Chinese financial market. The platform for investors to express their opinions on the Chinese market is mainly financial websites such as stock bars. In addition, the stock bar section is also rich, which can provide users with a lot of financial market dynamics. Therefore, investors in the Chinese financial market are more inclined to use the stock bar platform to express their views and opinions on certain financial institutions. Second, due to policy reasons, there will be permission problems for Chinese users to register for Twitter accounts that cannot be registered. In addition, the anti-crawler settings of the stock bar are also relatively loose. Therefore, considering the availability and comprehensiveness of information obtained by the website, the author chooses the stock bar for data collection. Third, the collection of public opinions can usually be obtained through crawler software or by writing code. However, when using crawler software to obtain information, more functions need to be recharged, and the collection cost is high. Therefore, the author writes a program through python software to crawl the web to collect comments from the masses. Finally, this article collects nearly 1.5 million stock comment data for 45 listed financial institutions from January 2019 to November 2020 through web crawler technology. The data include information such as post title, clicks, the number of replies, posting usernames, post contents, etc. Then the collected comment data were classified and processed by deleting advertising posts, removing repeated sentences and words, organizing financial sentiment.

\(^2\) https://guba.eastmoney.com/
vocabulary, and removing stop words. Next, according to the collated financial sentiment vocabulary, network public opinion is divided into positive, neutral, and negative public sentiment, respectively. To read: Next, the processed comment data is segmented by supervised machine learning. On this basis, the sentiment dictionary construction method and machine learning method are used to classify its sentiment, that is, the network public opinion is divided into positive, neutral, and negative public sentiment, respectively. The number of positive, negative, and neutral words are calculated on the stock bar comment data after information classification. Each positive, negative, and neutral emotional word is assigned a value of 1, -1, and 0, respectively. In addition, if there is a positive word before the emotional word, the emotional tendency will change and the weight is set to -1; for degree adverbs such as “too” and “incomparable”, the weight is set to 2; and for degree adverbs such as “mere” and “a little bit”, the weight is set to 0.5. Then, the network public opinion index of each financial institution is defined as

\[ NPO_{i,t} = M_{i,t}^{pos} + M_{i,t}^{neg} + M_{i,t}^{neu}, \quad 1 \leq i \leq N_j, \quad j \in \{1, 2, 3\}, \quad t \in T, \]

where

\[ M_{i,t}^c = \sum_{k \in K} \omega_{i,k} x_{i,k} \]

represents the sum of the weighted number of stock bar reviews of type \( c \in \{\text{pos, neu, neg}\} \) on date \( t \), where \( \text{pos, neu, neg} \) represent positive, neutral and negative words, respectively. \( \omega_{i,k} \) represents the positive, neutral, and negative words of each review, \( x_{i,k} \) represents the weight of each comment, \( T \) is the set of dates for the entire sample period, \( K \) represents the total number of comments on date \( t \), and \( k \) stands for each comment on date \( t \). Finally, the market values of financial institutions are used to define the network public opinion index of the financial industry \( j \) on date \( t \):

\[ NPO_{j,t} = \frac{\sum_{i=1}^{N_j} m v_{i,t}^{j} NPO_{i,t}}{\sum_{i=1}^{N_j} m v_{i,t}^{j}}, \quad j = 1, 2, 3. \]

4. Empirical analysis

In this section, we analyze the pandemic’s impact on the systemic risks of the banking, securities, and insurance industries of the horizontal, trend, and public opinion effects with selected sample data.

4.1. Data

To fully reflect the systemic risk of the financial industry, and to analyze the horizontal effect, trend effect, and public opinion effect, we select 45 listed companies from the banking, securities, and insurance industries as samples (including 16 banking institutions, 25 securities institutions, and 4 insurance institutions). The sample interval of time is from January 2, 2019, to November 30, 2020, and the index corresponding to each of the three financial industries is used to calculate the systemic risk value of each industry. The data of closing prices and market values of financial institutions come from the China Stock Market & Accounting Research (CSMAR) database, while those for the treasury bonds, corporate bonds, CSI 300 Bank Index, CSI 300 Capital Index, and CSI 300 Insurance Index come from the Wind database. The computations involved in this study were carried out with R, and the network public opinion index was obtained through web crawlers and text analysis using Python. Detailed sources for each specific variable used in our estimation are given in Table 1. Due to space limitations, the data are not included in the article.

The descriptive statistical results of the explanatory variables used in calculating the systemic risk value of various industries are shown in Table 2.

4.2. Empirical analysis

In the empirical analysis, we first analyze the systemic risk trends of the banking, securities, and insurance industries, and then construct dummy variables of 6 days \( (6 \leq s \leq 46) \) before and after the outbreak of COVID-19 to further analyze the horizontal, trend and public opinion effects of systemic risk.

4.2.1. Systemic risk trend analysis

According to the calculation of systemic risk described above, the trend chart of systemic risk value of various industries can be obtained and is given in Fig. 1.

The following conclusions can be drawn from Fig. 1: after the outbreak of COVID-19, the systemic risk levels of the three financial industries increased, which is specifically manifested is that during the occurrence of the COVID-19 (the period between the lockdown of Wuhan and the reopening of Wuhan), the average of systemic risk values of the banking, securities, and insurance industries is higher than the overall sample average. The occurrence of COVID-19 has changed the trend of systemic risk values in the banking, securities, and insurance industries over time. The specific manifestation is that the systemic risk values of banking, insurance, and securities industries during the 46 days before the lockdown of Wuhan are relatively flat (black x’s shown in Fig. 1), but these values during the 46 days after the lockdown of Wuhan...
and control policy can only suppress the occurrence of systemic financial risks as much as possible, and will not eliminate banks and securities have been suppressed to a certain extent. However, the promulgation of epidemic prevention and control measures has led to great volatility in the systemic financial risk levels of the insurance industry. The systemic financial risk value of the insurance industry will face greater volatility after the pandemic, as the demand for insurance in high-risk positions will become higher, which will stimulate the demand for insurance products. In addition, with the further advancement of the resumption of work and production, purchases will increase, and many insurance companies will also include COVID-19 epidemic in the insurance liability of insurance products. Therefore, during this period, the general public demand for the systemic risk of the financial system will be larger and the fluctuations will be small. Therefore, during the pandemic, the systemic financial risk value of the insurance industry does not fluctuate too much. As the pandemic eases, the demand for insurance purchases will increase, and many insurance companies will also include the COVID-19 epidemic in the insurance liability of insurance products. In addition, with the further advancement of the resumption of work and production, the demand for insurance in high-risk positions will become higher, which will stimulate the demand for insurance products. The systemic financial risk value of the insurance industry will face greater volatility after the pandemic. Banks and securities have higher systemic financial risk values in the early stages of the pandemic. This may be due to the limit of thousands of stocks in the stock markets of China on February 3, 2020, and the stock markets are facing huge turbulence. Therefore, the systemic financial risk value of the banking and securities industries is relatively high. Since then, due to the promulgation of epidemic prevention and control measures, the systemic financial risk levels of banks and securities have been suppressed to a certain extent. However, the promulgation of the epidemic prevention and control policy can only suppress the occurrence of systemic financial risks as much as possible, and will not eliminate

**Table 1**

| Variable                          | Name                                | Calculation                                                                 | Sources  |
|-----------------------------------|-------------------------------------|-----------------------------------------------------------------------------|----------|
| $\Delta\text{CoVaR}_t^{yi}$      | Systemic risk of the $i$th financial institution at date $t$ | From Eq. (12)                                                              | Estimated |
| $R_i^t$                           | Daily rate of return of each financial institution | $R_i^t = \ln(P_i^t) - \ln(P_{i-1}^t)$                                      | CSMAR    |
| $\text{Vol}_i$                    | Stock market volatility             | $\text{Vol}_i = \alpha_1 \text{Vol}_{i-1} + \beta \text{Vol}_{i-1}^2 + \epsilon_i$ | Estimated |
| $R_{c_i}^t$                       | Stock market return (CSI 300 Index) | $R_{c_i}^t = \ln(P_{c_i}^t) - \ln(P_{c_i-1}^t)$                           | CSMAR    |
| $\text{Risk}_i$                   | Month-on-month credit risk          | $\text{Risk}_i = (R_{c_i}^{AAA}) - (R_{c_i}^{AA}) - (R_{c_i}^{A}) - (R_{c_i}^{BBB})$ | Wind     |
| $\text{R}_0$                      | month-on-month change in the three-month yield to treasury bond | $\text{R}_0 = \text{R}_{c_i}^{AAA} - \text{R}_{c_i}^{AA}$                   | Wind     |
| $T_S$                             | month-on-month spread of the maturity spread | $T_S = \text{R}_{c_i}^{AAA} - \text{R}_{c_i}^{AA}$                         | Wind     |
| $\Delta\text{CoVaR}_t^{yi,i}$    | Systemic risk of the $i$th financial institution at date $t$ | From Eq. (11)                                                              | Estimated |
| $m_{i/1,t}$                       | Market value of each financial institution | From Eq. (13)                                                             | Estimated |
| $NPO_{i,t}$                       | Network public opinion of each financial institution | From Eq. (14)                                                             | Estimated |

Note: AAA1y represents the 1-year maturity of AAA corporate bond, tb3 m represents the 3-month maturity of treasury bond, tb1y represents the 1-year maturity of treasury bond, $P_{c_i}^{yi}$ including closing prices of CSI 300 Bank Index, CSI 300 Capital Index, and CSI 300 Insurance Index.

**Table 2**

| Variable name | Calculation | Sources |
|---------------|-------------|---------|
| $R_{c_i}^t$   | $\ln(P_{c_i}^t) - \ln(P_{c_i-1}^t)$ | CSMAR    |
| $\text{Vol}_i$ | $\alpha_1 \text{Vol}_{i-1} + \beta \text{Vol}_{i-1}^2 + \epsilon_i$ | Estimated |
| $\text{Risk}_i$ | $(R_{c_i}^{AAA}) - (R_{c_i}^{AA}) - (R_{c_i}^{A}) - (R_{c_i}^{BBB})$ | Wind     |
| $\text{R}_0$   | $\text{R}_{c_i}^{AAA} - \text{R}_{c_i}^{AA}$ | Wind     |
| $T_S$          | $\text{R}_{c_i}^{AAA} - \text{R}_{c_i}^{AA}$ | Wind     |
| $m_{i/1,t}$    | $\ln(P_{c_i}^{yi}) - \ln(P_{c_i-1}^{yi})$ | Wind     |
| $NPO_{i,t}$    | From Eq. (13) | Estimated |

**Table 3**

| Variable name | Min   | Max    | Mean   | Std    |
|---------------|-------|--------|--------|--------|
| $R_{c_i}^t$   | -0.0821 | 0.0578 | 0.0009 | 0.0135 |
| $\text{Vol}_i$ | 0.0076 | 0.0350 | 0.0133 | 0.0047 |
| $\text{Risk}_i$ | -1.6463 | 16.3810 | 0.0908 | 0.9511 |
| $\text{R}_0$   | -0.01853 | 0.1846 | -0.0004 | 0.0337 |
| $T_S$          | -0.01958 | 0.2430 | 0.0002 | 0.0581 |
| $m_{i/1,t}$    | 574.1147 | 693.8675 | 638.0660 | 29.0663 |
| $NPO_{i,t}$    | 127.6323 | 188.4233 | 157.0937 | 11.5179 |
| $R_{c_i}^{yi}$ | 125.1720 | 205.1472 | 177.3870 | 17.9209 |

show an upward trend and are higher than those during the 46 days before the lockdown of Wuhan (black dots shown in Fig. 1). COVID-19 has increased systemic risk fluctuations in the banking, securities, and insurance industries. The specific manifestation is that after the lockdown of Wuhan, the systemic risk observations of the banking, securities, and insurance industries exceeded the sample observation period by 5% and 95% is more than before the lockdown of Wuhan.

In addition, according to Fig. 1, we can also find that during the COVID-19 pandemic period considered, the systemic risk trends of the banking, securities, and insurance industries are different. One of the possible reasons is that after the outbreak, the state has repeatedly issued epidemic medical protection measures to ensure that the medical expenses of confirmed and suspected patients are paid by the state. Therefore, during this period, the general public demand for the insurance industry will decrease and the fluctuations will be small. Therefore, during the pandemic, the systemic financial risk value of the insurance industry does not fluctuate too much. As the pandemic eases, the demand for insurance purchases will increase, and many insurance companies will also include the COVID-19 epidemic in the insurance liability of insurance products. In addition, with the further advancement of the resumption of work and production, the demand for insurance in high-risk positions will become higher, which will stimulate the demand for insurance products. The systemic financial risk value of the insurance industry will face greater volatility after the pandemic. Banks and securities have higher systemic financial risk values in the early stages of the pandemic. This may be due to the limit of thousands of stocks in the stock markets of China on February 3, 2020, and the stock markets are facing huge turbulence. Therefore, the systemic financial risk value of the banking and securities industries is relatively high. Since then, due to the promulgation of epidemic prevention and control measures, the systemic financial risk levels of banks and securities have been suppressed to a certain extent. However, the promulgation of the epidemic prevention and control policy can only suppress the occurrence of systemic financial risks as much as possible, and will not eliminate
the potential systemic financial risks of the financial industries. Therefore, when the epidemic is alleviated, the financial industry will not only face the market itself but also the lagging impact of the epidemic. Thus, the systemic financial risk fluctuations in the financial industry after reopening will be greater than during the pandemic lockdown.

According to Fig. 1, we can intuitively observe the change in the trend of the systemic risk value of various financial industries before and after the occurrence of COVID-19. However, Fig. 1 cannot precisely quantify the impact of the COVID-19 epidemic on the systemic risk of various financial industries. This is because Fig. 1 cannot digitally reflect the impact of this pandemic on systemic risks (the horizontal, the trend, and the public opinion effects), so further empirical analysis is needed with the help of Eqs. (1), (2) and (3).

4.2.2. Analysis of the horizontal effect of systemic risk

The analysis of the horizontal effect is obtained by regressing the dummy variables $D_{-s}$ and $D_s$ before and after the occurrence of the COVID-19 pandemic, that is, $\phi_j$ and $\varphi_j$ in Eq. (1). Moreover, it also shows the change in the average risk
such as working from home for employees. The government allocated funds for epidemic prevention and control, and many companies changed their office methods, local governments introduced the highest class of emergency response policies. The Ministry of Finance of the central government emphasized the impact on the systemic risk of various financial industries. This might be because, after the lockdown of Wuhan, various local governments introduced the highest class of emergency response policies. The Ministry of Finance of the central government allocated funds for epidemic prevention and control, and many companies changed their office methods, such as working from home for employees.

Table 3

| s | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 6 | 1.63*** | 1.59*** | 1.54*** | 1.47*** | 1.43*** | 1.34*** | 1.28*** | 1.18*** | 1.13*** | 1.07*** | 0.98*** | 0.91*** | 0.87*** | 0.84*** |
| 7 | 0.26 | 0.24 | 0.31 | 0.30 | 0.35 | 0.31 | 0.37 | 0.33 | 0.34 | 0.38 | 0.39 | 0.45 | 0.51* | 0.51** |
| 8 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 |
| 9 | −0.91*** | −0.87*** | −0.86*** | −0.84*** | −0.80*** | −0.81*** | −0.80*** | −0.84*** | −0.86*** | −0.87*** | −0.92*** | −0.93*** | −0.94*** | −0.94*** |
| 10 | 0.54*** | 0.52** | 0.52*** | 0.52*** | 0.50*** | 0.51*** | 0.53*** | 0.54*** | 0.55*** | 0.55*** | 0.55*** | 0.56*** | 0.56*** | 0.56*** |
| 11 | −0.95*** | −0.93*** | −0.96*** | −0.95*** | −0.94*** | −0.95*** | −0.96*** | −0.96*** | −0.92*** | −0.89*** | −0.87 | −0.81 | |
| 12 | 0.56*** | 0.56*** | 0.55*** | 0.56*** | 0.55*** | 0.55*** | 0.54*** | 0.54*** | 0.54*** | 0.54*** | 0.53*** | 0.53 | 0.54 | |

Note: *** means significant at the level of 0.01, ** means significant at the level of 0.05, and * means significant at the level of 0.1.

Fig. 2. The effect of systemic risk level in various financial industries, where the negative abscissa represents the result of $\phi_j$, and the positive represents the result of $\phi_i$.

of each financial industry relative to the average of the overall sample before the outbreak. The calculation results of the horizontal effect of systemic risk in each financial industry are shown in Table 2.

It can be seen from Table 2 that after the outbreak of the COVID-19, the values of the regression coefficient $\phi_j$ of the banking and securities were all significantly negative, and the values of the regression coefficient $\phi_i$ of the insurance industry were negative but not significant, while the values of the regression coefficient $\phi_j$ for the securities industry were significantly positive at the level of 10% before the outbreak of the COVID-19 (from 7 days before the lockdown of Wuhan in the first 46 days). Moreover, the values of $\phi_j$ of the insurance industry were significantly positive at the 10% level (the first 18 days to 46 days before the lockdown of Wuhan). According to the definition of horizontal effect ($\phi_j$ is significantly greater than 0), there is no horizontal effect for the systemic risks of various financial industries after the outbreak of COVID-19. The trend of systemic risk horizontal effects in various industries is shown in Fig. 2.

Results presented in Table 2 and Fig. 2 show that after the outbreak of COVID-19, its impact does not have a horizontal effect on the systemic risks of various financial industries. This might be because, after the lockdown of Wuhan, various local governments introduced the highest class of emergency response policies. The Ministry of Finance of the central government allocated funds for epidemic prevention and control, and many companies changed their office methods, such as working from home for employees.
The systemic risk of the banking and securities industries after the COVID-19 were greater than those before the outbreak. According to the graph on the right side of Fig. 3, the following two conclusions can be drawn:

1. A significantly greater than those before the outbreak; that is, the banking and securities industries have a trend effect.
2. The trend effect can be obtained as shown in Fig. 3.

According to the calculation results given in Table 4, the trend effect of systemic risks in various financial industries can be obtained as shown in Fig. 3.

The left side of Fig. 3 shows the regression coefficients $\theta_j$ of COVID-19 on the systemic risk level of various financial industries. According to the graph on the left side of Fig. 3, it can be found that the regression coefficients of the banking and securities industries after the outbreak of the pandemic are significantly greater than those before the outbreak; that is, the banking and securities industries have a trend effect. According to the graph on the right side of Fig. 3, the following two conclusions can be drawn:

First, COVID-19 has had a significant positive trend effect on the systemic risks of the banking and securities industries; the systemic risks of the banking and securities industries after the COVID-19 were greater than those before the outbreak.

### Table 4

Analysis of the effect of systemic risk trends in various financial industries ($\times 10^{-5}$).

|          | Banking Industry |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
|----------|------------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
|          | $s$              | $\theta_1$| $\theta_2$| $\theta_3$| $\theta_4$| $\theta_5$| $\theta_6$| $\theta_7$| $\theta_8$| $\theta_9$| $\theta_{10}$| $\theta_{11}$| $\theta_{12}$| $\theta_{13}$| $\theta_{14}$| $\theta_{15}$| $\theta_{16}$| $\theta_{17}$| $\theta_{18}$| $\theta_{19}$| $\theta_{20}$| $\theta_{21}$| $\theta_{22}$| $\theta_{23}$| $\theta_{24}$|
| $s$      | 6                | −8.30    | −2.08    | 1.00     | 5.60     | 6.63     | 9.13     | 7.75     | 8.44     | 10.75    | 10.35    | 9.68     | 10.23    | 10.17    | 10.59    | 10.09    | 10.06    | 9.86     | 10.06    | 9.86     | 10.06    | 9.86     | 10.06    |
|          | 7                |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | 8                |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | 9                |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | 10               |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | 11               |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | 12               |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | 13               |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | 14               |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | 15               |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | 16               |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | 17               |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | 18               |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | 19               |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |

Fig. 3. The effect of systemic risk trends in various financial industries. The left figure shows the results of $\rho_j$ and $\theta_j$, where the negative abscissa represents the result of $\rho_j$, and the positive represents the result of $\theta_j$. The right figure shows the results of $(\theta_j - \rho_j)$.

4.2.3. Analysis of the trend effect of systemic risk

To analyze the trend effect, time variable and the cross term of time variable and dummy variables are introduced, and the trend effect is empirically analyzed through basic regression (Eq. (2)). The size of the trend effect is represented by $(\theta_j - \rho_j)$, where $\theta_j$ and $\rho_j$ represent the regression coefficients of the cross term of $D_j$ & time variable $t$, the cross term of $D_{j-1}$ & the time variable $t$, respectively. The calculation results are shown in Table 3.

According to the calculation results in Table 3, the regression coefficient $D_{j-1}$ of the dummy variable $\rho_j$ of banks, securities, and insurance and the time variable is not significant, and the regression coefficient $\theta_j$ of the banking industry is from the 14th to the 28th day after the lockdown of Wuhan significantly greater than 0. The regression coefficient $\theta_j$ of the securities industry is significantly greater than 0 from the 8th to the 32nd day after the lockdown of Wuhan, which shows that the systemic risks of the banking and securities industries have shown a significant increase during this period after the outbreak of the pandemic $(\theta_j > 0)$, but the insurance industry does not follow this trend. According to the calculation results given in Table 4, the trend effect of systemic risks in various financial industries can be obtained as shown in Fig. 3.

The left side of Fig. 3 shows the regression coefficients $\rho_j$ and $\theta_j$, and the right side shows the trend effect $(\theta_j - \rho_j)$ of COVID-19 on the systemic risk level of various financial industries. According to the graph on the left side of Fig. 3, it can be found that the regression coefficients of the banking and securities industries after the outbreak of the pandemic are significantly greater than those before the outbreak; that is, the banking and securities industries have a trend effect. According to the graph on the right side of Fig. 3, the following two conclusions can be drawn:

First, COVID-19 has had a significant positive trend effect on the systemic risks of the banking and securities industries; the systemic risks of the banking and securities industries after the COVID-19 were greater than those before the outbreak.
In addition, the \((\delta_j - \rho_j)\) values of the banking and securities industries reached their peaks for some time after the outbreak of the pandemic and then began to gradually decline, indicating that the trend effect of the banking and securities industries has a trend of rising first and then falling. However, their impact will gradually weaken and these two industries will have the ability to gradually absorb the impact of this external shock (even if it takes a long time). From the results listed in Table 4, we can see that the banking and securities industries did not have a significant value of \(\delta_j\) greater than 0 on the 29th and 33rd days after the lockdown of Wuhan, respectively. From the graph on the right side of Fig. 3, it can be seen that the values of \((\delta_j - \rho_j)\) have flattened out since then. This shows that the trend of systemic risks in the banking and securities industries over time after this is not much different from that before the outbreak. This also supports that these two financial industries are capable of digesting the impact of COVID-19. The reason for the absence of trend effect in the insurance industry maybe because, after the outbreak, the Ministry of Finance of the central government frequently issued epidemic prevention and control funds, and all sectors of society have also donated money and materials to actively respond to the epidemic. This has reduced the pressure on the insurance industry to a certain extent, allowing it to be unaffected by the epidemic.

Second, there are two differences in the trend effect between the banking and the securities industries. The first one is the difference in size. According to Fig. 3, it is evident that the trend effect of the securities industry is much higher than that of the banking industry. The second one is that the significance level of the trend effect is different, and the significance level of the securities industry is higher than that of the banking industry. Therefore, it can be seen that the banking industry is more stable than the securities industry when facing external shocks, that is, the ability of the banking industry to face external shocks is stronger than that of the securities industry.

### 4.2.4. Analysis of the public opinion effect of systemic risk

To analyze the public opinion effect, we introduce the cross term of the network public opinion index and the dummy variables.

According to the calculation results in Table 5, the regression coefficient \(\kappa_j\) of the banking and securities industries after the outbreak is significantly greater than 0 and greater than the regression coefficient \(\theta_j\) before the outbreak, while the regression coefficient of the insurance industry after the 10th day after the outbreak significantly greater than 0. However, the regression coefficient \(\kappa_j\) from the 17th day to the 32nd day is less than the regression coefficient \(\theta_j\), and then the reversal begins. According to the results given in Table 4, the trend of public opinion effects on the three financial industries is shown in Fig. 4.

The left picture of Fig. 4 shows the regression coefficients \(\theta_j\) and \(\kappa_j\), and the right picture shows the size of the public opinion effect (\(\kappa_j - \theta_j\)) of each financial industry. According to the left chart of Fig. 4, it can be observed that the regression coefficients of the banking and securities industries after the outbreak are significantly greater than those before the outbreak, while the insurance industry does not reflect this trend. The figure on the right of Fig. 4 shows the effect of public opinion in various financial industries. According to Fig. 4, the following two conclusions can be drawn: after the outbreak of the COVID-19, both the banking and securities industries have public opinion effects, and the public opinion
Fig. 4. The public opinion effect of systemic risks in various financial industries. The left figure shows the results of \( \theta_j \) and \( \kappa_j \), where the negative abscissa represents the result of \( \theta_j \), and the positive represents the result of \( \kappa_j \). The right figure shows the results of \( (\kappa_j - \theta_j) \).

...effects reach the largest at the initial moment (the 6th day). Since then, the public opinion effect has gradually weakened. This may be due to the stage victory of the COVID-19 control and the public’s panic about the financial market weakened.

However, there is no public opinion effect on the insurance industry after the outbreak. This may be because the public’s attention to the insurance industry is not as high as that of the banking and securities industries. Therefore, the public opinion of the insurance industry is not as high as that of the banking and securities industries; in addition, the implementation of several policies has eased people’s panic and eased the pressure on the insurance industry, which made the insurance industry less affected by public opinion.

According to the right figure of Fig. 4, it can be seen that the sizes of the public opinion effects in the three financial industries are different. The public opinion effect of the securities industry is the largest, followed by the banking industry, and finally the insurance industry.

4.2.5. Robustness test

To illustrate the robustness of the above empirical results, this paper conducts the following robustness tests. (1) Change the 95% quantile of Calculation \( \Delta CoVaR^{sys}_{jt} \) to the 90% quantile to conduct robustness tests on the horizontal, trend and public opinion effects of each financial industry \( \Delta CoVaR^{sys}_{jt} \). (2) The sample period was shortened from January 2019–November 2020 to January 2019–June 2020 to test the robustness of the empirical results. The calculation results are shown in Figs. 5 and 6.

When calculating systematic risk, Figs. 5 and 6 show the results of changing the confidence level and shortening the sample interval, respectively; wherein both figures, Parts a, b and c represent the horizontal effect, the trend effect, and the public opinion effect, respectively. Comparing Fig. 5(a) and Fig. 6(a) with Fig. 2, the regression results of changing the confidence level for calculating systematic risk and shortening the sample interval are roughly the same as the results of the 95% confidence level, and there is no horizontal effect. Comparing Figs. 5(b) and 6(b) with the right panel of Fig. 3, it is found that whether the confidence level is changed or the sample interval is shortened, there is no trend effect in the insurance industry, while there is a significant positive trend effect in the banking and securities industries. Comparing Fig. 5(c), Fig. 6(c), and the right figure of Fig. 4, it is found that the banking and securities industries have sustained public opinion effects from the 6th day, while the insurance industry has no public opinion effect, which is different from the 95% quantile level (the right side of Fig. 4). Figure came to the same conclusion. To sum up, the results show that the empirical results are robust.

5. Conclusions

In this paper, we take the occurrence of COVID-19 as an impact event and use an improved event study method to analyze the impact of COVID-19 on the systemic risks of the three financial industries and to depict the horizontal, trend, and public opinion effects of the COVID-19 on the systemic risks of the financial industries. We can at least draw the following conclusions based on our current study.

First, COVID-19 will increase the level of systemic risk and volatility in the financial industries. After the outbreak of COVID-19, the average systemic risks of the banking, securities, and insurance industries are higher than those during the overall sample average. There are more cases of the systemic risk value of each financial industry after the outbreak that exceeds the interval of 5% and 95% quantiles after the outbreak than before the outbreak.

Second, after the outbreak of COVID-19, there is no horizontal effect in all financial industries; that is, although the systemic risk value of each financial industry after the outbreak is higher than that of the overall sample average, this situation is not significant. This may be because the trend effect lasts for a long time.

Third, after the outbreak of COVID-19, the systemic risks of the banking and securities industries have a significant positive trend effect and last a long time. Although the insurance industry does not show a trend effect, it is necessary to...
strengthen the risk supervision of the insurance industry. The reason for strengthening supervision is that the financial industries are correlated, and systemic risks are easily contagious among financial institutions.

Fourth, after the outbreak of COVID-19, both the banking and securities industries have had a long-term public opinion effect, and the public opinion effect has gradually weakened, while the insurance industry has no public opinion effect. It
Fig. 6. Robustness test — shortening the sample interval.
may be due to the low public interest in the insurance industry and the promulgation of pandemic prevention and control measures that have caused no public opinion effect in the insurance industry.

Fifth, from the perspective of the trend effect, the banking industry is more stable than the securities industry in the face of external shocks. Specifically, the level of trend effect and the level of significance of the trend effect of the banking industry after the outbreak of COVID-19 are lower than those of the securities industry. This shows that the banking industry is more stable than the securities industry in the face of external shocks.

**CRediT authorship contribution statement**

**Zisheng Ouyang:** Research logic, Result analysis. **Shili Chen:** Data collection, Sorting, Model calculation, Writing – original draft. **Yongzeng Lai:** Writing – review & editing. **Xite Yang:** Calculation, Sorting of network public opinion data.

**Acknowledgments**

This research was supported partially by the National Social Science Foundation of China (No. 21ATJ009) and the Natural Science & Engineering Research Council (NSERC) of Canada (RGPIN-2019-05906).

**References**

[1] L. Alfaro, A. Chari, A.N. Greenland, P.K. Schott, Aggregate and Firm-Level Stock Returns During Pandemics, in: Real-Time, NBER Working Papers, 2020, http://dx.doi.org/10.3386/w26950.

[2] M.S. Rizwan, G. Ahmad, D. Ashraf, Systemic risk: The impact of COVID-19, Finance Res. Lett. (2020) 101682, http://dx.doi.org/10.1016/j.frl.2020.101682.

[3] R. Greenwood, A. Landier, D. Thesmar, Vulnerable banks, J. Financ. Econ. (3) (2015) 471–485, http://dx.doi.org/10.1016/j.jfineco.2014.11.006.

[4] A. Tversky, D. Kahneman, Prospect theory: An analysis of decision under risk, Econometrica 47 (2) (1979) 263–291, http://dx.doi.org/10.1142/97898144173580006.

[5] H.Y. Yang, K.H. Chen, A general equilibrium analysis of the economic impact of a tourism crisis: a case study of the SARS epidemic in Taiwan, J. Policy Res. Tourism Leisure Events 1 (1) (2009) 37–60, http://dx.doi.org/10.1080/19404960902738313.

[6] A.W. Bartik, M. Bertrand, Z.B. Cullen, E.L. Glaeser, M. Luca, C.T. Stanton, How are Small Businesses Adjusting to COVID-19? Early Evidence from a Survey, NBER Working Papers, 2020, http://dx.doi.org/10.3386/w26989.

[7] M.S. Rizwan, G. Ahmad, D. Ashraf, Systemic risk contagion between energy and stock markets and their implications in the context of COVID-19, Int. Rev. Financ. Anal. (2021) 101828, http://dx.doi.org/10.1016/j.irfa.2021.101828.

[8] B. Abuzayed, E. Bouri, N. Al-Fayoumi, N. Jalik, Systemic risk spillover across global and country stock markets during the COVID-19 pandemic, Econ. Anal. Policy 71 (14) (2021) 180–197, http://dx.doi.org/10.1016/j.eap.2021.04.010.

[9] D. Wang, P. Li, L. Huang, Volatility Spillovers Between Major International Financial Markets During the Covid-19 Pandemic, 2020, http://dx.doi.org/10.2139/ssrn.364946, Available at SSRN 364946.

[10] Y. Lai, Y. Hu, A study of systemic risk of global stock markets under COVID-19 based on complex financial networks, Physica A 566 (2021) 125613, http://dx.doi.org/10.1016/j.physa.2020.125613.

[11] D. Zhang, M. Hu, Q. Ji, Financial markets under the global pandemic of COVID-19, Physica A 566 (2021) 125613, http://dx.doi.org/10.1016/j.physa.2020.125613.

[12] G. Kaplaniski, H. Levy, Sentiment and stock prices: The case of aviation disasters, J. Financ. Econ. 95 (2) (2010) 174–201, http://dx.doi.org/10.1016/j.jfineco.2009.10.002.

[13] P.O. Gourinchas, M. Obstfeld, Stories of the twentieth century for the twenty-first, Am. Econ. J. Macroecon. (1) (2012) 226–265, http://dx.doi.org/10.1257/mac.1.1.226.

[14] M. Schularick, A.M. Taylor, Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008, Am. Econ. Rev. 102 (2) (2012) 1029–1061, http://dx.doi.org/10.1257/aer.102.2.1029.

[15] J.B. De Long, A. Shleifer, E. Slovak, Noise traders and risk in financial markets, J. Polit. Econ. 98 (4) (1990) 703–738, http://dx.doi.org/10.1086/261456, 9789814417358006.