



The Impact of COVID-19 on China's Capital Market and Major Industry Sectors

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Abstract

This paper studies the impact of COVID-19 on China's capital market and major industry sectors via an improved ICSS algorithm, a time series model with exogenous variables and nonparametric conditional probability estimation. Through the empirical analysis of the stock market, the bond market and different industry sectors, it is found that the pandemic has had no significant impact on the return of the stock and bond markets; however, it has increased market volatility. There are significant differences in the significance, direction and duration of the impact of the pandemic in different sectors. In addition, the impacts of COVID-19 have been gradual in some industries but rapid in others. Different industries show different sensitivities in their response to COVID-19. Based on the impact analysis, this paper proposes corresponding suggestions for investment strategies and macrocontrol decisions.

Keywords COVID-19 · Capital market · Industry sector index · Nonparametric conditional probability estimation

1 Introduction

Public health emergencies are sudden events that cause serious damage to public health, such as major infectious diseases. The rapid spread and strong infectivity of COVID-19 have caused a serious public health emergency in China and around the world, seriously challenging every government [1], threatening people's lives and property safety, and affecting people's mode of production. With the rapid development of China's financial industry, the connection between the financial industry and the real

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economy has become deeper and more complex, and the capital market has played a more important role in the economy. However, since supervision has not yet matured, the hidden dangers of financial risks have also increased. As a result, the impact of COVID-19 on production activities can be transmitted to capital markets through various channels and mechanisms. A previous study has shown that the impact of crises significantly increases risk spillovers [2]. Therefore, it is important to defuse major financial risks and prevent short-term shocks from evolving into trend changes. Studying the impact of COVID-19 on the capital market and industry sectors can help to avoid risks and provide suggestions for control countermeasures. At the micro level, this research helps investors adjust their investment decisions; at the macro level, it helps to understand the specific performance and continuity of the impact of COVID-19 on the market, thus improving risk prevention countermeasures and macrocontrol strategies for similar major public health emergencies.

With the explosive growth of available data and the continuous advancement of information technology, data science is playing an increasingly important role in solving social and economic problems [3]. Complex and diverse data mining and artificial intelligence technologies have been applied to finance, management, medical diagnosis, network security, the Internet of Things, decision sciences and many other fields [4–6]. In addition, increasing research on infectious diseases uses the knowledge and methods of data science. Temesgen et al. [7] used joint modeling to study the time-to-death of HIV/TB coinfecting patients. Kumar [8] applied cluster analysis to classify real groups of COVID-19 datasets covering different states and union territories in India to optimize monitoring techniques and improve government policies. Mohamed et al. [9] used a power odd generalized exponential Lomax distribution to study the daily recovery cases of COVID-19 in Egypt.

As a kind of public emergency, public health emergencies have similarities with other public emergencies, such as natural disasters, sudden wars, and terrorist attacks. The suddenness and strong destructive power of public emergencies often cause strong volatilities in the financial market. Based on their characteristics, public emergencies can generally be divided into three types, i.e., stepped, impulsive and progressive. Different types of emergencies have different continuous, immediate and weakening effects on the capital market [10], and the impacts on some specific stocks and industry sectors are especially obvious. Lanfear et al. [11] found that US hurricanes had a significant impact on the return of stock portfolios with specific characteristics, and factors such as the book-to-market value ratio and portfolio size were very sensitive to extreme weather events. Raby [12] analyzed the impact of terrorist attacks on different industries, and the results showed that aviation, tourism, accommodation, catering and other industries were particularly vulnerable to increased terrorist risks. Liu et al. [13] used the event-study approach to study the influence of the Wenchuan earthquake on the index of various industries in China and found that the machinery and equipment industry and the real estate industry were strongly negatively affected.

However, the impact of public health emergencies on the capital market is rarely discussed in existing research. Compared with other emergencies, public health emergencies have many specific characteristics of their own. On the one hand, they do not fall into any of the categories of stepped, impulsive, and gradual emergencies. An outbreak is the result of the interaction of natural and human factors [14], and

the public emergency usually has a certain duration and evolves over time. Therefore, more attention should be paid to the continuity and variability of the impact, rather than focusing on the significant effect 1 day after the incident [15]. On the other hand, the evolution of an epidemic is closely related to the implementation of epidemic prevention and control measures [16]. Therefore, public health events can be effectively controlled by humans, which is different from natural disasters such as earthquakes. As a result, an in-depth analysis of the impact on the market and industries is beneficial for the formulation of epidemic control measures. Some scholars analyzed the abnormal returns of some financial markets during the SARS epidemic through a traditional event-study approach [17]. Yang et al. [18] studied the impact of SARS on various industries in the stock market and found that the results were not significant. However, he believed that the economic environments of COVID-19 and the SARS are different; thus, compared with the SARS period, it is currently easier to generate a concentration of financial risk.

As COVID-19 has spread around the world, an increasing number of scholars have studied its impact on various real economies and financial markets, including the real estate market [19], the insurance industry [20], the airline industry [21], etc. COVID-19 has increased the risk spillover between sectors in the financial market [18]. Sharif et al. [22] found that the COVID-19 outbreak had a greater effect on geopolitical risk and economic uncertainty than on the stock market in the US. Ali et al. [23] studied the influence of COVID-19 on financial markets around the world and found that their decline and volatility were serious especially in the later phase of the spread. Phan and Narayan [24] investigated the reactions of stock prices to different stages in the evolution of COVID-19 at the country level. Bildirici et al. [25] analyzed crude oil prices under the impact of COVID-19 using their proposed innovative model. Moreover, Mensi et al. [26] examined the impacts of COVID-19 on the asymmetric multifractality of gold and oil and found that gold and oil became more inefficient after the outbreak of the pandemic compared to the pre-COVID-19 period. However, there has been little analysis of the impacts of COVID-19 on the capital market and various industry sectors during different periods of the pandemic in China.

Due to data limitations, studies on the impact of emergencies typically use the traditional event-study approach or set emergencies as dummy variables in a time series model. We took COVID-19 as an example and supplemented research on the impact of public health emergencies on the capital market. In this paper, we integrated data describing the pandemic with capital market data, and introduced actual data on the changes of COVID-19 into the model. Compared with dummy variables, the variables obtained by real data more accurately reflect the evolution of the pandemic. In addition, the event-study approach often uses the parametric method to detect the significance of statistics, and this approach has strict assumptions on the distribution of the sample data. We combined the event-study approach with nonparametric conditional cumulative probability estimation to estimate the cumulative probability of abnormal and cumulative abnormal returns. Nonparametric estimation methods avoid high computational costs and strict parameter restrictions [15]. Combining the two methods allows us to analyze the significance of daily abnormal returns during the event window, thereby providing the distribution of daily abnormal returns.

This paper selects the stock market and the bond market to represent China's capital market and studies the impact of COVID-19 over the course of its whole duration and in different stages by detecting fluctuation points and constructing a time series model. For the main industry sectors of the Shanghai Stock Exchange, we studied the differences in the duration and sensitivity of different industries affected by the pandemic. Our study makes the following contributions. Based on the severity of the pandemic, we divided COVID-19 into two stages, i.e., the rapid growth in the number of confirmed diagnoses and the slow decline in this number, and we analyzed the differences in the impacts of different stages. In addition, we examined the effects of COVID-19 at the industry level and visualized the significance of daily abnormal returns after the outbreak of COVID-19, which is helpful in observing the dynamic changes in the impact of the pandemic and assisting in further prediction and monitoring. In Sect. 2, we discussed related work and proposed our research hypotheses. In Sect. 3 we constructed the model and explained data. Section 4 is the empirical analysis, and in the last section, we summarized the conclusions and proposed policy recommendations.

2 Related Research

2.1 COVID-19 and the Capital Market

Public health emergencies can disrupt a country's normal production order and slow down the pace of production and life, causing enormous impacts on market entities such as enterprises and consumers [27]. Such emergencies squeeze the supply side and demand side in both directions and exert a serious short-term influence on the economy and society. On the one hand, an epidemic endangers people's health and changes consumers' behavior, and it simultaneously increases the pressure on the government's public health expenditures, which has a direct impact on the economy. On the other hand, due to the high risk of infection and the necessary prevention measures, enterprises are faced with crises such as low production efficiency, a loss of human capital, forced shutdowns, and breakages of capital chains. The shutdown of microenterprises will lead to a disruption of supply chains, which will affect more industries and even the whole economy. Yang et al. [18] found that SARS had a short-term impact on China's macroeconomy, resulting in a temporary decline in the economic prosperity index and a significant negative impact on consumer confidence and the production price index. In addition, Gupta et al. [28] found that as Chinese industries ceased production due to COVID-19, the global prices of raw materials fell worldwide, leading to a major slowdown in producing economies. COVID-19 has had an enormous and sustained negative impact on the global economy [29].

The performance of the capital market is closely related to the real economy, and shocks can be easily transmitted to the capital market through capital chains. Moreover, the capital market serves as an indicator to a certain degree. The negative impact of the COVID-19 pandemic has lowered people's expectations about the economy, increasing risks in the capital market.

The influence of COVID-19 is transmitted to the capital market not only through the real economy, but also through psychological factors such as investor sentiment. According to fear management theory, when people face threats to their lives and think about things related to death, they will have serious negative emotions of anxiety and fear. The theory of behavioral finance also shows that emergencies will have an impact on both the basic values of stocks and the psychological and behavioral factors of investors [30]. Lee et al. [31] found that investor optimism reduced return volatility and that pessimism increased volatility. COVID-19's high speed of transmission and its uncertainties have caused serious threats to people's lives and health, leading to a spread of panic. Investors' negative emotions will affect their decisions and corresponding asset prices. Anxiety, panic and other emotions will make investors have pessimistic expectations about the future and increase their degree of risk aversion [32, 33]. Based on the theory of behavioral finance, Chu and Liu [34] explained the impact of SARS on the securities market. They believed that irrational investors generated an information-enhanced herd effect and overreaction after receiving external panic information about the epidemic, which increased the risk of the whole market. Similarly, COVID-19 is also characterized by high contagion and uncertainty. Its impact will change investment behavior through the psychological factors of investors and increase the uncertainty of the capital market.

Based on the above analysis, we proposed Hypothesis 1.

H1 COVID-19 will have a shock effect on the capital market and increase the market volatility.

2.2 COVID-19 and Major Industry Sectors

Similarly, the impact of COVID-19 on different industry sectors is mainly transmitted through real industries and the psychology and behavior of investors. Smith [35] analyzed the impact of major infectious diseases at three levels, i.e., risk perception, communication, and management. He believed that a higher risk of infection reduced direct contact between people, thereby reducing people's demand for tourism, transportation, retail, and other entertainment industries. For example, studies have shown that H1N1 influenza pandemic caused significant losses to the tourism, catering, and aviation industries in some countries [36, 37]. During the SARS outbreak, China's tourism and hotel sector also suffered a strong negative impact [17]. Sobieralski [21] found that COVID-19 has caused an obvious shock to the airline industry. Moreover, the pharmaceutical industry plays a special role in major public health emergencies. The demand for medical resources has exploded during the COVID-19 pandemic. Pandemic prevention and control policies have also provided a large amount of financial support for relevant enterprises and institutions and expanded the scale of special credit. In addition, the opacity of information and the uncertainty of the pandemic increased panic in the early stage. Based on the perception and fear of health threats, investors may overreact and have higher expectations for the pharmaceutical industry. He et al. [30] studied COVID-19's impact on stock prices across different sectors in China and found that transportation, mining, electricity and heating, and environment

industries were adversely impacted by the pandemic while manufacturing, information technology, education and health-care industries were resilient to the pandemic.

Therefore, the COVID-19 pandemic will influence industries and further affect the industry sectors of the capital market. Different industries have different relationships with the pandemic, and they digest and process information at various speeds. Investors also have varying expectations for each industry based on “good” and “bad” information. Hence, Hypothesis 2 is proposed.

H2 COVID-19 has significant impacts on some industry sectors, and the impacts on different industry sectors are obviously heterogeneous.

3 Model and Data Description

3.1 Modeling

3.1.1 Model of COVID-19 and the Capital Market

We first used the improved ICSS algorithm proposed by Sanso et al. [38] to find structural changes in stock indices and bond indices before and after the pandemic. Based on the original iterative cumulative sum of squares (ICSS) algorithm, this method considers the characteristics of the conditional heteroscedasticity of financial time series and enhances the accuracy of detection of volatility structural breaks.

The improved algorithm determines a break by calculating the AIT statistic and comparing it with the threshold.

$$AIT = \sup_k \left| T^{-1/2} G_k \right| \quad (1)$$

$$G_k = \hat{\omega}^{-1/2} \left(C_k - \frac{k}{T} C_T \right) \quad (2)$$

In this paper, C_k represents the cumulative sum of squares of the stock and bond indices' return sequences from the beginning of the sample interval to a certain moment. $\hat{\omega}$ is estimated using parameter estimation methods [38]. If AIT is larger than the threshold under a certain level of significance, the point at that moment is a volatility structural change point. The algorithm will continue to divide the sequence based on the position to find other change points. Otherwise, there is no significant structural change point of volatility in the index return.

To further analyze the direction and magnitude of the impact on the stock and bond markets, we used the EGARCH model, which considers the aggregation effect of volatility and the imbalance of positive and negative information. Moreover, we introduced exogenous variables to describe changes in the pandemic and studied the impact of the whole sample window and different stages on the stock and bond indices. GARCH models combined with exogenous dummy variables have been widely used to study the impact of emergencies and special events on price volatility. In our research, since the bond return had no obvious ARCH effect in the sample interval, the EGARCH

model was established only for the stock indices. By comparing the fitting results of the models, we introduced the exogenous variables of COVID-19 only into the variance equations.¹

The model for analyzing the impact of the overall sample interval is as follows.

$$r_t = a + \sum_{i=1}^m \alpha_i r_{t-i} + \sum_{j=1}^n \beta_j \mu_{t-j} + \mu_t \quad (3)$$

$$\ln(\sigma_t^2) = c + \sum_{j=1}^q \varphi_j \ln(\sigma_{t-j}^2) + \sum_{i=1}^p \theta_i \left| \frac{\mu_{t-i}}{\sigma_{t-i}} - E\left(\frac{\mu_{t-i}}{\sigma_{t-i}}\right) \right| + \sum_{k=1}^r \rho_k \frac{\mu_{t-k}}{\sigma_{t-k}} + \gamma D_{t-1} \quad (4)$$

r_t is the return of the stock indices, r_{t-i} is the lagged return, $\ln(\sigma_t^2)$ ensures non-negativity, and $\frac{\mu_{t-k}}{\sigma_{t-k}}$ reflects the asymmetric effect of positive and negative information on volatility. Moreover, D_{t-1} is an exogenous pandemic variable. Since daily news on COVID-19 is data on the previous day, a lagged variable is selected for modeling. D_{t-1} is 0 before the outbreak and is processed pandemic data after the outbreak. Although the return rate and volatility of the capital market are affected by many factors, the impact of COVID-19 on the entire economy and society in China is relatively more systematic, direct and significant during the sample window. Compared with other factors, its impact on the capital market is more obvious and sustainable. Therefore, except for COVID-19, the major public health emergency, it can be considered that the main factors affecting the capital market do not change significantly before and after the outbreak in the sample interval.

Furthermore, we divided the sample interval into two stages based on the evolution of COVID-19 in China, and analyzed the differences in various stages. The phased impact model is as follows.

$$r_t = a + \sum_{i=1}^m \alpha_i r_{t-i} + \sum_{j=1}^n \beta_j \mu_{t-j} + \mu_t \quad (5)$$

$$\begin{aligned} \ln(\sigma_t^2) = & c + \sum_{j=1}^q \varphi_j \ln(\sigma_{t-j}^2) + \sum_{i=1}^p \theta_i \left| \frac{\mu_{t-i}}{\sigma_{t-i}} - E\left(\frac{\mu_{t-i}}{\sigma_{t-i}}\right) \right| \\ & + \sum_{k=1}^r \rho_k \frac{\mu_{t-k}}{\sigma_{t-k}} + \gamma_1 D_{1t-1} + \gamma_2 D_{2t-1} \end{aligned} \quad (6)$$

D_{1t-1} and D_{2t-1} are exogenous variables describing the two stages of COVID-19.

¹ See Sect. 4 of the empirical results analysis for details.

3.1.2 Model of COVID-19 and Industry Sectors

To study the impact of COVID-19 on different industry sectors of the capital market, this paper drew on the idea of the event-study approach and combined it with non-parametric conditional probability estimation which is intuitive and avoids the data assumption of a normal distribution. In addition, this method can analyze both the cumulative abnormal returns and abnormal returns for each single day.

The event-study approach assumes that the market is rational and that the impact of an event will be reflected in the asset prices. This method selects the time period during which an event occurs as the event window and judges the impact on asset prices by analyzing the abnormal returns and the cumulative abnormal returns in the window. The abnormal returns and the cumulative abnormal returns for a period of time are shown in Eqs. (7) and (8).

$$AR_t = R_t - ER_t \tag{7}$$

$$CAR_{t_1, t_2} = \sum_{t=t_1}^{t_2} AR_t \tag{8}$$

In this paper, AR_t is the abnormal return of a certain industry sector index in period t , and R_t is the actual observed return in the period. ER_t is the expected return in t , and CAR_{t_1, t_2} is the cumulative abnormal return in the period from t_1 to t_2 . We used the market model to calculate the expected return of the industry index, namely, using the period before the event as the estimation window, using the composite index for the entire market, and calculating the expected return based on regression results.

Following the method of Chesney et al. [15], we further obtained the nonparametric conditional probability distribution of abnormal returns through local polynomial regression. Different from the parameter method for calculating statistics, this method calculates the conditional cumulative probability of being less than or equal to a certain number. We conducted the analysis of abnormal returns for every day. We took the abnormal return on a certain day as an example to briefly introduce the method.

The conditional distribution function of the abnormal returns of a certain industry sector index is

$$\pi(z|x) \equiv P(Z_i \leq z | X_i = x) \tag{9}$$

The condition X_i is the lagged abnormal return, i.e., Z_{i-1} . Let $Y_i = I(Z_i \leq z)$, then $E(Y_i | X_i = x) = \pi(z|x)$. The local polynomial is used to minimize Eq. (10).

$$\sum_{i=1}^n (Y_i - \beta_0 - \beta_1(X_i - x_0))^2 K_h(X_i - x_0) \tag{10}$$

In $Y_i = I(Z_i \leq z)$, $i = (1, \dots, n)$, and Z_i is the sequence of abnormal returns. z is the abnormal return observed by the industry index on a certain day in the event window. In this paper, we used the mean value of abnormal returns in the estimated

window as the condition x_0 . Moreover, $K_h(X_i - x_0)$ is the kernel function, and h is the bandwidth. Since the purpose of nonparametric estimation here is to identify whether the estimated value deviates from the normal range instead of obtaining an accurate value, the Epanechnikov kernel function form is adopted, as shown in Eq. (11). The bandwidth refers to the method of Fan and Yao [39], as shown in Eq. (12), where σ_s is the standard deviation of the samples.

$$K_h(X_i - x_0) = \frac{3}{4h} \left(1 - \frac{(X_i - x_0)^2}{h^2}\right) \mathbf{I}\left(\left|\frac{X_i - x_0}{h}\right| \leq 1\right) \quad (11)$$

$$h = 2.34\sigma_s n^{-1/5} \quad (12)$$

Constructing the Lagrangian equation for Eq. (10) and setting the partial derivative of β_0 and β_1 to 0, the following results can be obtained.

$$\hat{\mathbf{f}} = (\mathbf{X}'\mathbf{W}\mathbf{X})^{-1}\mathbf{X}'\mathbf{W}\mathbf{Y} \quad (13)$$

\mathbf{W} is a diagonal matrix with diagonal elements equal to $K_h(X_i - x_0)$. The first column of matrix \mathbf{X} is the unit column vector, and the second column is $X_i - x_0$. Using this result, we can find the conditional cumulative probability, i.e., $E(Y_i|X_i = x)$. It is the probability of an abnormal return less than or equal to a number on a certain day in the event window under the condition of the mean value of the abnormal return in the estimated window.

In addition, this method can be similarly used to analyze the cumulative abnormal returns of industry sector indices. Using the cumulative abnormal return sequences over a period with nonoverlapping estimation windows, we can estimate the probability distribution conditioned on the mean value, and analyze the immediate and continuous impact of the event on different industry sectors.

3.2 Data Selection and Processing

To analyze the overall impact of the pandemic on the capital market, this paper selected the Shanghai Composite Index, Shenzhen Component Index, and Shanghai and Shenzhen 300 Stock Composite Index (CSI 300) to represent the stock market, and it selected the government bond index and corporate bond index to represent the bond market. To study the impact of COVID-19 on different industry sectors, 10 SSE industry indices were selected, i.e., SSE Materials, SSE Energy, SSE Industry, SSE Optional, SSE Consumption, SSE Medicine, SSE Finance, SSE Telecommunications, SSE Information and SSE Utilities. We used the daily closing prices of all indices to calculate their logarithmic returns, as shown in Eq. (14).

$$R_t = \ln P_t - \ln P_{t-1} \quad (14)$$

In terms of COVID-19 data, the number of confirmed cases in mainland China² was selected for research. The data sources are the official website of the Wuhan Municipal Health Commission and NetEase News.³ An increase in the number of confirmed diagnoses across the country indicates that the pandemic is becoming more serious, while a decrease indicates that the pandemic situation has improved. Therefore, taking the number of people diagnosed can better reflect the evolution of and changes in COVID-19. Although the Wuhan Municipal Health Commission started to release news about COVID-19 in the city on December 31, 2019, people knew little about the pandemic before the speech by Nanshan Zhong in the media on January 20, 2020. Thus, COVID-19 had almost no impact on the capital market at the beginning of 2020. As a result, for the pandemic data, we selected the sample interval from January 20, 2020, to May 13, 2020, and deleted the samples from December 31, 2019, to January 19, 2020, due to few confirmed diagnoses and little impact. In addition, since the number of confirmed diagnoses reached the maximum on February 17, 2020, we used this date as the boundary and divided the pandemic into two stages, i.e., the rapid increase and the slow decrease in confirmed cases. On this basis, we analyzed the differences in the impact of COVID-19 at different stages.

When studying the impact of COVID-19 on the capital market, we selected the closing price data of the stock and bond composite indices from August 30, 2019, to May 13, 2020. To match the pandemic data, we removed the data from December 31, 2019, to January 19, 2020. When studying the impact of COVID-19 on different industry sectors, we set the estimation window from January 2, 2019, to December 30, 2019. Moreover, the event window interval is from December 31, 2019, to May 13, 2020. All capital market index data come from Flush software.

4 Empirical Results Analysis

In this section, we judged whether fluctuations in the stock and bond markets changed significantly after the pandemic and analyzed the impacts of the whole pandemic and its different stages on the capital market. In addition, we studied the impact of COVID-19 on representative industries.

4.1 The Impact of COVID-19 on the Capital Market

We used the improved ICSS algorithm to detect the structural break points of the volatility of three stock indices and two bond indices in the sample interval. The results show that at the 5% significance level, only the Shenzhen Component Index has a volatility change point; additionally, at the 10% significance level, all indices except the corporate bond index have a change point. The positions of the detected change points are shown in Table 1.

Table 1 shows that the break points of stocks are all located at the 96th point (January 22, 2020) in the sample interval, while the break points of the government bond are

² Excluding Hong Kong, Macao and Taiwan districts.

³ Data source: https://wp.m.163.com/163/page/news/virus_report/index.html?_nw_=1&_anw_=1.

Table 1 Positions of the structural break points of volatility

| α | Index | | | | |
|----------|--------------------------|--------------------------|---------------------------------|-----------------------|----------------------|
| | Shanghai Composite Index | Shenzhen Component Index | Shanghai and Shenzhen 300 Index | Government bond index | Corporate bond index |
| 5% | No point | 96 | No point | No point | No point |
| 10% | 96 | 96 | 96 | 97, 122, 127 | No point |

on January 23, March 6 and March 13, 2020. Figure 1 shows the changes in volatility of all indices under the 10% significance level. The dotted line is the average return, and the upper and lower lines represent the three times standard deviation bands of returns in different periods separated by the structural break points. Figure 2 shows the change in the number of daily diagnosed people from December 31, 2019, to May 13, 2020, and the positions of the fluctuation break points of the capital market indices. Figures 1 and 2 show that the structural break points of volatility in the stock indices are at the beginning of the rapid growth in diagnosed people, which is in the early stage of the pandemic. The occurrence date of the structural break point (January 22, 2020) is very close to the starting point of the selected pandemic sample interval (January 20, 2020), which also verifies the rationality of the pandemic data interval for analyzing the impact of COVID-19 on the capital market. The government bond index also shows structural changes in the early stage of COVID-19. However, the

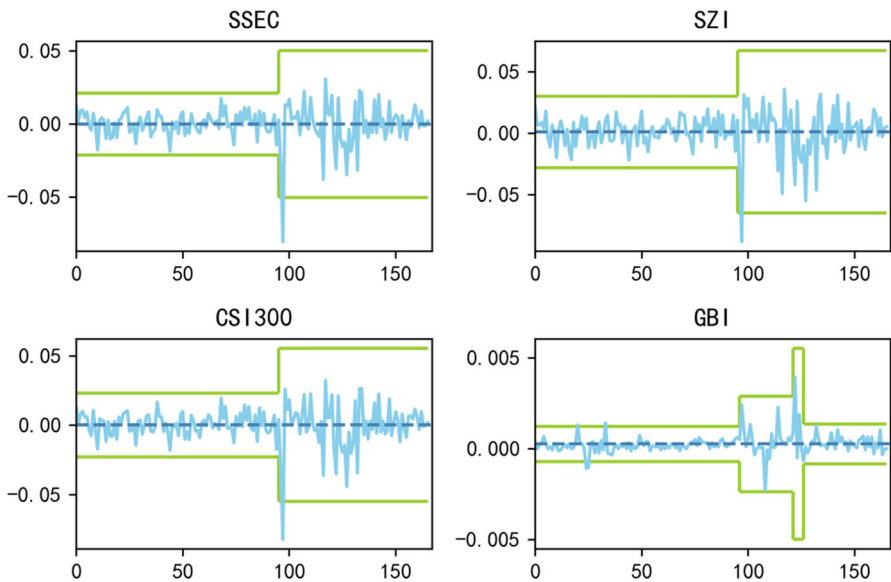


Fig. 1 Structural breaks in the volatility of indices

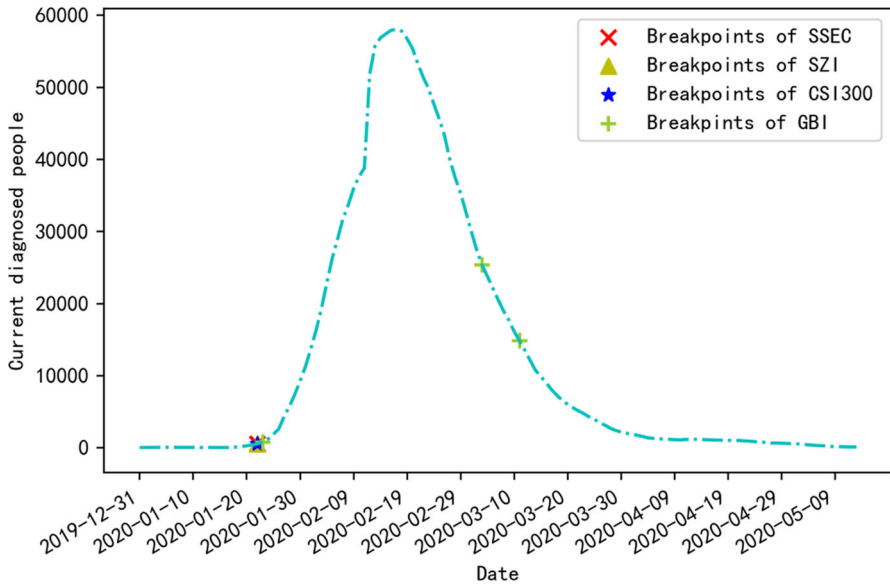


Fig. 2 The changes in diagnosed people and break points

fluctuation changes later and returns to a smaller level. In addition, the volatility of the corporate bond index is always small and unchanged during the sample period.

Therefore, at a certain level of significance, the volatility of the stock and bond markets increased after the outbreak of COVID-19, and the stock market was more affected than the bond market. Although the volatility of the government bond index increased after the outbreak, the duration was relatively short. The main reason for the difference in effects on the bond market and the stock market is that bonds have lower risk than stocks and have a better ability to withstand shocks caused by emergencies.

We further used EGARCH models with exogenous variables to model index returns and pandemic changes, and we quantitatively analyzed the impact on market returns and volatility. Choosing the number of diagnosed people from January 20, 2020, to May 13, 2020, we removed the data covering holidays and normalized the number of people to $[0, 1]$. The processed pandemic data were recorded as $Di g_t(t = 1, 2, \dots, n)$.

The results of unit root tests on the logarithmic returns of the stock and bond indices showed that the return sequences were stable under a certain level of significance, indicating that the EGARCH model was reasonable. Based on judgment criteria such as the autocorrelation function, the partial correlation function and goodness of fit, autoregressive moving average models were established for the return series of five indices, and the conditional heteroscedasticity of their residuals was detected by the ARCH-LM method. The results show that in the sample interval, the stock indices have an obvious ARCH effect, but the bond indices do not. Therefore, we established EGARCH models with pandemic variables only for the stock indices, and built

autoregressive moving average models with pandemic variables for the bond indices to determine COVID-19's impact on bond returns.

First, we analyzed the stock market. The whole-stage and separated-stage models were established for the Shanghai Composite Index, Shenzhen Component Index and CSI 300 Index. Considering the parameter significance, the R^2 , the AIC, the SC, and other model fitting performance indicators, we found that adding the COVID-19 variable to the mean equations of the model failed to improve the fitting results and the coefficient significance; thus, the COVID-19 variable was introduced into only the variance equations. The volatility models of the index returns are as follows.

The model of the Shanghai Composite Index is

$$\hat{r}_t^{sh} = \alpha_1 r_{t-1}^{sh} + \alpha_2 r_{t-2}^{sh} + \beta_1 \mu_{t-1}^{sh} + \beta_2 \mu_{t-2}^{sh} \quad (15)$$

$$\ln(\hat{\sigma}_t^{2sh}) = c + \varphi_1 \ln(\sigma_{t-1}^{2sh}) + \theta_1 \left| \frac{\mu_{t-1}^{sh}}{\sigma_{t-1}^{sh}} \right| + \rho_1 \frac{\mu_{t-1}^{sh}}{\sigma_{t-1}^{sh}} + \gamma D_{t-1} \quad (16)$$

The model of the Shenzhen Component Index is

$$\hat{r}_t^{sz} = \alpha_1 r_{t-1}^{sz} + \alpha_2 r_{t-2}^{sz} + \beta_1 \mu_{t-1}^{sz} + \beta_2 \mu_{t-2}^{sz} \quad (17)$$

$$\ln(\hat{\sigma}_t^{2sz}) = c + \varphi_1 \ln(\sigma_{t-1}^{2sz}) + \theta_1 \left| \frac{\mu_{t-1}^{sz}}{\sigma_{t-1}^{sz}} \right| + \theta_2 \left| \frac{\mu_{t-1}^{sz}}{\sigma_{t-1}^{sz}} \right| + \rho_1 \frac{\mu_{t-1}^{sz}}{\sigma_{t-1}^{sz}} + \gamma D_{t-1} \quad (18)$$

The model of the CSI 300 is

$$\hat{r}_t^{hs} = \alpha_1 r_{t-1}^{hs} + \alpha_2 r_{t-2}^{hs} + \alpha_3 r_{t-3}^{hs} + \beta_1 \mu_{t-1}^{hs} + \beta_2 \mu_{t-2}^{hs} + \beta_3 \mu_{t-3}^{hs} \quad (19)$$

$$\ln(\hat{\sigma}_t^{2hs}) = c + \varphi_1 \ln(\sigma_{t-1}^{2hs}) + \theta_1 \left| \frac{\mu_{t-1}^{hs}}{\sigma_{t-1}^{hs}} \right| + \rho_1 \frac{\mu_{t-1}^{hs}}{\sigma_{t-1}^{hs}} + \gamma D_{t-1} \quad (20)$$

The value of D_t is 0 before January 20, 2020, and after that date, the value changes to D_t . The parameter estimation results are shown in Tables 2, 3 and 4.⁴ The ARCH effect tests on the residuals after the establishment of the EGARCH model show that the conditional heteroscedasticity was eliminated. In Tables 2–7, z statistics are shown in brackets. Single asterisk, double asterisk and triple asterisk mean significant at the 10% level, 5% level and 1% level, respectively.

From the estimation results of the stock index models, the coefficients of the COVID-19 variables are significant and positive, which means that the overall impact of the pandemic on the stock market is relatively obvious and increases the volatility and the risk of the stock market.

Furthermore, taking February 17 as the boundary, we separated the evolution of COVID-19 into two stages and analyzed the differences in the impact of the stages. In

⁴ z statistics are shown in brackets, “**” means significant at the 5% level, and “***” means significant at the 1% level.

Table 2 Estimation results of the Shanghai Composite Index model

| | | | | | | |
|-------------------|---------------------------|-----------------------------------------------------------|--------------------------------------------|----------------------------------|----|--------|
| Mean equation | | | | | | |
| Variables | r_{t-1}^{sh} | r_{t-2}^{sh} | μ_{t-1}^{sh} | μ_{t-2}^{sh} | | |
| Coefficients | 0.13 (0.05) | 0.02 (0.26) | -4.98×10^6 (-0.04) | 4.69×10^7 (11.87***) | | |
| Variance equation | | | | | | |
| Variables | $\ln(\sigma_{t-1}^{2sh})$ | $\left \frac{\mu_{t-1}^{sh}}{\sigma_{t-1}^{sh}} \right $ | $\frac{\mu_{t-1}^{sh}}{\sigma_{t-1}^{sh}}$ | D_{t-1} | | |
| Coefficients | -0.77*** (-2.70) | 0.07 (1.07) | -0.01 (-3.29) | 3.71*** (3.34) | | |
| Fitting results | R-sq | 1.00 | AIC | -41.29 | SC | -41.21 |

Table 3 Estimation results of the Shenzhen Component Index Model

| | | | | | | |
|-------------------|---------------------------|-----------------------------------------------------------|-----------------------------------------------------------|--------------------------------------------|------------------|--------|
| Mean equation | | | | | | |
| Variables | r_{t-1}^{sz} | r_{t-2}^{sz} | μ_{t-1}^{sz} | μ_{t-2}^{sz} | | |
| Coefficients | 0.69*** (2.67) | -0.03 (-0.30) | 89.65*** (11.54) | -70.63*** (-2.99) | | |
| Variance equation | | | | | | |
| Variables | $\ln(\sigma_{t-1}^{2sz})$ | $\left \frac{\mu_{t-1}^{sz}}{\sigma_{t-1}^{sz}} \right $ | $\left \frac{\mu_{t-2}^{sz}}{\sigma_{t-2}^{sz}} \right $ | $\frac{\mu_{t-1}^{sz}}{\sigma_{t-1}^{sz}}$ | D_{t-1} | |
| Coefficients | -0.26 (-0.80) | 0.09 (0.41) | 0.64** (2.10) | -0.29* (-1.77) | 2.48** (2.32) | |
| Fitting results | R-sq | 0.99 | AIC | -14.47 | SC | -14.24 |

Table 4 Estimation results of the CSI 300 model

| | | | | | | |
|-------------------|---------------------------|-----------------------------------------------------------|--------------------------------------------|------------------------------|--------------------------------------|--------------------------------|
| Mean equation | | | | | | |
| Variables | r_{t-1}^{hs} | r_{t-2}^{hs} | r_{t-3}^{hs} | μ_{t-1}^{hs} | μ_{t-2}^{hs} | μ_{t-3}^{hs} |
| Coefficients | -0.07 (-0.05) | 0.01 (0.06) | 0.04 (0.82) | 2.54×10^3 (0.00) | 2.72×10^{10} *** (11.53) | -5.49×10^3 (-0.00) |
| Variance equation | | | | | | |
| Variables | $\ln(\sigma_{t-1}^{2hs})$ | $\left \frac{\mu_{t-1}^{hs}}{\sigma_{t-1}^{hs}} \right $ | $\frac{\mu_{t-1}^{hs}}{\sigma_{t-1}^{hs}}$ | D_{t-1} | | |
| Coefficients | 0.13 (1.10) | 0.35** (2.11) | -0.47*** (-4.08) | 1.26*** (2.88) | | |
| Fitting results | R-sq | 1.00 | AIC | -54.00 | SC | -53.77 |

the variance equations of the stock models, the variables D_{1t} and D_{2t} describing the two-stage pandemic were introduced in the form of Eq. (21), where u_1 is January 20, 2020, u_2 is February 18, 2020, and u_3 is May 13, 2020.

$$D_{1t} = \begin{cases} Dig_t, & u_1 < t \leq u_2 \\ 0 & \end{cases}, \quad D_{2t} = \begin{cases} Dig_t, & u_2 < t \leq u_3 \\ 0 & \end{cases} \quad (21)$$

The two-stage models of the three stock indices were built as follows. The two-stage model of the Shanghai Composite Index is

$$\hat{r}_t^{sh} = \alpha_1 r_{t-1}^{sh} + \alpha_2 r_{t-2}^{sh} + \alpha_3 r_{t-3}^{sh} + \beta_1 \mu_{t-1}^{sh} + \beta_2 \mu_{t-2}^{sh} + \beta_3 \mu_{t-3}^{sh} \quad (22)$$

$$\begin{aligned} \ln(\hat{\sigma}_t^{2sh}) &= c + \varphi_1 \ln(\sigma_{t-1}^{2sh}) + \theta_1 \left| \frac{\mu_{t-1}^{sh}}{\sigma_{t-1}^{sh}} \right| + \theta_2 \left| \frac{\mu_{t-2}^{sh}}{\sigma_{t-2}^{sh}} \right| \\ &+ \rho_1 \frac{\mu_{t-1}^{sh}}{\sigma_{t-1}^{sh}} + \gamma_1 D_{1t-1} + \gamma_2 D_{2t-1} \end{aligned} \quad (23)$$

The two-stage model of the Shenzhen Component Index is

$$\hat{r}_t^{sz} = \alpha_1 r_{t-1}^{sz} + \alpha_2 r_{t-2}^{sz} + \beta_1 \mu_{t-1}^{sz} + \beta_2 \mu_{t-2}^{sz} \quad (24)$$

$$\begin{aligned} \ln(\hat{\sigma}_t^{2sz}) &= c + \varphi_1 \ln(\sigma_{t-1}^{2sz}) + \theta_1 \left| \frac{\mu_{t-1}^{sz}}{\sigma_{t-1}^{sz}} \right| + \theta_2 \left| \frac{\mu_{t-2}^{sz}}{\sigma_{t-2}^{sz}} \right| \\ &+ \rho_1 \frac{\mu_{t-1}^{sz}}{\sigma_{t-1}^{sz}} + \gamma_1 D_{1t-1} + \gamma_2 D_{2t-1} \end{aligned} \quad (25)$$

The two-stage model of the CSI 300 Index is

$$\hat{r}_t^{hs} = \alpha_1 r_{t-1}^{hs} + \alpha_2 r_{t-2}^{hs} + \alpha_3 r_{t-3}^{hs} + \beta_1 \mu_{t-1}^{hs} + \beta_2 \mu_{t-2}^{hs} + \beta_3 \mu_{t-3}^{hs} \quad (26)$$

$$\ln(\hat{\sigma}_t^{2hs}) = c + \varphi_1 \ln(\sigma_{t-1}^{2hs}) + \theta_1 \left| \frac{\mu_{t-1}^{hs}}{\sigma_{t-1}^{hs}} \right| + \rho_1 \frac{\mu_{t-1}^{hs}}{\sigma_{t-1}^{hs}} + \gamma_1 D_{1t-1} + \gamma_2 D_{2t-1} \quad (27)$$

The estimation results of the two-stage models for the stock indices are shown in Tables 5, 6 and 7.⁵

The estimation results of the two-stage model show that for all stock indices, the coefficients of the pandemic variables of the two stages in the variance equations are positive. However, only the coefficients for the pandemic variables of the rapid increase in the number of confirmed diagnoses are significant, and those of the slow decrease stage are smaller and not significant. In addition, the coefficients of D_{1t-1}

⁵ z statistics are shown in brackets. “*” means significant at the 10% level, “**” means significant at the 5% level, and “***” means significant at the 1% level.

Table 5 Results of the two-stage model of the Shanghai Composite Index

| Mean equation | | | | | | |
|-------------------|-----------------------------------------|-----------------------------------------------------------|-----------------------------------------------------------|--------------------------------------------|--------------------|--------------------------------|
| Variables | r_{t-1}^{sh} | r_{t-2}^{sh} | r_{t-3}^{sh} | μ_{t-1}^{sh} | μ_{t-2}^{sh} | μ_{t-3}^{sh} |
| Coefficients | - 0.01 (- 2.60 $\times 10^{-3}$) | - 0.03 (- 0.01) | 0.02 (0.09) | - 1.75 \times 10^9 *** (- 10.85) | - 4.03 (- 0.00) | 2.91×10^2 (- 0.00) |
| Variance equation | | | | | | |
| Variables | $\ln(\sigma_{t-1}^{2sh})$ | $\left \frac{\mu_{t-1}^{sh}}{\sigma_{t-1}^{sh}} \right $ | $\left \frac{\mu_{t-2}^{sh}}{\sigma_{t-2}^{sh}} \right $ | $\frac{\mu_{t-1}^{sh}}{\sigma_{t-1}^{sh}}$ | D_{1t-1} | D_{2t-1} |
| Coefficients | - 1.00*** (- 93.41) | 0.64*** (2.90) | 0.54** (2.47) | - 0.07 (- 1.11) | 3.98*** (3.00) | 2.08 (1.53) |
| Fitting results | R-sq | 1.00 | AIC | - 48.69 | SC | - 48.42 |

Table 6 Results of the two-stage model of the Shenzhen Composite Index

| Mean equation | | | | | | |
|-------------------|---------------------------|-----------------------------------------------------------|-----------------------------------------------------------|--------------------------------------------|-----------------|----------------|
| Variables | r_{t-1}^{sz} | r_{t-2}^{sz} | μ_{t-1}^{sz} | μ_{t-2}^{sz} | | |
| Coefficients | - 0.84*** (- 38.77) | - 0.17*** (- 13.36) | 12.63*** (8.23) | 13.09*** (7.51) | | |
| Variance equation | | | | | | |
| Variables | $\ln(\sigma_{t-1}^{2sz})$ | $\left \frac{\mu_{t-1}^{sz}}{\sigma_{t-1}^{sz}} \right $ | $\left \frac{\mu_{t-2}^{sz}}{\sigma_{t-2}^{sz}} \right $ | $\frac{\mu_{t-1}^{sz}}{\sigma_{t-1}^{sz}}$ | D_{1t-1} | D_{2t-1} |
| Coefficients | 0.71*** (8.76) | 4.78 (1.43) | 4.26 (1.52) | 0.09 (0.22) | 8.58* (1.91) | 5.84 (1.45) |
| Fitting results | R-sq | 0.99 | AIC | - 10.00 | SC | - 9.76 |

Table 7 Results of the two-stage model of the CSI 300

| Mean equation | | | | | | |
|-------------------|-------------------------------------------|-----------------------------------------------------------|--------------------------------------------|-------------------|----------------------------------------|------------------|
| Variables | r_{t-1}^{hs} | r_{t-2}^{hs} | r_{t-3}^{hs} | μ_{t-1}^{hs} | μ_{t-2}^{hs} | μ_{t-3}^{hs} |
| Coefficients | - 0.14 (- 0.06) | - 0.03 (- 0.09) | 0.03 (0.39) | 0.48 (0.00) | $4.70 \times$ 10^6 *** (13.33) | - 0.88 (0.00) |
| Variance equation | | | | | | |
| Variables | $\ln(\sigma_{t-1}^{2hs})$ | $\left \frac{\mu_{t-1}^{hs}}{\sigma_{t-1}^{hs}} \right $ | $\frac{\mu_{t-1}^{hs}}{\sigma_{t-1}^{hs}}$ | D_{1t-1} | D_{2t-1} | |
| Coefficients | - 1.01*** (- 4.15 \times 10^2) | 0.11 (1.13) | - 0.15*** (- 2.73) | 3.98*** (3.52) | 1.50 (1.32) | |
| Fitting results | R-sq | 1.00 | AIC | - 36.60 | SC | - 36.35 |

are larger than those of other terms in the model, indicating relatively great impacts on the volatility of the capital market. The results of the two-stage model analysis show that during the rapid growth in the number of confirmed diagnoses, COVID-19 has a significant impact on the stock market and increased the fluctuations in stock returns and the risk of the market. However, the impact of COVID-19 on the market risk is not obvious during the period when the pandemic was gradually alleviated.

Furthermore, we took the government bond index and the corporate bond index to study the impact of COVID-19 on the bond market with the whole-stage and two-stage models. Since the test results of the ARCH effect showed no obvious conditional heteroscedasticity of the two bond indices, we established ARMA models for their return rates and introduced exogenous pandemic variables D_{t-1} , D_{1t-1} and D_{2t-1} to compare the model fitting effects. The results show that only the coefficient of the rapid growth stage in the government bond model is significant at the 10% level, and its value is -5.32×10^{-4} . The coefficients of the exogenous variables in the other models are not significant and are much smaller than the coefficients of other AR and MA terms. In addition, the fitting results show that the pandemic variables do not improve the performance of the models. Therefore, the negative impacts of the pandemic on bond returns were very small and negligible.

In summary, the volatilities of the Shanghai Composite Index, Shenzhen Component Index, CSI 300 Index and government bond index underwent structural changes after COVID-19. The outbreak of the pandemic increased market volatilities and the impacts on the stock market were more significant. Moreover, the impacts of different stages of the pandemic showed certain differences. Regarding the returns of the market, the pandemic had almost no impact on the returns of the stock and bond indices.

4.2 The Impact of COVID-19 on Different Industry Sectors

To study the influence on different industry sectors of the capital market, we selected ten SSE industry indices, including the SSE Energy index, SSE Pharmaceutical index, SSE Finance index, etc. We combined the event-study approach and the nonparametric conditional probability estimation method, and analyzed the daily abnormal returns and cumulative abnormal return of each industry index over the event window period.

We used the Shanghai Composite Index to represent the market level and estimated the market model through the logarithmic return of each industry index in the estimation window. On this basis, we calculated the abnormal returns and cumulative abnormal returns of each industry index in the event window after the outbreak of COVID-19. The results are shown in Figs. 3 and 4.

The straight line parallel to the y-axis in the figures divides the two stages of the pandemic. The two figures show that after the pandemic, the SSE Materials, SSE Energy and SSE Finance indices had more negative abnormal returns, and the cumulative abnormal returns showed a downward trend. Furthermore, the SSE Pharmaceuticals index had more positive abnormal returns, and the cumulative abnormal returns showed an upward trend. The cumulative abnormal returns of SSE Information and SSE Telecom increased rapidly in the previous stage of the pandemic and decreased slightly in the later stage, while the cumulative abnormal returns of SSE Consumption increased

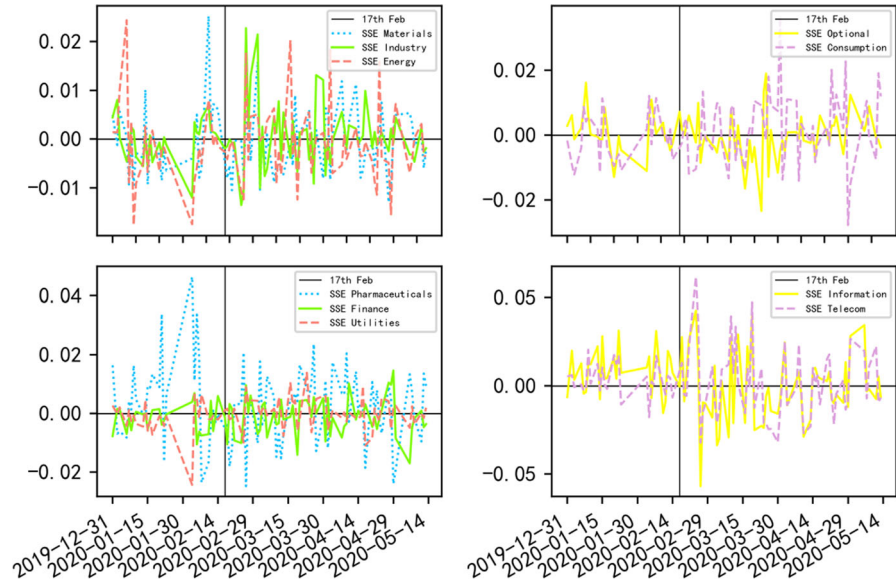


Fig. 3 Abnormal returns of the industry indices

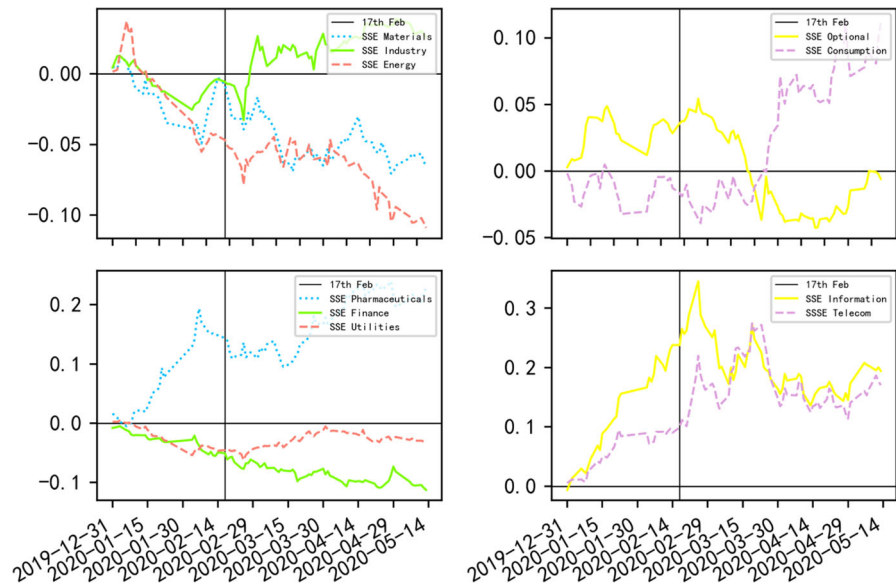


Fig. 4 Cumulative abnormal returns of the industry indices



Fig. 5 The judgement of daily abnormal returns

significantly in the later stage. Moreover, the cumulative abnormal returns of other industry indices fluctuated around zero.

Through the nonparametric conditional probability estimation, we analyzed the daily abnormal returns of each index in the event window. Based on the rules of Chesney et al. [15], when the abnormal return on a certain day is negative and the conditional cumulative probability of being less than or equal to that abnormal return is in the range of $[0.05, 0.1)$, the abnormal return is significant and we define the change as an abnormal change. When the conditional cumulative probability is in the range of $[0, 0.05)$, the abnormal return is very significant and we define the change as an extreme change. Similarly, if the abnormal return on a certain day is positive and the conditional cumulative probability is in the range of $[0.9, 0.95)$, it is called an abnormal change, and the influence is obvious. If the conditional cumulative probability is in the range of $(0.95, 1]$, the change is called an extreme change and the impact is significantly obvious. In other words, when there are abnormal changes or extreme changes, the return of the index is obviously affected. The estimated results of the conditional probability of each index are shown in Fig. 5.

From Fig. 5, some sectors experienced more abnormal and extreme changes, while others experienced fewer. In addition, the abnormal returns of some sectors were positive, while some sectors received more negative impacts. During the entire period of the window, the abnormal returns of the pharmaceutical and information sectors showed obvious positive deviations. The positive abnormal returns of the pharmaceutical sector showed significant deviations for 26 days, and the 15-day probabilities among them exceeded 0.95, indicating extreme changes. The information sector had 27 days of positive abnormal returns; most of them were only abnormal changes and were mainly concentrated in the previous stage of COVID-19. Therefore, the returns of the pharmaceutical industry and the information industry during the entire pandemic were mainly positively affected, and the impact on the pharmaceutical industry was even more significant. This result is closely related to the important role of the pharmaceutical industry in the anti-pandemic process. The demand for medical equipment, medical supplies, and pharmaceutical production brought benefits to the industry and positive expectations to the market. In addition, one of the possible reasons for the increase in the information sector is that the worsening of the pandemic and the national control measures restricted people's outing activities. The increases in online activities and remote work increased people's needs for information technology.

In contrast, the finance sector suffered a significant negative impact during the entire period, with negative abnormal returns for 27 days. Almost all these abnormal returns were extreme changes, showing great risks. Furthermore, COVID-19 had negative

Table 8 Judgment of cumulative abnormal returns

| Industry | 10CAR-P | 30CAR-Z | 60CAR-Z | 86CAR-Z |
|-----------------|--------------|----------------|---------------|----------------|
| Materials | (-) 0.4916 | (-) - 0.5495 | (-) - 0.9263 | (-) - 0.9139 |
| Industries | (+) 0.6210 | (-) - 0.3207 | (+) - 0.1323 | (+) - 0.0842 |
| Energy | (+) 1.0298** | (-) - 1.6540** | (-) - 1.3655* | (-) - 1.8376** |
| Optional | (+) 1.0000** | (+) 1.2014 | (-) - 0.7137 | (-) - 0.1021 |
| Consumption | (-) 0.2270 | (-) - 0.3025 | (+) 0.7562 | (+) 1.1880 |
| Pharmaceuticals | (+) 0.6424 | (+) 2.3901** | (+) 2.1869** | (+) 2.4175** |
| Finance | (-) 0.2478 | (-) - 1.6543** | (-) - 1.5452* | (-) - 1.7276** |
| Information | (+) 1.1463** | (+) 3.2146** | (+) 1.3776* | (+) 1.3079* |
| Telecom | (+) 0.8927 | (+) 1.4789* | (+) 1.2950* | (+) 1.2698 |
| Utilities | (-) 0.5417 | (-) - 1.6193* | (-) - 0.2510 | (-) - 0.5508 |

effects on the consumption sector in general, but the impact was relatively small compared to the financial sector, and most of the changes were abnormal. In addition, the optional consumption sector showed positive abnormal changes in the early stage of the pandemic, while more negative deviations occurred with the evolution of COVID-19, indicating a lag in the impact on the sector. The optional consumption sector needed a certain amount of reaction time to digest pandemic information. Moreover, the consumption and optional consumption sectors showed positive abnormal deviations at the end of the window. In addition to the easing of the pandemic and the revival of consumer confidence, one of the possible reasons is that the government's consumption subsidies and other stimulating measures brought positive information to the market.

For other industry sectors, the number of days with significant negative changes was slightly higher than that with significant positive changes in general, and the number of days with abnormal and extreme changes was higher in SSE Materials. In addition, for different stages of the epidemic, the abnormal and extreme changes of SSE Telecom and SSE Industry mainly occurred in the later stage, and there were fewer significant deviations during the rapid growth stage. This finding indicates that these sectors reacted slowly to the pandemic and that the impact was characterized by a certain lag and gradualness.

To further study the persistence of the impact on different industry sectors, we analyzed the cumulative abnormal returns of each index for 10 days, 30 days, 60 days and the whole event window periods. The 10-day analysis used the nonparametric conditional probability method to calculate the conditional cumulative probability value P ,⁶ and the nonoverlapping 10-day CAR was estimated. Due to the limitation of the sample size, other analyses of CAR used the method of Liu et al. [13]. The results are shown in Table 8.

(+) means that cumulative abnormal value is positive, while (-) means that the cumulative abnormal value is negative. P values with '*' mean an abnormal change,

⁶ Theoretically, the conditional probability is in the range of [0, 1], but due to the deviation of the estimation, the actual result may overflow the interval, which also shows that the return is significantly deviated.

and ‘***’ means extreme change; a Z value with ‘*’ means significant at the 10% level, and ‘**’ means significant at the 5% level.

In the first 10 days after December 31, the number of diagnosed people was small, and the growth rate was slow. Therefore, the early stage of COVID-19 had little impact on various industry sectors. For the SSE Materials, SSE Industry, SSE Optional, SSE Consumption and SSE Utilities sectors, although the results of daily abnormal returns during the event window show many abnormal changes, the impacts of COVID-19 were not significant from the cumulative abnormal returns. This finding means that the returns of these sectors deviated greatly only on certain days, which means that they did not have a continuous significant impact.

Furthermore, the cumulative abnormal return of the consumption sector turned from negative to positive in the later stage of the pandemic with the passage of time, and its negative impact in the early stage was alleviated due to the improvement in the pandemic situation and policy supports. The return of SSE Industry was significantly positive in the initial stage of COVID-19, indicating that it was less sensitive to information about the pandemic. During the whole event window, its cumulative abnormal returns fluctuated around zero and were basically unaffected by the pandemic. This result is mainly due to the relatively complete industrial system and strong risk-defense capabilities in industrial sectors. Moreover, the cumulative abnormal returns of the materials and utilities sectors quickly turned from positive to negative. In contrast, the optional industry showed negative abnormal returns only in the mid-term (60-day CAR), which is consistent with the analysis results of the daily abnormal returns. This finding once again indicates that the impact of COVID-19 on the optional sector had a lag, mainly in the middle and late stages of the pandemic.

In addition, the energy sector and finance sector suffered significant negative impacts during the pandemic, and the cumulative abnormal returns of the entire window were still significant, indicating the long duration of the effect. Moreover, the energy sector had an obvious lag in response to the epidemic information, while the finance sector is more sensitive. In contrast, the SSE Pharmaceuticals and SSE Information indices were continuously and positively affected, and their response to pandemic information was relatively fast. From the perspective of cumulative abnormal returns, the telecom sector showed a positive deviation, but the significance and sustainability of the impact were weaker than those of the impact on the pharmaceutical and information industries.

Therefore, from the analysis of the probability of cumulative abnormal returns, we see that the persistence and the time lag of the impact of COVID-19 on different industrial sectors were heterogeneous.

5 Conclusion

Using the improved ICSS algorithm, a time series model with exogenous variables, and nonparametric conditional probability estimation for the event-study approach, we studied the impact of COVID-19 on China’s capital market and different industries through stock indices, bond indices and industry sector indices. We detected structural changes in market volatility and analyzed the direction and magnitude of the impacts

on market returns and volatility. Moreover, we studied the changes in the returns of different industry sectors during the pandemic period.

For the whole capital market, COVID-19 mainly impacted risk. Although, as a major public health emergency, COVID-19 was sudden and continuous, its occurrence and evolution generally had no impact on the returns of the stock and bond markets because of effective anti-pandemic policies and the rational performance of the market. From a risk perspective, after the outbreak of COVID-19, the volatility of the stock market and bond market increased to a certain level, and the impact on the volatility of the stock market was more obvious, leading to higher risk. From the differences in the impact of the two stages of the pandemic, it can be seen that in the severe stage of the pandemic, the impact of COVID-19 on the stock market was more obvious and increased market volatility, while with the improvement in the pandemic situation, its impact was no longer significant. There are two main reasons for the increase in stock volatility. On the one hand, as a new highly infectious disease, COVID-19 has been considerably uncertain and has caused investors to panic and to be risk averse. On the other hand, the real economy has suffered a shock due to the suspension of projects and affected enterprises, which has also affected investors' expectations about the market.

For each industry sector, there are differences in the direction, significance and continuity of the impact on various industries. During the pandemic, the returns of the pharmaceutical and information sectors showed significant and continuous positive deviations, indicating obviously positive effects. In contrast, the finance sector and the energy sector suffered sustained and significant negative impacts. However, the negative impacts on other industry sectors were relatively small. In addition, sectors responded to the influence of COVID-19 at different speeds. The impact of COVID-19 on some industry sectors, such as the energy sector, the optional consumption sector, and the telecom sector, had a certain lag, while other industry indices had a faster response speed, such as the finance sector. The main reason is that various industries have different sensitivities to information, and the transmission mechanisms and speeds are heterogeneous. In general, although many sectors showed negative cumulative abnormal returns during the window, they were not significant. Therefore, except for sectors such as pharmaceuticals, information and finance, the impact of COVID-19 on industry sectors was limited.

In summary, we found that the impact of COVID-19 on market fluctuations have been continuous and gradual and that the impacts on various industries have been different. The following suggestions are obtained based on the conclusions.

Investors should avoid an excessive emotion of panic. Overall, public health emergencies have a limited impact on the return of the capital market. Investors can formulate or adjust their investment strategies based on the characteristics of various industries to effectively avoid risk. In addition, compared with stock market investment, bond market investment shows a better risk resistance ability when similar public emergencies occur.

Regulatory agencies and government departments should pay more attention to monitoring abnormal market fluctuations, and they should prevent and control financial risks in key industries in the capital market, and adopt targeted measures for the real economy. The government could give support to industries that suffer significant

negative impacts, for example, by providing consumer subsidies to stimulate consumption demand, broadening the financing channels of companies, and cutting taxes to reduce corporate capital pressure.

With the continuous optimization and upgrading of the economic structure, various industries have formed increasingly complex network relationships in the supply chain and capital chain, and the finance sector and capital market play an increasingly vital role. Public health emergencies have unpredictable suddenness and contingency. On the one hand, their suddenness and uncertainty will lead to a strong initial impact on the market, such as the sharp volatility of the stock market in the early stage of COVID-19. Although the initial volatility is relatively short, the increase in overall market risk cannot be ignored. Moreover, due to the close and complex links between the industrial chain, supply chain and capital chain, the transmission of risks between various departments and industry sectors has accelerated and the degree of risk spillover has deepened. Therefore, timely and powerful risk monitoring and preventive measures are very important. On the other hand, the characteristics of public health emergencies also enable targeted macrocontrol policies and measures to play a positive role in a relatively short period of time and obtain significant results. Therefore, it is necessary to continuously improve the emergency response capabilities of financial risk supervision in the capital market. An improved early warning mechanism and the strengthened prevention of cross-risks can realize timely attention to changes in key industries and ensure that risks related to the entire market are controllable when public health emergencies occur, which will help to maintain the stability and security of the financial market.

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Ethical statements All authors consciously assure that for the manuscript fulfills the following statements: 1) This material is the authors' own original work, which has not been previously published elsewhere. 2) The paper is not currently being considered for publication elsewhere. 3) The paper reflects the authors' own research and analysis in a truthful and complete manner. 4) The paper properly credits the meaningful contributions of co-authors and co-researchers. 5) The results are appropriately placed in the context of prior and existing research.

Data availability All the data and codes, as well as, the supplementary material used in this study can be made available from the corresponding author, upon reasonable request.

Code availability All the codes used in this study, as well as, the supplementary material can be made available from the corresponding author, upon reasonable request.

Author contributions The theoretical analysis and empirical analysis were completed by Aihua Li and Weijia Xu. The data collection, discussion and review were done by Lu Wei.

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