Mathematical Biosciences and Engineering

MBE, 20(1): 1229–1250.
DOI: 10.3934/mbe.2023056
Received: 02 June 2022
Revised: 26 September 2022
Accepted: 16 October 2022
Published: 26 October 2022

http://www.aimspress.com/journal/MBE

Research article

Visual analysis of social events and stock market volatility in China and the USA during the pandemic

Xiao Ren[1], Jie Hua[1,*], Xin Chi[1] and Yao Tan[2]

[1] Faculty of Information Engineering, Shaoyang University, Shaoyang 422000, China
[2] School of Information, Southwest Petroleum University, Nanchong 637001, China

* **Correspondence:** Email: jie.hua@alumni.uts.edu.au; Tel: +61435425678.

Abstract: The COVID-19 pandemic is one of the most severe infectious diseases in recent decades, and has had a significant impact on the global economy, and the stock market. Most existing studies on stock market volatility during the pandemic have been conducted from a data science perspective, with statistical analysis and mathematical models often revealing the superficial relationship between Covid and the stock market at the data level. In contrast, few studies have explored the relationship between more specialised aspects of the pandemic. Specifically, the relationship found between major social events and the stock market. In this work, a multi-source, data-based relationship analysis method is proposed, that collects historical data on significant social events and related stock data in China and the USA, to further explore the potential correlation between stock market index fluctuations and the impact of social events by analysing cross-timeline data. The results suggest and offer more evidence that social events do indeed impact equity markets, and that the indices in both China and the USA were also affected more by the epidemic in 2020 than in 2021, and these indices became less affected by the epidemic as it became the world adapted. Moreover, these relationships may also be influenced by a variety of other factors not covered in this study. This research, so far, is in its initial stage, and the methodology is not rigorous and cannot be applied as an individual tool for decision; however, it could potentially serve as a supplementary tool and provide a multi-dimensional basis for stock investors and policymakers to make decisions.

Keywords: COVID-19; data analytics; graph drawing; stock market; visual analysis

1. Introduction

In December 2019, the Novel Coronavirus Disease (COVID-19) outbreak caused by SARS-CoV-2 rapidly increased the number of patients infected worldwide [1–3]. Same as the two other coronaviruses that have emerged in the last 18 years-Severe Acute Respiratory Syndrome (SARS) (2002 and 2003) and Middle East Respiratory Syndrome (MERS) (2012-present) - the Covid outbreak poses a severe public challenge [4]. Many countries were forced into social isolation and border closures to fight against the pandemic. Casualties have been inflicted globally in more than two hundred countries and territories [5]. The outbreak has also had far-reaching social consequences caused primarily by isolation, social distancing, and restrictions on social activities. There are also severe effects on global agriculture [6], the environment [7], and public mental health [8,9].

The health crisis has rapidly transformed into an economic crisis. The spread of the virus has caused incalculable economic losses [10] and seriously affected the major stock markets [11]. Considerable losses to the total value of the global economy [12–14], resulting in a dramatic increase in poverty worldwide[15]. To explore these influences, artificial intelligence [16,17], big data [18], communication technologies [19,20], and data visualisation [21] have been applied to Covid-related data research. The combination of data mining and visualisation can reveal insights from pandemic data [22]. Visualisation can also work with machine learning methods to predict future outbreaks of Covid [23,24]. In addition, the bibliometric analysis and visualisation tools can assist in understanding the impacts of Covid on the world [25,26].

Existing studies have focused on three main areas in the epidemic and stock data research. One is to analyse the causes of stock market volatility. There is an analysis of data from the Standard and Poor's (S&P) 1500 in March 2020 to find the causes of the USA stock market crash through examination of the different responses of stock prices to the rapid spread of the coronavirus and the sudden government intervention that triggered the crash [27]. This study is specific to S&P 1500, and is not broad enough to be mapped to other exchanges. A study was conducted to analyse the causes of stock volatility based on factors relating to the outbreak, and these possible impacts on the stock market was investigated using the Maki (2012) cointegration test in conjunction with the daily number of deaths and the Covid cases [28]. Another study discusses the fluctuation of the index in terms of a single factor of infection and death cases, ignoring factors such as government and societal interventions. The short-term impact of Covid on 21 major stock market indices in the main affected countries was compared using an event study methodology, and it concluded that stock markets in those countries and regions fell rapidly following the virus outbreak, and Asian countries experienced more negative abnormal returns than Western countries [29]. However, the period selected for this study is limited and lacks comparability and data integrity. One study investigated the impact of Covid on emerging equity markets between 10/03/2020 and 30/04/2020, analysing equity indices as a function of exchange rates, oil price shocks, and Covid cases. The findings suggest that the negative impact of the pandemic on emerging equity markets has gradually declined and started to taper off by mid-April 2020. By region, emerging markets in Asia were the most affected by the pandemic, and emerging markets in Europe were the least affected. It was also found that official response times and the size of government-provided stimulus packages were important in offsetting the impact of the pandemic [30]. This study was selected from emerging equity markets only and cannot be extended to other equity markets for reference. The third study discusses how stock market volatility affects other regions or countries. Japanese scholars compared the relationship between the Japanese yen and the stock returns, applying several econometric models and empirical specifications. It was found that a depreciation of the yen against the USA dollar leads to higher stock returns in Japan. A one standard deviation depreciation of the yen (equivalent to 0.588%) during the pandemic raised stock market returns by 71% of the average return [31]. The study links the yen's value to the volatility of stocks and fails to capture how the Covid feeds into the stock market.

The related existing studies are usually limited by raw data, such as the dataset's size, and do not cover an extended period, only the impact of the number of confirmed cases and deaths was considered in to study of the stock market data, and they did not examine how relevant pandemic factors have affected the stock market. Few studies have approached it from the perspective of social events and stock index volatility triggered by Covid. Our study aims to further develop the connection between stock index volatility and the pandemic-related social events in China and the USA by analysing representative exchanges in both countries, spanning from 01/01/2020 to 31/12/2021 from a non-economic perspective, and correlating two data sets to discover insights in the data. We also examined the difference and sameness of the stock index volatility in the USA and China. Additionally, this study may serve as a supplement to provide more evidence from a data analysis perspective to existing research in the financial sector.

The hypotheses below were mainly summarised based on relevant literature. The purpose is not to prove but to provide more evidence from a data analysis angle.

H1: There are connections between stock indices and local pandemics in the USA and China.

H2: The stock market index was more severely affected in 2020 than in 2021.

H3: The stock markets in the USA and China were affected by the outbreak during similar periods.

H4: The outbreak affected China's stock market indices more than the USA.

H5: The impact on equity indices in the USA and China will gradually become less severe as the epidemic becomes normalised globally.

H6: The same volatility trend on the respective USA and Chinese exchanges.

H7: The visualisation approach can assist in better understanding related stock market data and pandemic events.

In the following sections: Section 2 provides the sources and processing of the relevant data and describes the experimental procedure; Section 3 presents a general overview of the results, including graphs and statistics; a detailed discussion regarding the observed outcomes and hypotheses is provided in Section 4; and Section 5 summarises our work, its shortcomings, and future research.

2. Materials and methods

We have downloaded and collected two types of raw data, namely, significant Covid-related events, and the stock market index data, from China and the USA, both datasets covering 01/01/2020 to 31/12/2021. This Section covers data collection, data processing, methods applied, and research procedure.

2.1. Data collection

This Subsection introduces major datasets collected, namely, social event data and stock market index data.

1) Public health social event data

This dataset contains significant social events from the pandemic, with a primary scope in the USA and China, including event date, event location, event published date (dd/mm/yyyy format), and the data source. The raw data were collected from various official and certified websites, such as Xinjing News [32], CCTV News [33], Xinhua [34], etc. A total of 383 data entries were collected. For example, events such as “the first Covid death was reported in the USA on 29/02/2020” were collected.

2) Stock market index data

The data in this Section contains two parts: The historical stock data in the USA. This data set involves six major USA exchanges, namely, NYSE Composite (NYA), S&P 500 Index (SPX), Dow Jones Industrial Average (DJI), Russell 2000 Index (RUT), NASDAQ Composite (IXIC), and CBOE Volatility Index (VIX); the historical stock data in China, which includes six representative Chinese exchanges: CSI Smallcap 500 Index (CSI500), Hang Seng Index (HSI), Shanghai Securities Composite Index (SSEC), Shenzhen Component Index (SZI), Taiwan Weighted Index (TWII), and CBOE China ETF Volatility Index (VXFXI). A total of 5,997 data entries were collected in this Section, with each data entry containing opening and closing prices, trading volume and stock gains and losses. The raw data were downloaded from Investment [35]. The date range is from 01/01/2020 to 31/12/2021. Please see below regarding the data sources of each stock index.

- CSI500-https://cn.investing.com/indices/csi1000-historical-data
- DJI-https://cn.investing.com/indices/us-30-historical-data
- HSI-https://cn.investing.com/indices/hang-sen-40-historical-data
- IXIC-https://cn.investing.com/indices/nasdaq-composite-historical-data
- NYA-https://cn.investing.com/indices/nyse-composite-historical-data
- RUT-https://cn.investing.com/indices/russell-2000-nr-historical-data
- SPX-https://cn.investing.com/indices/us-spx-500-historical-data
- SSEC-https://cn.investing.com/indices/shanghai-composite-historical-data
- SZI-https://cn.investing.com/indices/szse-component-historical-data
- TWII-https://cn.investing.com/indices/taiwan-weighted-historical-data
- VIX-https://cn.investing.com/indices/volatility-s-p-500-historical-data
- VXFXI-https://cn.investing.com/indices/cboe-china-etf-volatility-historical-data

2.2. Data processing

Cleaning and formatting of the data need to be completed before starting the experiment. The processing of the USA and Chinese stock data is carried out first. The rate of change of two adjacent dates (only the dates on which that exchange is open. Not all dates in a year) was calculated by creating a set of dates and trading volumes $I = \{i_{d1}, i_{d2}, \ldots, i_{dn}\}$, where d_1, d_2, d_3 to d_n denote the date of the trading day, i_{dn-1} denotes the volume at the close of the previous trading day, i_{dn} denotes the volume at the close of the day and c_n represents the change.

$$c_n = \frac{i_{dn} - i_{dn-i}}{i_{dn}} * 100 \tag{1}$$

The final result is expressed as a percentage, i.e., c_n%. For example, to calculate the rate of change of NYA on 12/03/2020, query the collected datasheet to know that the closing volume on 11/03/2020 is 11,177.30, and then query the closing volume on 12/03/2020 is 10,060.80, brought into the above function, the result is 9.989%, the result retains two decimal places, there are $c_{12/03/2020}$=9.99%. The daily change rates for each exchange are sorted on the basis given above, and the ascending order of the daily change rates for each exchange is obtained by sorting in ascending order. For example, sorting the data for NYA: the most volatile date was 16/03/2020, with a volume of 9,567.50 and volatility of −11.84% when the exchange ended on that day. In this study, we need to screen for dates when there is a significant change in the rate of change on each exchange to investigate whether there is a correlation between the negative social events caused by the epidemic and these dates. For this purpose, the dates with significant changes will be selected. To define "significant" here, we propose the concept of using the relationship with the median value to determine whether it is "significant". The above is done by finding the median value of a set of ascending series $Y = \{y_1, y_2, \ldots, y_n\}$. If n is odd, the median value is at position $(n+1)/2$, i.e., $(y_{n+1})/2$. If n is even, the median value is $(y_{n/2} + y_{(n/2+1)}) / 2$. For clear comparisons, so that the rate of change is greater than a particular value, we have defined a specific set of values $R = \{r_1, r_2, \ldots, r_n\}$. To widen the difference, we have named the "expansion factor" so that $Y(1 \pm R)$ is greater than this particular value. Adding the expansion factor results in an exponentially significant increase, while subtracting the expansion factor results in an exponentially significant decrease. For example, if the median value of the NYA rate of change is 0.13% and the coefficient of expansion is determined to be 17, the part of the rate of change that is less than and greater than 0.13% × (1–17) is what needs to be discussed. The median value and *R-value* obtained are shown in Table 1. Based on the rate of change of the stock index data, data on socially significant events in the relevant period, and adjustments based on actual experiments, we ended up with a collection of around 50 combined data entries with positive and negative sums, i.e., $\{y_1, y_2, \ldots, y_{50}\}$. We then extracted the ones filtered out as negative for each exchange for comparison to see if there were overlapping dates. For a more obvious comparison, there are dates where most exchanges are down, but one or more are down by a smaller amount and will be filtered out of the discussion.

Table 1. Median values and *R-value* of each stock market index.

Stock Market Index	Median Value (%)	*R-Value*
NYA	0.13	17
VIX	1.1	10
DJI	0.1	21
RUT	0.08	35
SPX	0.15	13
IXIC	0.19	13

1) With the above work, we list the dates that match the requirements to get the partial results in Table 2. According to the above method, the magnitude of a particular one or several was small and, therefore, not retained. On this basis, we filtered 15 sets of data with significant volatility and date overlap (i.e., most exchanges show the same ups and downs on the dates that meet the above criteria).

2) In addition, we also use the variance to describe the stability of a data set. This is calculated as follows: there is a set of numbers $\{x_1, x_2, \ldots, x_n\}$, and the mean of this set is M. The variance s^2 can be expressed as (2). In the following, we denote the variance by S. The standard deviation E is also used to indicate the degree of dispersion of a set of data scores; the smaller the standard deviation, the less these values deviate from the mean, and vice versa. This is calculated as (3). In addition, the *P-Value* model was used to indicate the correlation between the distribution of the two sets of data. If P is less than 0.01, the two sets of data are significantly different; if $0.01 < P < 0.05$, the two sets of data

are quite different; if $P > 0.05$, the two sets of data are non-significantly different.

$$s^2 = \frac{(M-x_1)^2+(M-x_2)^2+\cdots+(M-x_n)^2}{n} \tag{2}$$

$$E = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - M)^2} \tag{3}$$

3) Based on the above data, graphs of social events and stock market changes related to the pandemic were generated.

Table 2. Date comparison.

NYA	VIX	DJI	RUT	SPX	IXIC
16/03/2020	13/03/2020	16/03/2020	16/03/2020	16/03/2020	16/03/2020
12/03/2020	28/01/2021	12/03/2020	12/03/2020	12/03/2020	12/03/2020
09/03/2020	14/05/2021	09/03/2020	18/03/2020	09/03/2020	09/03/2020
18/03/2020	04/11/2020	11/06/2020	09/03/2020	11/06/2020	11/06/2020
11/06/2020	02/03/2020	18/03/2020	11/06/2020	18/03/2020	03/09/2020

2.3. Methods

The relevant graph drawing methods are introduced in this Section, as well as the features of the data collected.

1) Feature selection

A stock market index is a market-capitalisation-weighted average of a specific and relatively static list of securities, and it acts as an indicator of time-varying risk versus reward mechanics and as a benchmark for performance evaluation, attribution, and enhancements [36]. We have selected representative exchanges in China and the USA to better reflect local conditions.

Social events and government announcements relating to the COVID-19 outbreak in China and the USA during the outbreak were also collected to measure the impact on the index.

2) Graph visualisation method

In this work, bar graphs, line graphs, area graphs, and stacked bar graphs are applied to present the results of the experiment. The line/bar/stacked chart component is capable of displaying multiple series of data on a chart. Parallel coordinates have been widely used in multivariate data and high-dimensional geometry visualisation; it is equipped to assist in finding differences among the events' impact [37]. Timeline visualisation is an approach used to visualise temporal data; it provides insights into the joint work by presenting all features and relative temporal information, and it reduces crossings and overlaps of saccade lines [38–40]. To provide more detail, Tableau was adopted in experiments for visualisation purposes. Tableau is a powerful tool widely used in data analytics due to its capability to visualisation complex datasets [41,42].

2.4. Procedure

Based on the raw data above, graphs are generated in terms of three characteristics: time, events, and the rate of change of the stock indices. In turn, graphs are generated for each US exchange as a whole, for the USA against one or more Chinese exchanges, and the USA against China, to most directly observe social events and index changes and to gain insight into whether there is some connection between social events in the USA and stock indices. The main processes included in this research work are shown below.

1) Presenting our vision and collecting primary data from various sources.

2) The original data collected is filtered and removed to reduce the impact of irrelevant data on this study.

3) Analysis of key social events.

4) Visualisation methods are used to visualise the data collected, using statistical information visualisation to explore the potential connections.

5) Observe the similarities and differences in each figure and discuss our findings, see if they match existing work and could offer more convincing evidence.

Figure 1 shows the workflow of this research, as well as the purpose, which is to offer evidence to the hypotheses from related existing work.

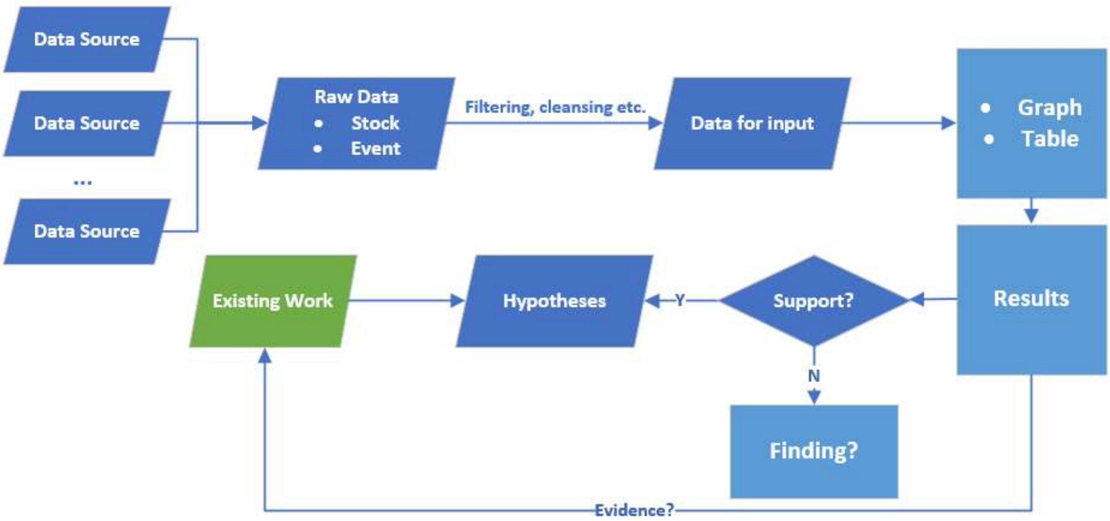


Figure 1. Workflow of this work.

3. Results

We have divided this Section into five subsections, depending on the camp to which they belong, the trend in the size of the fluctuations, etc. Namely, significant overall trend and decline in stock indices in the USA; significant overall trend and decline of stock indices in China; overall performance of China and the USA on the respective dates during the most decline; comparison of the leading exchanges in China and the USA; VIX and VXFXI. Those results are used to validate the hypotheses.

The experiments were processed using the hardware and software below.

- Hardware: Lenovo XiaoXin 310-14IKB, Intel(R) Core (TM) 17-7500UCPU @ 2.70GHz, 4GB ram.
- Software: Windows10 Pro, Tableau Desktop 2021.4, Excel 2016, Google Chrome 104.0.5112.102.

3.1. Significant overall trend and decline in stock indices in the USA

The significant overall trends in the USA are analysed here. In the Materials and Methods section, we extracted 15 sets of data and cross-referenced these 15 sets of data with the collected Covid social events table and found that 11 data entries were able to be matched in terms of dates. The dates corresponding to each event are shown in Table 3. Therefore, it is believed that the filtered dates align with expectations.

Table 3. Selected social events during the outbreak in the USA and China.

Country	Date	Event detail
USA	27/02/2020	The first case reported; A military exercise between the USA and ROK was postponed.
	04/03/2020	153 cases, and California declared a state of emergency.
	09/03/2020	The epidemic reached 34 states, and many parts of the USA were in an emergency.
	11/03/2020	More than 1,000 cases have been diagnosed.
	12/03/2020	Washington announced an emergency; A travel ban on Europe; the CDC director acknowledged "influenza" decedents might acquire new corona pneumonia.
	18/03/2020	The USA – Canada border was closed.
	20/03/2020	California announced the "closure order" of the whole state; The USA announced a suspension of all routine visa services.
	23/03/2020	330,000 confirmed cases worldwide, the WHO stated that Covid was spreading fast.
	27/03/2020	the USA became the largest number of confirmed cases of Covid worldwide.
	11/06/2020	Confirmed Covid cases exceed 2 million in the USA.
China	23/01/2020	Access to Wuhan was suspended; Wuhan lockdown; Construction of Huoshenshan hospital began; The first cases were confirmed in other provinces; Other provinces launched the first-level response to major public health emergencies; Hebei had the first death rate except for Hubei Province;
	03/02/2020	Hubei isolated all suspected cases; Huoshenshan hospital officially delivered; Wuhan Jianfangcang hospital was used to treat patients with mild symptoms;
	28/02/2020	WHO announced that the global risk level should be raised to “very high”; The first case was confirmed in China.
	16/03/2020	The import of external prevention by the National Health Commission (NHC) has become the top priority of epidemic prevention and control in China.
	23/03/2020	Shanghai emergency response level is adjusted to level II response.
	16/07/2020	No cases in Heilongjiang.
	23/07/2020	Dalian tested 190,000 people.
	23/02/2021	NHC stated that there were 22 Covid cases, and 10 cases were from overseas.
	26/07/2021	Further Strengthening the control of traffic and transportation epidemic situations.

Figure 2 shows the volatility of the DJI, IXIC, NYA, RUT, SPX and VIX in the USA over the 15 trading days from 01/01/2020 to 31/12/2021, using the methodology in the Materials and Methods section. A stacked bar chart shows the relationships based on the sequence of events as a timeline. The horizontal axis divides up or down, and the absolute value of the height of the bars corresponding to the different exchanges indicates the magnitude of the fluctuations. It can be clearly seen that the most significant fluctuations were recorded on 16/03/2020.

Excluding the VIX from the above 15 dates in Figure 3, there is some correlation between the trends and magnitudes of volatility in the five exchanges DJI, IXIC, NYA, RUT and SPX for the dates selected. As for the eighth to twelfth dates, the five exchanges have similar trends in index volatility, but there is some variation in the magnitude of the index volatility, with a maximum difference of 0.06 in the eighth to twelfth dates and a maximum difference of 0.03 in the rest of the dates. Figure 4 shows the overall volatility of the six US exchanges, including DJI, IXIC, NYA, RUT, SPX and VIX, on the dates we selected for the experiment in weeks, and it can be clearly seen that the most significant change in volatility is around 03/2020.

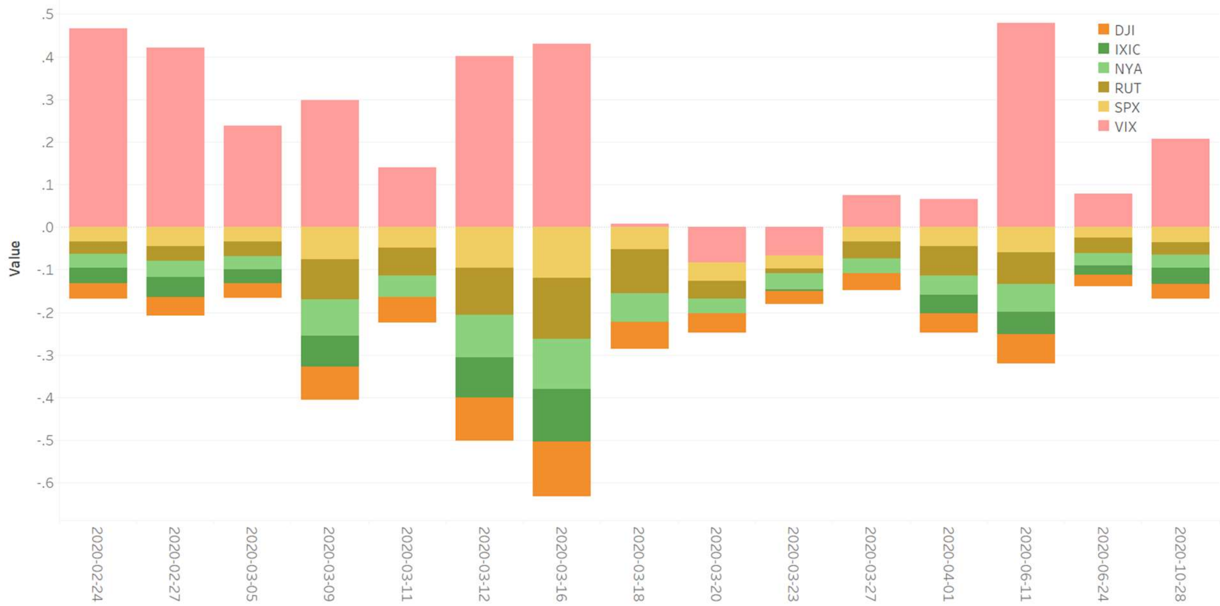


Figure 2. The worst dates of decline in the USA.

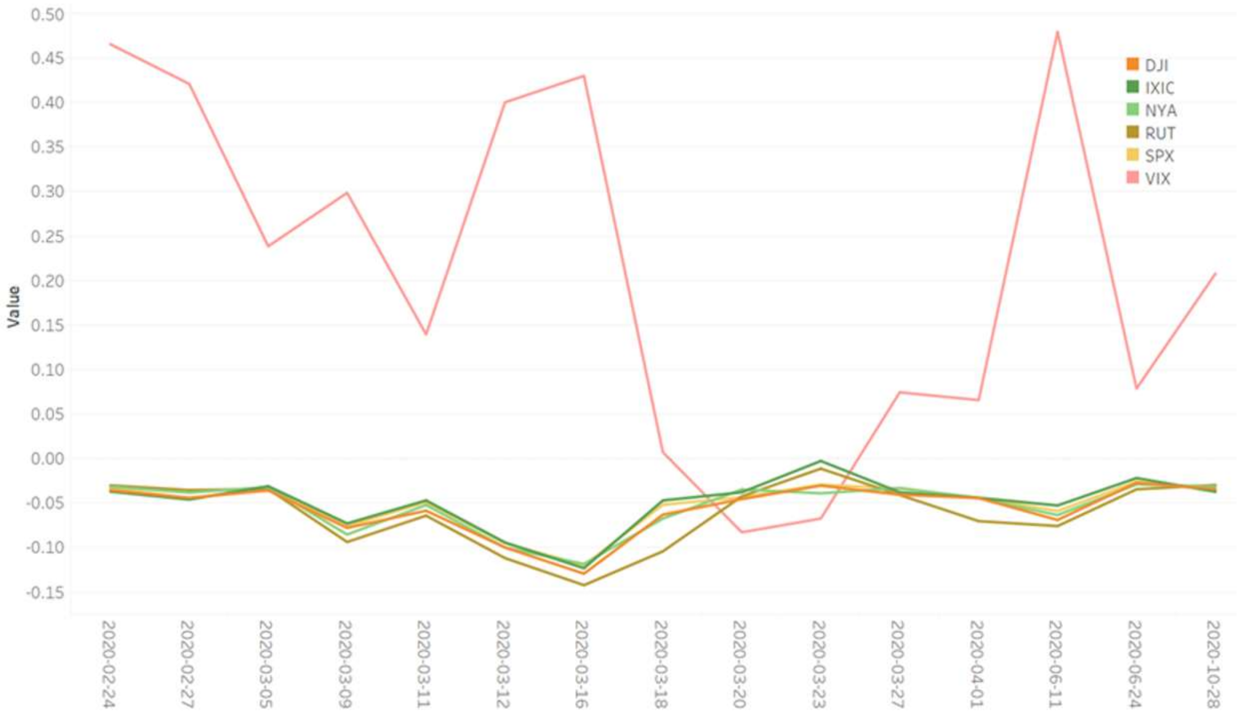


Figure 3. Significant dates of decline in the USA.

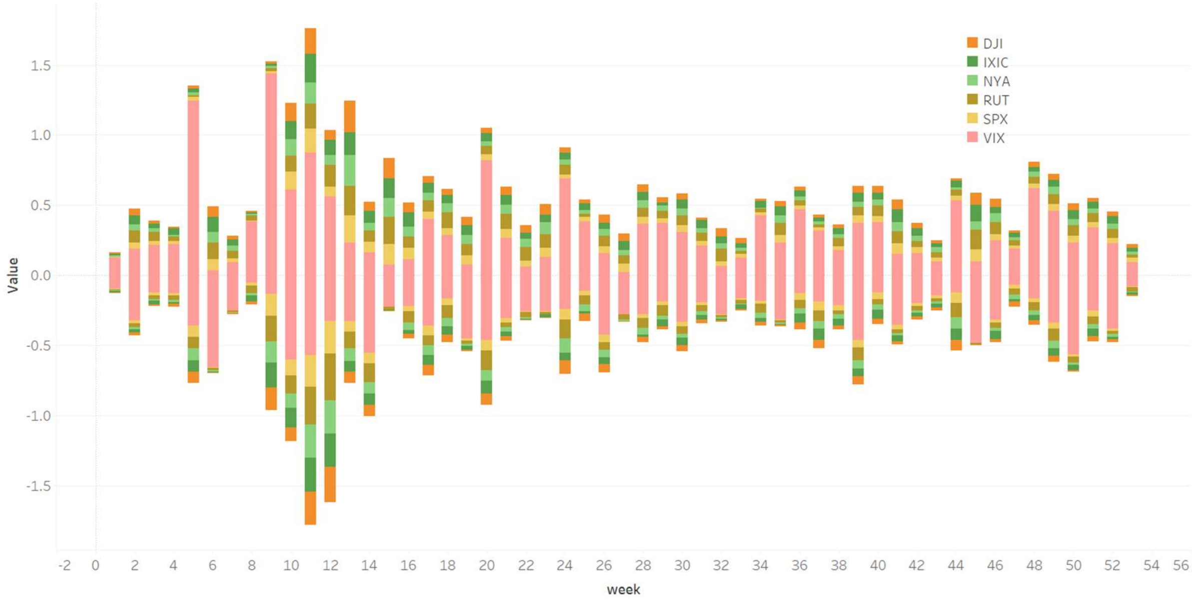


Figure 4. Two-year overall trend across the USA exchanges.

3.2. Significant overall trend and decline of stock indices in China

The significant overall trends in China are analysed here. Figure 5 shows the volatility of the VXFXI, CSI500. HSI, SSEC, SZI, TWII. For China, over the 15 trading days from 01/01/2020 to 31/12/2021, the dates were selected in the same way as in subsection 3.1 above. The first thing that can be seen in Figure 5 is that the dates of the decline of the Chinese stock index do not match the dates of the decline of the USA stock index. In the USA, all the dates filtered are in 2020, while in China, 46.66% of the dates filtered are in 2021. This is not what we would have expected. However, the magnitude of volatility is greater in 2020 than in 2021, comparing the average volatility of the six exchanges VXFXI, CSI500, HSI, SSEC, SZI and TWII for the filtered dates in 2020 to −1.53% and the average volatility of the six exchanges for the filtered dates in 2021 to −0.28%. The absolute value of the volatility of the former index is more than five times that of the latter. It can also be seen in the table that the dates of the Covid social events occurring in 2020 account for 77%. Comparing the dates in Table 3 with the filtered trading days. The following dates were found to coincide with the dates we screened. Additionly, VXFXI, CSI500. HSI, SSEC, SZI and TWII are not as uniform as the USA volatility trends in 3.1. Table 4 shows the *P-value* between the three stocks.

The maximum difference between the three indices was 0.019 on 16/03/2020, but the maximum difference was 0.001 on 26/02/2021. The overall volatility of the VXFXI, CSI500. HSI, SSEC, SZI, and TWII for China for the two years of the selected experimental dates in weeks. A similar situation can be seen in the USA, i.e., leaving aside the VXFXI, it can also be seen that there is a greater concentration of dates around March 2020 when the indices are more volatile. The average volatility of the VXFXI, CSI500, HSI, SSEC, SZI, and TWII indices for the March 2020 trading day is calculated to be −0.079%, while the average volatility of the index for the periods 02/01/2020-28/02/2020 and 01/04/2020-31/12/2021 is 0.156%. As in the case of the USA, the index fluctuations for 03/2020 are significantly below average.

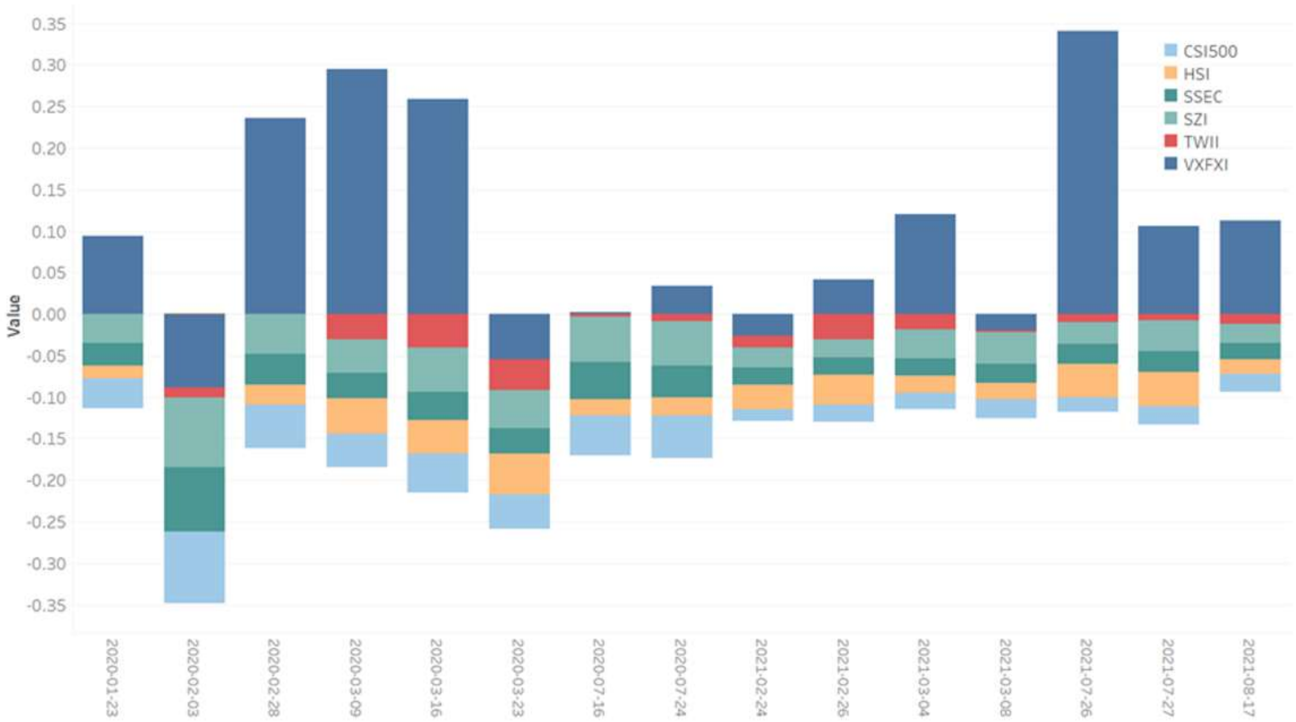


Figure 5. The worst dates of decline in China.

Table 4. *P-value* between the three stock indices.

Stock Marke	*P-value*
CSI500 and SSEC	0.349
CSI500 and SZI.	0.807
SSEC and SZI.	0.214

3.3. Overall performance of China and the USA on the respective dates during the most decline

The dates of the most declines in the two countries are compared in this Subsection. Figure 6 compares the six exchanges VXFXI, CSI500, HSI, SSEC, SZI and TWII and the six US exchanges DJI, IXIC, NYA, RUT, SPX and VIX, after screening out the trading days with significant declines on the major US exchanges. It can be seen that there is a specific correlation between the trend and the magnitude of the indexes of the five exchanges CSI500. HSI, SSEC, SZI and TWII, for example, in the 2^{nd}–5^{th} trading days, the trend of the five exchanges is identical, almost coinciding in terms of value. This phenomenon is also found in the five US exchanges DJI, IXIC, NYA, RUT, and SPX. In addition, another noticeable phenomenon is the absolute value of index volatility of the five Chinese exchanges CSI500. HSI, SSEC, SZI and TWII are smaller than the five US exchanges, DJI, IXIC, NYA, RUT, and SPX. The average index volatility of the five Chinese exchanges over the 15 trading days is −1.04%, corresponding to the average index volatility of −5.41% for the five US exchanges, 5.2 times higher than in China. The exception to this is on 23/03/2020.

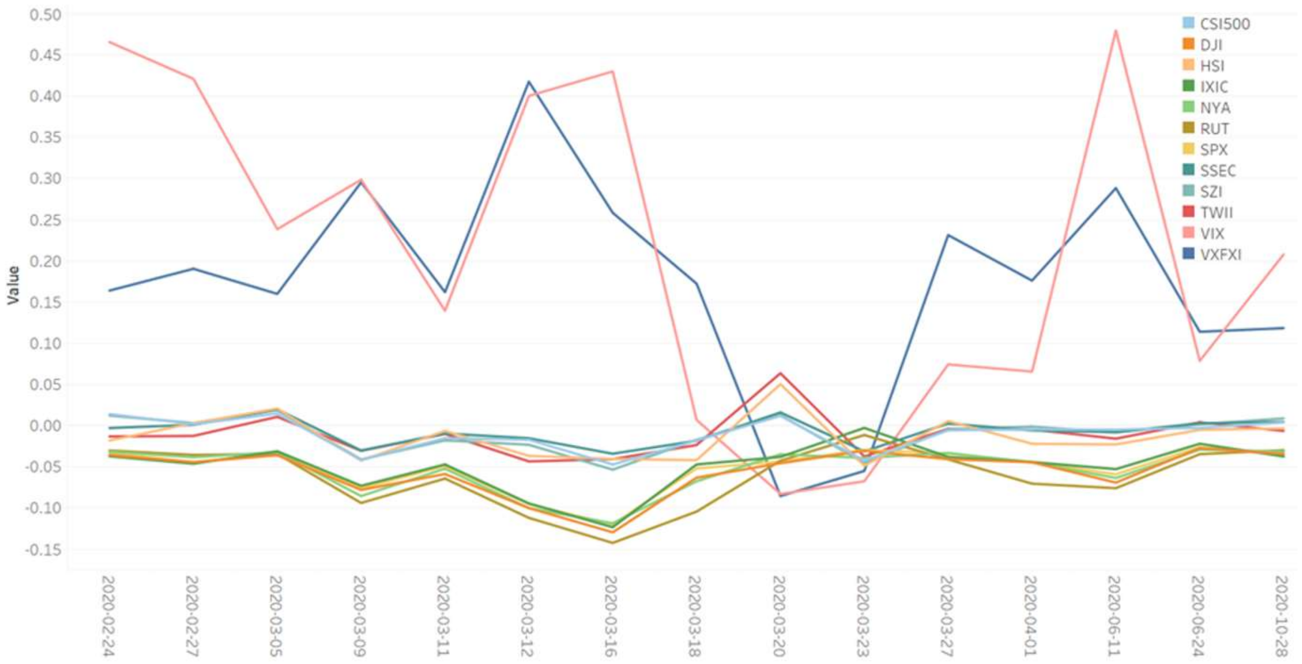


Figure 6. Overall performance of the stock indices in China and the USA on the most significant dates of decline in the USA.

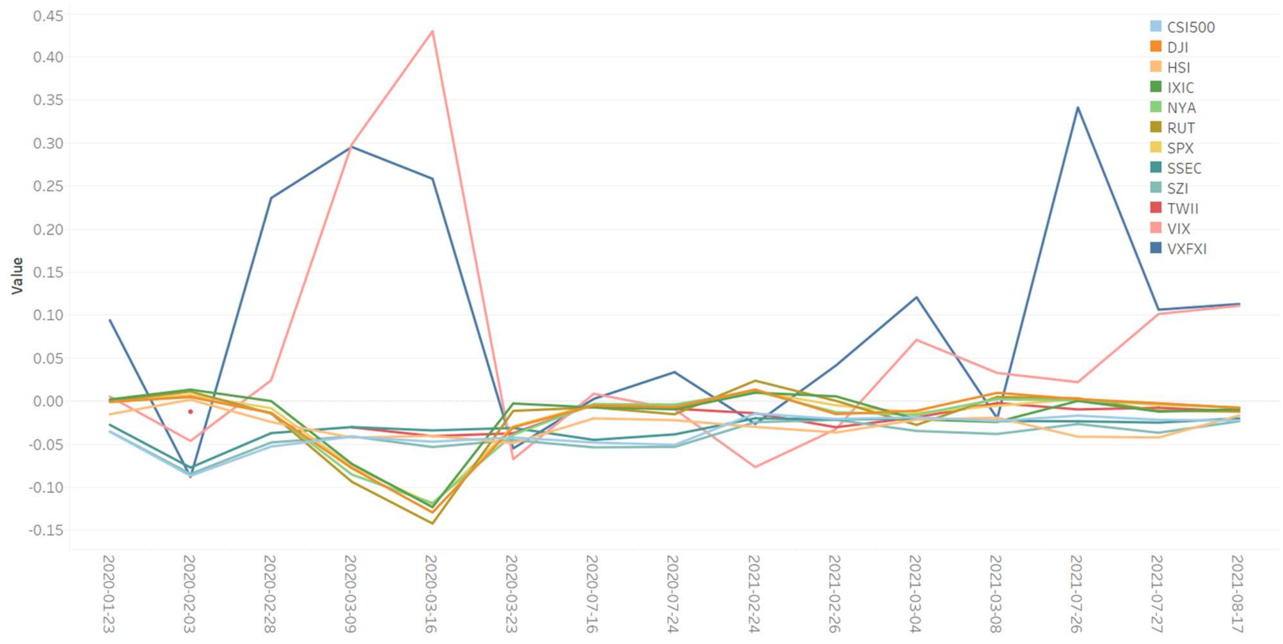


Figure 7. Overall performance of the stock indices in China and the USA on the most significant dates of decline in China.

Figure 7 shows the overall comparison between the six exchanges VXFXI, CSI500, HSI, SSEC, SZI and TWII and the six exchanges DJI, IXIC, NYA, RUT, SPX and VIX in the USA for the days with significant declines. It can be seen that the five US exchanges, DJI, IXIC, NYA, RUT and SPX, have similar upward and downward trends over the filtered trading days, while the upward and downward movements of the five Chinese exchanges CSI500. HSI, SSEC, SZI and TWII cannot be observed in a particular pattern after the sixth trading day. The absolute value of index volatility for the five Chinese exchanges is greater than that of the five US exchanges, with the average index volatility for the five Chinese exchanges on the dates filtered being −3.12% compared to −1.80% for the USA counterparts. In Figure 6, it can be seen that the movements of the exchanges in both countries are broadly similar over the first nine and last five dates (except for the VIX and VXFXI). In Figure 7, the movements of the two national exchanges are broadly similar over the second ten dates, but there is a clear crossover in the first five trading days, which is not reflected in Figure 6.

3.4. Comparison of the leading exchanges in China and the USA.

Major stock market indices in two countries are compared in this Subsection. The dates of the most declines in the two countries are compared in this Subsection. Similar to the above, there are significant fluctuations around 03/2020, in weeks. The average value of these eight exchanges in March 2020 was calculated to be −0.50%, but the average value for the periods 01/01/2020–28/02/2020 and 01/04/2020–31/12/2021.

3.5. VIX and VXFXI

VIX and VXFXI are all from CBOE and located in the USA, while VXFXI is China-related. It measures the market's expectation of 30-day volatility implicit in the prices of near-term China ETF options. Due to the special features of those two indices, the trends are compared here.

The volatility of the VIX and VXFXI on the worst days of the decline in China and the USA were compared. The volatility trends of both are almost synchronised, and the volatility of the VIX and VXFXI is almost synchronised between 09/03/2020 and 20/03/2020. The P-Value of VXFXI and VIX for the dates in the USA is 0.441 and for the date in China is 0.550, thus indicating no significant difference between the index fluctuations of VIX and VXFXI for the above dates. Additionally, the VXFXI as a whole is more volatile than the VIX. The standard deviation of VXFXI is calculated to be E = 0.108. The standard deviation of VIX is E = 0.095, which is smaller than that of VXFXI, demonstrating that the dispersion of the VIX index volatility distribution is smaller than that of VXFXI.

4. Discussion

Based on the results in Section 3, the hypotheses are discussed in this Section.

4.1. For H1

For the most significant fluctuations in the USA stock market on 16/03/2020, which was DJI (12.93%), IXIC (−12.32%), NYA (−11.84%), SPX (−11.98%), RUT (−14.22%), and VIX (−23.37%). It can be found that, as we expected, the most significant declines occurred on exchanges other than the VIX on 16/03/2020. A search of news events on this day and the previous day reveals the existence of numerous events linked to COVID-19, shown as follows: On 16/03/2020, South Africa declared a state of national disaster emergency; On 15/03/2020, Spain announced a national closure measure;

Spanish Prime Minister's wife diagnosed with Covid; France claimed the highest stage of epidemic prevention efforts; 712 people diagnosed on the Diamond Princess; Serbian Football Federation President diagnosed; Trump's Covid test results released.

For DJI, IXIC, NYA, RUT and SPX other than VIX, the trend of fluctuation in the above dates are consistent, and we check the table of social events to get: the USA reported on 09/03/2020 that the epidemic continues to worsen, affecting 34 states, many places in the USA into a state of emergency; On 12/03/2020 the USA has more than 1000 confirmed cases, the capital city of Washington declared a state of emergency and a state of emergency is declared, a travel ban on Europe is announced, and the director of the CDC admits that some of the "flu" victims may be suffering from Newcastle pneumonia. On those two days, NYA (−8.53%/−9.99%), SPX (−7.60%/−9.51%), DJI (−7.79%/−9.99%), RUT (−9.37%/−11.18%), IXIA (−7.29%/−9.43%) fell severely.

As for the difference in the values of the index fluctuations between the eighth and twelfth dates, we have not yet found solid arguments for this phenomenon and expect to be able to resolve it in future work.

March 2020 is the most pronounced and dramatic index fluctuation in all the experimental dates. We consulted the USA social events table and found that 22.6% of the events related to COVID-19 occurred in March 2020 within two years. The average index volatility of DJI, IXIC, NYA, RUT, SPX and VIX in March 2020 was calculated to be −0.016%, while the moderate fluctuations of the above six exchanges in the selected experimental dates 01/01/2020–28/02/2020 and 01/04/2020–31/12/2021 was 0.15%. There is a significant difference between the two, with one positive and one negative value.

March 2020 accounts for 71.11% of the dates screened. However, the most severe decline was also seen this month, when a series of measures to stimulate the stock market were implemented in the USA, as shown in Table 5.

Table 5. US economic stimulus in March 2020.

Date	Event
04/03/2020	The first batch of financial plans of $2.5 billion was used for vaccine research and development, treatment, and protective equipment (later raised to $8.3 billion)
14/03/2020	The second batch of financial plans was proposed, with no less than $50 billion.
15/03/2020	The Federal Reserve announced zero interest rates and implemented $700 billion in quantitative easing.
17/03/2020	The third batch of financial plans was proposed, with a total amount of 850 billion to 1 trillion US dollars (subsequently raised to 2 trillion US dollars)
18/032020	The second batch of financial plans was voted through in the Senate.
19/03/2020	The Federal Reserve announced the establishment of a temporary dollar swap mechanism with the nine major central banks.
23/03/2020	Federal Reserve announces unlimited QE.

The average increase in the six US exchanges over March 2020 is 7.10%. China's was 4.69%, much smaller than the USA's. The available data shows that when market stimulus measures were announced, the stock market rose within nine days of the above dates, with an average increase of 5.05%. A Brazilian academic has studied the situation in Brazil and concluded that the government fiscal stimulus partially mitigated the expected decline in GDP under the outbreak [43]. We, therefore, speculate that the stimulus measures related to the USA stock market were effective.

Additionally, the dates filtered in Subsection 3.2 were found to correspond to nine Covid social events by looking up the social events table, with a match rate of 60%. Therefore, there was a link between changes in stock indices in the USA and China and the outbreak. We consider the hypothesis valid and match the conclusion from [44] that the pandemic has effects on the stock markets.

4.2. For H2

Compared to the USA, where 100% of the dates extracted were for 2020, China extracted 53.33% for 2020 and 46.66% for 2021. However, the magnitude of volatility in 2020 is greater than that in 2021, comparing the average fluctuations of the six exchanges VXFXI, CSI500, HSI, SSEC, SZI and TWII for the filtered 2020 date with −1.53%, and the average volatility of the six exchanges for the filtered 2021 date with −0.28%, with the former having average volatility of more than five times higher than the latter. In the table of social events collected, China accounts for 85% of the total number of social events collected in 2020; the corresponding figure for the USA is 73%. Therefore, in relation to 4.1, hypothesis H2 holds in experiments, and [45,46] shows some similar results; however, there are few existing studies that offer the same conclusion. Hence, this work only provides evidence partly to H2 at this stage.

4.3. For H3

The most severe declines in the USA occurred on the same trading days, and the dates of six Chinese exchanges where the most pronounced declines are no longer the same. But the three exchanges SZI, SSEC, and CSI500, have the same date of maximum decline, all on 03/02/2020, and different from the date of the most severe decline in the USA. By looking up the table of social events, the following events occurred in China on this day (03/02/2020) or within the previous two days: On 31/01/2020, the cumulative number of cases nationwide exceeded 10,000; people in many places rushed to buy Shuanghuanglian. On 02/02/2020, Hubei focused on isolating all suspected cases; Vulcan Hill Hospital was officially delivered. On 03/02/2020, Wuhan built a square cabin hospital to treat minor patients. For such a disparity in the maximum date of decline in the index across exchanges in the two countries, we speculate that it is the different periods of COVID-19 outbreaks in the two countries, with China preceding the USA outbreak. Still, we have not found solid arguments for this. Therefore, the speculation that the USA and Chinese stock indices were affected by the outbreak in parallel is not valid for H3. Table 6 shows the values of the most significant declines in the indices of the various Chinese exchanges and the corresponding dates.

Table 6. Worst declining values in China and their dates.

Stock	The maximum value of decline	Date
VXFXI	−49.94%	07/05/2021
CSI500	−8.68%	03/02/2020
HSI	−5.56%	22/05/2020
SSEC	−7.72%	03/02/2020
SZI	−8.45%	03/02/2020
TWII	−5.83%	19/03/2020.

Additionally, the VXFXI is significantly different from other exchanges regarding the date of maximum index decline. The VXFXI is substantially different from the other exchanges in terms of both the date of maximum index decline and the value of the maximum index decline, and we have yet to find relevant evidence to explain this phenomenon.

For the anomaly in Subsection 3.3 on 23/03/2020, we looked for social events related to Covid on that day and the day before: on 23/03/2020, Singapore banned all foreigners from entering or transiting the country, and on 23/03/2020, the Chinese mega-city of Shanghai adjusted its emergency response level to a Level 2 response. This also confirms that the H3 is not valid.

The absolute change in the indices of the Chinese exchanges CSI500, HSI, SSEC, SZI and TWII during the period from 28/02/2020 to 23/03/2020 is smaller than that of NYA, SPX, DJI, RUT and IXIC in the USA. The overall picture is interesting to study because the global picture in Figure 7 shows that the absolute change in the indices of the major Chinese exchanges is larger than that of the major USA exchanges. The average difference over the 15 trading days we filtered was −1.80% for NYA, SPX, DJI, RUT, IXIC and −3.12% for CSI500, HSI, SSEC, SZI, TWII. We collected 109 news items about COVID-19 within the USA during this period and found that 27 news items occurred within this period, accounting for about 24% of the time span of 24 months. Among them that on 12/03/2020, Washington declared a state of emergency, and the USA announced a travel ban on Europe, a day when NYA, SPX, DJI, RUT, IXIC are down −10.02% on average. On 13/03/2020, Trump declared a state of emergency in the USA, and on 20/03/2020, the Governor of California declared a statewide On this day NYA, SPX, DJI, RUT, IXIC were down −4.07% on average due to a series of national-level news such as the "city closure order". But before 28/02/2020, Wuhan began its city closure on 23/01/2020, and as of 08/02/2020, Mt. Thor Vulcan has been delivered, and various countermeasures such as the temporary opening of schools and neighbourhood closures have been implemented. This confirms that H3 is invalid, and we cannot find literature to support this hypothesis.

4.4. For H4

As March 2020 is considered the worst month of the epidemic and the time when people were the most frightened, the data from both countries were selected for comparison at this stage. The average decline in the index for the six USA exchanges is −0.016%, while the average decline in the index for the six Chinese exchanges is −0.079%. The average absolute value of the decline in China is much larger than that of the USA. Therefore, we believe that China was relatively more affected by the epidemic, which matches conclusions from another study [47]. We do not use the method of comparing values across all selected dates here because index fluctuations outside of this period are not significantly different from the period when COVID-19 did not occur, and too many factors influence changes in stock data. Therefore, only this period was selected for comparison, which may be a flawed comparison method, but it is the most effective method that can be proposed at this stage.

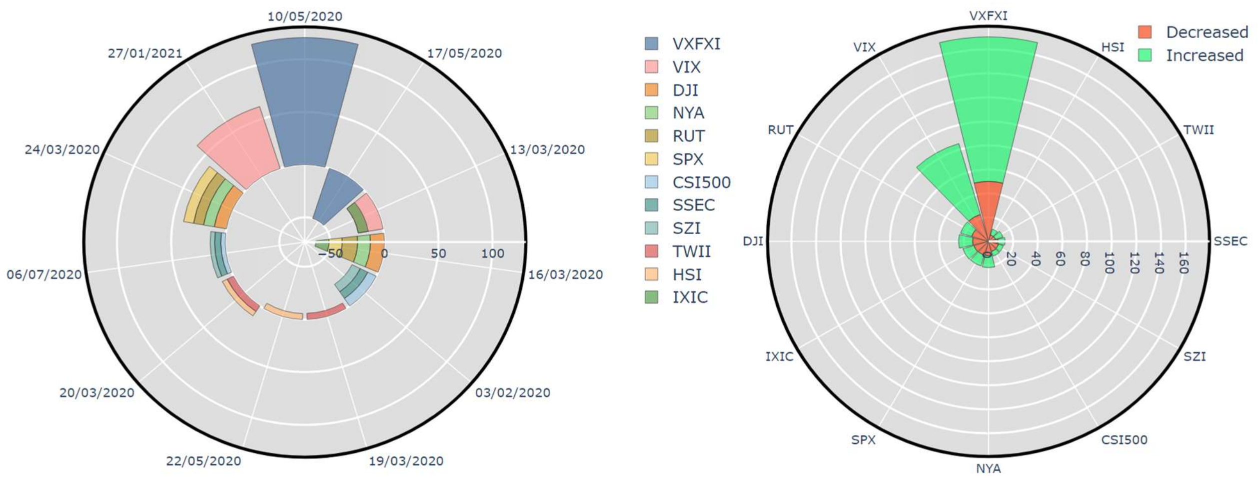
4.5. For H5

For the exceptional crossover phenomenon in Subsection 3.3; the most volatile phenomenon in 03/2020. It can be seen that prior to 23/03/2020, there was no clear correlation between the up and down trends of the major Chinese and USA exchanges. Still, March 2020 was the most volatile in our chosen time period, with peaks of −8.68 and −14.22% for the major exchanges (except VXFXI and

VIX) in China and the USA, respectively. The period prior to 23/03/2020 was also when the global New Coronavirus outbreak raged, and people were most fearful of unknown viruses [48,49]. Here too, the H1 conjecture can be verified to hold true. Within the selected experimental phase, March 2020 was the period of greatest exponential fluctuations and the most frequent COVID-19 social events in both the USA and China. However, after this (03/2020), there is a gradual levelling off, which would validate that the stock index volatility becomes less volatile when the epidemic trend normalises, the hypothesis stands and matches existing research [50].

4.6. For H6

The volatility values of the VIX and VXFXI can be seen in each of the above graphs to be significantly different from the other exchanges in their respective countries and not linked. And both VIX and VXFXI have also shown opposite ups and downs. For example, on 27/07/2021, VIXI claimed an upward trend while VXFXI showed a decline in the index. Additionally, during the most pronounced dates of index declines on the various Chinese exchanges until April 2020, there were two opposed ups and downs with the USA exchanges. During the 23/04/2020 trading period, the two exchanges showed significantly opposite volatility trends. Chinese financial markets were the first to respond to the pandemic, and Covid has had a distinct and lasting impact on Chinese financial markets [51]. The facts above confirm that H6 is not valid.



(a) (b)

Date	IXIC	VIX	DJI	NYA	RUT	SPX	CSI500	SSEC	SZI	TWII	HSI	VXFXI
3/02/2020							-8.68	-7.72	-8.45			
13/03/2020	9.35	-23.37										
16/03/2020	-12.32		-12.93	-11.84	-14.22	-11.98						
19/03/2020										-5.83		
20/03/2020										6.37	5.05	
24/03/2020			11.37	10.04	9.39	9.38						
10/05/2020												120.45
17/05/2020												-49.94
22/05/2020											-5.56	
6/07/2020							4.1	5.71	4.09			
27/01/2021		61.64										

(c)

Figure 8. The significant changes in each stock index. (a) Stock indices changes by date; (b) Stock indices changes by name; (c) Each stock index's maximum rise and fall

4.7. For H7

In the above chart, we can see which time periods the indices fluctuate the most, and we can also see the size of the fluctuations at different times and so on. For example, we can see that the CSI500, SZI, and SSEC have similar trends, and we can also see that on 16/03/2020, the five USA indices fell most sharply. During the 03/2020 time frame, both countries saw the worst index declines in two years, and the values were significantly higher than on any other trading day in two years. Also, around 10/05/2021, China's significant exchanges saw large swings up and down and finding the reason for this, we learned that it was right at the end of China's May Day Golden Week, coupled with a plunge of over 13% in Bitcoin. These could be the reasons for the dramatic swings in the stock market. Additionally, Figure 8 applies two improved wind rose charts (this method is in progress) to present the maximum rise and fall of each stock index, in which it can be found that VXFXI and VIX had the most significant changes, all other indices' fluctuation values tend to be similar, and most important trends occurred in 2020. Visualisation methods can assist those involved get the information they want more clearly to understand better the event in question and the valid conjecture [52]. However, the effectiveness of relevant methods has not been validated yet.

5. Conclusions, limitations and future research

We have analysed the link between Chinese and USA stock markets and Covid-related social events by experimentally visualising various associated data. Some of the proposed hypotheses were validated and are corroborated by existing research, suggesting and further developing the idea that related social events do affect stock markets in China and the USA, and that the impact of different events on index changes varies between countries as well as the duration of the volatility in the index also varies by country. There is also a correlation between the two countries' stock markets, with the same rise and fall in a short time in response to a Covid-related social event. During the month of 03/2020, both the Chinese and the USA exchanges experienced more frequent falls or rises, and this was also the most frequently reported period for the related social events. This phenomenon was particularly evident around 20/03/2020. When the epidemic ceased to cause widespread panic, the volatility of the indices in both countries gradually levelled off.

To the best of our knowledge, this topic has not been fully discussed. Thus, this study has initially offered analytics results among multiple data sources in the stock market sector. It could potentially serve as a supplementary tool to help socio-economic stability and policymakers make decisions by considering related datasets and events. It could provide a direct source of information in the event of similar events in the future. At the same time, the study can offer investors and policymakers a potential reference, and gives a more intuitive, data-interpretable perception of the link between the COVID-19 outbreak and stock market movements. There are visual data references for investors when making risk predictions. It may also be possible to provide lessons for the emergence of similar socially significant events in the future, not only between social events and stocks, but also mapping to social events and other economic activities. It can further be extended to the impact of future major social events on stocks, not just in the case of the Covid pandemic.

Although this study has produced some results, there are some limitations. Firstly, the raw data for experiment input is not comprehensive. The collection of social events is incomplete, and some social events not explored may have an impact on the stock market, such as the government incentives during the pandemic not being fully considered. Additionally, events unrelated to Covid may also have an impact on the stock market, which we have not taken into account. Secondly, the data processing is flawed, and there may be issues relating to data completeness. The relationship among multiple data sources remains unclear, as well as a better method is being employed to process the data. Thirdly, the data analysing method, at this stage, is mainly depending on graphs generated and initial data statistics. The analytics process is not rigorous, leading the present outcomes and hypotheses validations to be more of a supplementary tool to further explore existing related research. More accurate test and comparison methods need to be imported for comprehensive analysing. Additionally, this study is in its initial stage, and the present graph drawing methods are not suitable for presenting multiple attributes of complex data. It is hard to offer an overview and details of the data; hence, fully insights can be potentially further brought out.

In the future, we will target those shortcomings. Collecting and categorising a broader range of data, such as more data on related social events and government policy, to ensure the raw data collected covers as many aspects as possible; more statistics methods for the test will be employed to compare the data processed, and hence to find suitable methods for datasets in our study; besides, a novel metaphor graph drawing method for multiple-dimension data viewing is in progress, and a dashboard including initial interaction features has been put into agenda as well. Deeper analytics in regard to multiple data sources' relationships will be managed.

Acknowledgments

This research was supported by Shaoyang University Innovation Foundation for Postgraduate, grant number CX2021SY038.

Conflict of interest

The authors declare there is no conflict of interest.

References

1. L. Yang, S. Liu, J. Liu, Z. Zhang, X. Wan, B. Huang, et al., COVID-19: immunopathogenesis and immunotherapeutics, *Signal Trans. Targeted Ther.*, **5** (2020), 1–8. https://doi.org/10.1038/s41392-020-00243-2
2. K. Yuki, M. Fujiogi, S. Koutsogiannaki, COVID-19 pathophysiology: A review, *Clin. Immunol.*, **215** (2020), 108427. https://doi.org/10.1016/j.clim.2020.108427
3. F. Saldaña, H. Flores-Arguedas, J. A. Camacho-Gutiérrez, I. Barradas, Modeling the transmission dynamics and the impact of the control interventions for the COVID-19 epidemic outbreak, *Math. Biosci. Eng.*, **17** (2020), 4165–4183. https://doi.org/10.3934/mbe.2020231
4. A. S. Fauci, H. C. Lane, R. R. Redfield, Covid-19-navigating the uncharted, *N. Engl. J. Med.*, **382** (2020), 1268–1269. https://doi.org/10.1056/NEJMe2002387
5. S. Pokhrel, R. Chhetri, A literature review on impact of COVID-19 pandemic on teaching and learning, *Higher Edu. Future*, **8** (2021), 133–141. https://doi.org/10.1177/2347631120983481
6. R. Siche, What is the impact of COVID-19 disease on agriculture?, *Sci. Agropecu.*, **11** (2020), 3–6. http://dx.doi.org/10.17268/sci.agropecu.2020.01.00

7. A. Kumar, V. Jain, A. Deovanshi, A. Lepcha, C. Das, K. Bauddh, S. Srivastava, Environmental impact of COVID-19 pandemic: more negatives than positives, *Environ. Sustainability*, **4** (2021), 447–454. https://doi.org/10.1007/s42398-021-00159-9
8. L. Sher, The impact of the COVID-19 pandemic on suicide rates, *QJM Int. J. Med.*, **113** (2020), 707–712. https://doi.org/10.1093/qjmed/hcaa202
9. J. Xiong, O. Lipsitz, F. Nasri, L. M. Lui, H. Gill, L. Phan, et al., Impact of COVID-19 pandemic on mental health in the general population: A systematic review, *J. Affect. Disord.*, **277** (2020), 55–64. https://doi.org/10.1016/j.jad.2020.08.001
10. W. Hong, X. Lu, L. Wu, X. Pu, Analysis of factors influencing public attention to masks during the COVID-19 epidemic-Data from Sina Weibo, *Math. Biosci. Eng.*, **19** (2022), 6469–6488. https://doi.org/10.3934/mbe.2022304
11. P. K. Ozili, T. Arun, Spillover of COVID-19: Impact on the global economy, in *Managing Inflation and Supply Chain Disruptions in the Global Economy, IGI Global*, (2020). https://doi.org/10.4018/978-1-6684-5876-1.ch004
12. B. Bagchi, S. Chatterjee, R. Ghosh, D. Dandapat, Impact of COVID-19 on global economy, in *Coronavirus Outbreak and the Great Lockdown, Springer*, (2020), 15–26. https://doi.org/10.1007/978-981-15-7782-6_3
13. W. Thorbecke, The impact of the COVID-19 pandemic on the USA Economy: evidence from the stock market, *J. Risk Financ. Manage.*, **13** (2020), 233. https://doi.org/10.3390/jrfm13100233
14. L. Tan, X. Wu, J. Guo, E. D. Santibane-Gonzalez, Assessing the impacts of COVID-19 on the industrial sectors and economy of China, *Risk Anal.*, **42** (2022), 21–39. https://doi.org/10.1111/risa.13805
15. P. A. Vitenu-Sackey, R. Barfi, The impact of COVID-19 pandemic on the Global economy: emphasis on poverty alleviation and economic growth, *Econ. Finance Lett.*, **8** (2021), 32–43. https://doi.org/10.18488/journal.29.2021.81.32.43
16. R. Vaishya, M. Javaid, I. H. Khan, A. Haleem. Artificial Intelligence (AI) applications for COVID-19 pandemic, *Diabetes Metab. Syndr. Clin. Res. Rev.*, **14** (2020), 337–339.
17. W. Dong, C. Zhao, Stock price forecasting based on Hausdorff fractional grey model with convolution and neural network, *Math. Biosci. Eng.*, **18** (2021), 3323–3347. https://doi.org/10.3934/mbe.2021166
18. N. L. Bragazzi, H. Dai, G. Damiani, M. Behzadifar, M. Martini, J. Wu, How big data and artificial intelligence can help better manage the COVID-19 pandemic, *Int. J. Environ. Res. Public Health*, **17** (2020), 3176. https://doi.org/10.3390/ijerph17093176
19. V. Tkachuk, Y. Yechkalo, S. Semerikov, M. Kislova, Y. Hladyr, Using mobile ict for online learning during covid-19 lockdown, in *International Conference on Information and Communication Technologies in Education, Research, and Industrial Applications*, (2020), 46–67. https://doi.org/10.1007/978-3-030-77592-6_3
20. M. Allam, S. Cai, S. Ganesh, M. Venkatesan, S. Doodhwala, Z. Song, et al., COVID-19 diagnostics, tools, and prevention, *Diagnostics*, **10** (2020), 409. https://doi.org/10.3390/diagnostics10060409
21. J. L. Comba, Data visualisation for the understanding of COVID-19, *Comput. Sci. Eng.*, **22** (2020), 81–86. https://doi.org/10.1109/MCSE.2020.3019834

22. C. K. Leung, T. N. Kaufmann, Y. Wen, C. Zhao, H. Zheng, Revealing COVID-19 data by data mining and visualization, in *International Conference on Intelligent Networking and Collaborative Systems*, (2021), 70–83. https://doi.org/10.1007/978-3-030-84910-8_8
23. A. H. M.Hassan, A. A. M.Qasem, W. F. M. Abdalla, O. H. Elhassan, Visualisation & prediction of COVID-19 future outbreak by using machine learning, *Int. J. Inf. Technol. Comput. Sci.*, **13** (2021), 16–32. https://doi.org/10.5815/ijitcs.2021.03.02
24. A. N. Roy, J. Jose, A. Sunil, N. Gautam, D. Nathalia, A. Suresh, Prediction and spread visualisation of COVID-19 pandemic using machine learning, **2020** (2020), https://doi.org/10.20944/preprints202005.0147.v1
25. Z. Deng, J. Chen, T. Wang, Bibliometric and visualisation analysis of human coronaviruses: prospects and implications for COVID-19 research, *Front. Cell. Infect. Microbiol.*, **529** (2020). https://doi.org/10.3389/fcimb.2020.581404
26. M. M. Hossain, Current status of global research on novel coronavirus disease (Covid-19): A bibliometric analysis and knowledge mapping, *F1000 Res.*, **9** (2020), 374. https://doi.org/10.12688/f1000research.23690.1
27. M. Mazur, M. Dang, M. Vega, COVID-19 and the march 2020 stock market crash. Evidence from S&P1500, *Finance Res. Lett.*, **38** (2021), 101690. https://doi.org/10.1016/j.frl.2020.101690
28. F. Zeren, A. Hizarci, The impact of COVID-19 coronavirus on stock markets: evidence from selected countries, *Muhasebe Finans İncelemeleri Dergisi*, **3** (2020), 78–84. https://doi.org/10.32951/mufider.706159
29. H. Liu, A. Manzoor, C. Wang, L. Zhang, Z. Manzoor, The COVID-19 outbreak and affected countries stock markets response, *Int. J. Environ. Res. Public Health*, **17** (2020), 2800. https://www.mdpi.com/1660-4601/17/8/2800
30. M. Topcu, O. S. Gulal, The impact of COVID-19 on emerging stock markets, *Finance Res. Lett.*, **36** (2020), 101691. https://doi.org/10.1016/j.frl.2020.101691
31. P. K. Narayan, N. Devpura, H. Wang, Japanese currency and stock market-What happened during the COVID-19 pandemic?, *Econ. Anal. Policy*, **68** (2020), 191–198. https://doi.org/10.1016/j.eap.2020.09.014
32. The Beijing News. Available from: https://www.bjnews.com.cn/.
33. CCTV NEWS. Available from: https://news.cctv.com/.
34. Xinhuanet. Available from: http://m.news.cn/.
35. Investing. Available from: https://cn.investing.com/.
36. A. W. Lo, What is an index?, *J. Portfolio Manag.*, **4** (2016), 21–36. https://doi.org/10.3905/jpm.2016.42.2.021
37. J. Heinrich, D. Weiskopf, State of the art of paralle coordinates, in *Eurographics (State of the Art Reports); The Eurographics Association: Geneva, Switzerland*, (2013), 95–116.
38. T. Blascheck, K. Kurzhals, M. Raschke, M. Burch, D. Weiskopf, T. Ertl, Visualization of eye tracking data: A taxonomy and survey, *Comput. Graph. Forum*, **36** (2017), 260–284. https://doi.org/10.1111/cgf.13079
39. T. Blascheck, L. M. Vermeulen, J. Vermeulen, C. Perin, W. Willett, T. Ertl, et al., Exploration strategies for discover ofinteractivity in visualisations, *IEEE Trans. Vis. Comput. Graph.*, **25** (2018), 1407–1420. https://doi.org/10.1109/TVCG.2018.2802520

40. S. Latif, F. Beck, VIS author profiles: Interactive descriptions of publication records combining text and visualization, *IEEE Trans. Vis. Comput. Graph.*, **25** (2018), 152–161. https://doi.org/10.1109/TVCG.2018.2865022
41. N. Akhtar, N. Tabassum, A. Perwej, Y. Perwej, Data analytics and visualisation using Tableau utilitarian for COVID-19-(Coronavirus), *Glob. J. Eng. Technol. Adv.*, **3** (2020), 28–50. https://dx.doi.org/10.30574/gjeta.2020.3.2.0029
42. S. Batt, T. Grealis, O. Harmon, P. Tomolonis, Learning tableau: A data visualisation tool, *J. Econ. Edu.*, **51** (2020), 317–328. https://doi.org/10.1080/00220485.2020.1804503
43. A. A. Porsse, K. B. de Souza, T. S. Carvalho, V. A. Vale, The economic impacts of COVID-19 in Brazil based on an interregional CGE approach, *Reg. Sci. Policy Prac.*, **12** (2020), 1105–1121. https://doi.org/10.1111/rsp3.12354
44. C. C. Ngwakwe, Effect of COVID-19 pandemic on global stock market values: A differential analysis, *Acta Univ. Danubius*, **16** (2020).
45. D. Bora, D. Basistha, The outbreak of COVID-19 pandemic and its impact on stock market volatility: Evidence from a worst-affected economy, *J. Public Affairs*, **21** (2021), e2623. https://doi.org/10.1002/pa.2623
46. M. Hasan, M. Mahi, T. Sarker, M. Amin, Spillovers of the COVID-19 pandemic: Impact on global economic activity, the stock market, and the energy sector, *J. Risk Financ. Manage.*, **14** (2021), 200. https://doi.org/10.3390/jrfm14050200
47. C. Zehri, Stock market comovements: Evidence from the COVID-19 pandemic, *J. Econ. Asymmetries*, **24** (2021), e00228. https://doi.org/10.1016/j.jeca.2021.e00228
48. NetEase News, On the eve of Wuhan lockdown, 29.9 million people left, and it was difficult to find a bed for severe patients. Available from: https://www.163.com/dy/article/F3K4AE3F0525W7OM.html.
49. Sina Finance, Shuanghuanglian should be snapped up or not? Can Chinese traditional medicine such as capsule of Hua Qing Wen fight new coronavirus pneumonia? The experts have spoken, 2020. Availavel from: https://baijiahao.baidu.com/s?id=1657292587311187004&wfr=spider&for=pc.
50. N. Fernandes, Economic effects of coronavirus outbreak (COVID-19) on the world economy, IESE Business School Working Paper, **2020** (2020). https://dx.doi.org/10.2139/ssrn.3557504
51. S. Corbet, Y. G. Hou, Y. Hu, L. Oxley, D. Xu, Pandemic-related financial market volatility spillovers: Evidence from the Chinese COVID-19 epicentre, *Int. Rev. Econ. Finance*, **71** (2021), 55–81. https://doi.org/10.1016/j.iref.2020.06.022
52. J. Sheng, J. Amankwah-Amoah, Z. Khan, X. Wang, COVID-19 pandemic in the new era of big data analytics: Methodological innovations and future research directions, *Br. J. Manage.*, **32** (2021), 1164–1183. https://doi.org/10.1111/1467-8551.12441