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Article

Impact of crisis events on stock market volatility and risks

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Abstract: The COVID-19 crisis, which occurred in 2020, brought crisis events back to the attention of scholars. With the increasing frequency of crisis events, the influence of crisis events on stock markets has become more obvious. This paper focuses on the impact of the subprime crisis, the Chinese stock market crash crisis and the COVID-19 crisis on the volatility and risk of the world's major stock markets. In this paper, we first fit the volatility using EGARCH model and detect asymmetry of volatility. After that, a VaR model is calculated on the basis of EGARCH to measure the impact of the crisis event on the risk of stock markets. This paper finds that the subprime crisis has a significant influence on the risk of the stock market in China, US, South Korea, and Japan. During the COVID-19 crisis, there was little change in the average risk of each country. But at the beginning of the COVID-19 crisis, there was a significant increase in the risk of each country's stock market. The Chinese stock market crash crisis had a more pronounced effect on the Chinese and Japanese stock markets and a lesser effect on the US and Korean stock markets.

Keywords: crisis event; risk; GARCH model

1. Introduction

Covid-19 is a virus that causes respiratory infections in humans. This virus was discovered in late 2019. Initially people thought that COVID-19 would not spread globally. But then COVID-19 spread to the vast majority of countries in the world through human mobility (Ozili, 2020; Xu, 2020). COVID-19 virus also brought serious impact to the world economy while jeopardizing human life and health. According to the World Bank, the global economic growth rate was −3.1% in 2020 due to the COVID-19 crisis. The total world unemployment rate also peaked at 6.9% in 2020. The COVID-19 crisis became the world's most widely spread and economically influential major public health event (Altig, 2020; Maital, 2020).

The emergence of the COVID-19 crisis in 2020 has brought crisis events back into the attention of scholars. Crisis events usually have a significant negative influence on the economy. This is because a crisis event affects the normal production and operations of a company, leading to a drop in revenue (Gunnigle, 2013; Kestens, 2011). Crisis events can also cause a decline in consumer confidence, leading to a reduction in consumer spending. Crisis events can increase the fiscal pressure on the government, making the government's fiscal deficit widen (Bordo, 2016). Therefore, people should increase the level of attention to crisis events and be wary of the recurrence of crisis events.

Each crisis event has had an impact on the economy. Production, employment and trade flows around the world suffered severe disruptions during the subprime crisis. Prices of global stock markets and commodities also plummeted during this period (Silva, 2022). The European debt crisis led to a sustained decline in economic activity in Europe and a slowdown in global economic growth during this period. The event also led to a significant decline in global stock markets and a rise in risk aversion among investors (Stracca, 2015). The frequency of crisis events within recent years is becoming higher. There have been twelve crises in the last 100 years, seven of them have happened in the last 20 years. (Sengupta, 2020). The increasing frequency of crisis events has caused concern among scholars. As a result, crisis events have regained the attention of many scholars.

Stock market plays an important role in finance. The trend of stock prices can reflect the health of economy. A rise in stock prices can also lead to more financing for companies (Masoud, 2013). The occurrence of crisis events can also have a negative impact on stock prices. The occurrence of a crisis event tends to cause the stock market prices to drop significantly. Investors and company manager with equity holdings often lose much of their wealth as a result (Li, 2021). Therefore, as the frequency of crisis events increases, so does the change in stock market risk. It is important to study the impact of crisis events on stock market risk.

Most of the current studies only examine the impact of a single crisis event on stock market risk, and do not provide a comprehensive insight into the impact of crisis events on stock market risk. And many studies usually select a short time frame for the study, which cannot show the changes of stock market risk in a comprehensive way. In this paper, four crisis events are selected, which can better analyze the impact of crisis events on stock market risk. Moreover, this paper selects the stock market closing prices in the last 20 years as the research object, which can clearly show the changes of stock market risk. By studying the impact of crisis events on the stock market, the results of this paper can help policy makers to better maintain the stability of the stock market. The results of this paper help investors to be able to choose the appropriate investment market according to their risk appetite. It also helps investors to adjust their investment portfolios in a timely manner during the crisis to avoid excess loss of funds.

Most of investors invest their money in developed countries such as the US, South Korea and Japan. The total market capitalization of the Chinese stock market is the second largest in the world. There are many investors who have invested their money in China (Ding, 2020). We choose the stock market of China, US, South Korea and Japan. The subprime mortgage crisis in 2008, the Chinese stock market crash crisis in 2015 and the COVID-19 crisis in 2020 are selected as research objects. This paper fully investigates the influence of the crisis events on the risk of the stock markets of major countries in the world.

In this paper, chapter 2 reviews the literature on the impact of crisis events on stock markets. Chapter 3 describes research methodology as well as the data sources. Chapter four presents the empirical results. Chapter 5 gives some suggestions for the results.

2. Review of literature

2.1. Theoretical basis

2.1.1. Efficient market hypothesis

The theory assumes that investors in the market are rational and that investors pay close attention to all kinds of information and are able to react quickly. The main idea of the theory is that in an efficient market with sound rule of law and transparent information, the price of stocks can fully respond to all the economic fundamentals information in the market that will affect the price of stocks (Borges, 2010; Rossi, 2018). Therefore, changes in the macroeconomy can cause fluctuations in stock prices. This provides a theoretical basis for crisis events to affect stock prices.

2.1.2. Behavioral economics

Behavioral economics provides an insight into the role of investor psychology and behavior in the decision-making process. In times of crisis, investors often suffer from cognitive biases and they usually overreact to negative information. This leads to sharp price fluctuations in the stock market, reflecting the irrational character of the market. Emotions have a more significant impact on market volatility in times of crisis. Panic exacerbates investors' risk aversion, causing them to sell assets quickly in the face of bad news. This emotion-driven decision-making pattern increases market instability, thereby increasing market volatility and risk (Bressan, 2023; Zouaoui, 2011). Behavioral economics provides a theoretical basis for the impact of crisis events on the stock market through the psychological lens of investors.

2.2. Crisis events and stock market return

Stock market return is one of main research directions to find the impact of crisis events on stock markets. Some scholars mainly measure the risk by calculating the return or abnormal return before and after the event. Zhu (2024) calculated the abnormal return to study the influence of COVID-19 crisis on China stock market. This author found that not all restrictive policies during the COVID-19 crisis had a negative influence on stock market. Mazur (2021) studied the stock market returns during the COVID-19 crisis in 2020. COVID-19 was found to have a negative influence on stock prices in different sectors in the US. Nguyen (2021) investigated the influence of the SARS crisis on Chinese stock market by calculating the rate of return. During the ten days of these two crises, most of the companies in China had negative returns on their stock prices. Rahman (2021) calculated the cumulative abnormal returns before and after the COVID-19 event and demonstrated that the crisis had a negative influence on Australian stock market.

Some scholars have also used VaR method to determine the influence of crisis events by calculating maximum loss of the stock market. Degiannakis (2012) used VaR method to calculate the risk of five markets during the subprime crisis. The results showed that VaR method can calculate the risk during the crisis better. And it also predicted the risk of the stock market better. Miletic (2015) used VaR method to calculate the risk profile of emerging markets in Eastern Europe during subprime crisis. The empirical results showed that the subprime crisis had significantly increased the risk of the stock market in Eastern European countries.

2.3. Crisis events and stock market volatility

Volatility is an indicator of stock market risk. Since GARCH model can calculate the volatility better, some scholars apply GARCH model to calculate the volatility during crisis events. Rehman and Karimullah (2023) investigated the impact of COVID-19 crisis and subprime crisis on the stock markets of Gulf countries using GARCH model. The results showed that both crisis events significantly affect the volatility of stock markets in Gulf countries. Endri (2021) investigated the effect of COVID-19 crisis on volatility and abnormal returns of stock markets using GARCH model. The empirical results showed that the COVID-19 crisis leads to an increase in the volatility of the Indonesian stock market, which leads to changes in the abnormal returns of stocks.

Mathur (2016) investigated the volatility of Indian stock market during subprime crisis using GARCH model. The empirical results showed that the volatility was high during the financial crisis. Wang (2019) used a GARCH model to find that the significant increase in the volatility of Chinese stock market during the market crash crisis in 2015 was mainly caused by the policies of the government. Setiawan (2021) used a GARCH model to measure the volatility of the Indonesian stock market during the subprime crisis and COVID-19 crisis. The empirical results showed that the volatility during COVID-19 was higher than that during the subprime crisis. COVID-19 had a greater influence on the risk of the Indonesian stock market.

It is evident from the above literature that most scholars usually study the impact of a single crisis event on the stock market only. This does not provide an in-depth study of the impact of crisis events on the stock market. Most of the scholars study the volatility of the stock market separately from the returns which fails to describe the level of risk in detail.

We mainly use GARCH model as main research method. A number of crisis events are selected as research objects to analyze the influence of crisis events on stock market volatility in detail. Then GARCH-VaR model is constructed on the basis of the GARCH result. This paper analyzes in detail the specific risk of the stock market under a certain confidence level (Cui, 2021). The influence of crisis events on the stock market is studied from two perspectives: volatility and risk.

3. Data and methodology

3.1. Data

The data are mainly from the Choice database. Subprime mortgage crisis (13 February 2007 to 31 December 2008), China's stock market crash crisis (15 June 2015 to 31 October 2015) and COVID-19 crisis (30 January 2020 to 31 December 2022) are selected as the objects. The SSE Composite Index of China, the S&P 500 of the US, the KOSPI of South Korea, and the Nikkei 225 Index of Japan are selected as the main research objects. Daily closing prices of these indices for the period from 1 January 2000 to 31 December 2023 were selected. And the log returns of these indices are calculated for the subsequent study (Chuang, 2012). Log returns are additive compared to returns. The formula for the logarithmic returns is:

$$R_t = 100ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

R_t is logarithmic return of the stock market. P_t is closing price on the current day. P_{t-1} is closing price on the previous day.

3.2. Methodology

3.2.1. GARCH

The GARCH model was proposed by Torben Bollerslev in 1986. Stock returns usually have volatility aggregation effect and heteroskedasticity. the GARCH model can capture these characteristics and can calculate the volatility more accurately (Chong, 1999). The model consists of the following two main formulas:

$$r_t = \mu + \varepsilon_t \tag{2}$$

$$\sigma_t^2 = \alpha_0 + \alpha_i \varepsilon_{t-1}^2 + \beta_j \sigma_{t-1}^2 \tag{3}$$

r_t is the log daily return. μ is mean of the return. ε_t is residual term. ε_{t-1}^2 is residual squared term for the previous period. σ_{t-1}^2 is the conditional variance for the previous period. σ_t^2 is conditional variance of the residuals. α_0 is the constant term. α_i and β_j are coefficients of the model for the degree of exposure of the explanatory variables to external shocks, respectively (Lin, 2018).

3.2.2. EGARCH

The EGARCH model was proposed to address the shortcomings of the GARCH model in dealing with the symmetric effects of returns on volatility. The model includes the ratio of the residuals to their standard deviation, which captures the different impacts of falling and rising stock prices on volatility. This allows EGARCH to naturally capture the impact of negative shocks on volatility. Below is the formula for the EGARCH model:

$$\log(\sigma_t^2) = \alpha_0 + \alpha_i \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_j \log(\sigma_{t-1}^2) \tag{4}$$

where the γ term is designed to find the effect of shocks on volatility asymmetrically. This parameter if non-zero implies that there is a leverage effect on volatility (Ahmed and Suliman, 2011).

3.2.3. TGARCH

In order to accurately study the asymmetry of asset prices, TGARCH was proposed by Zakoian (1994). The formula of the TGARCH is as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_i \varepsilon_{t-i}^2 + \beta_j \sigma_{t-j}^2 + \gamma \varepsilon_{t-i}^2 d_{t-1} \tag{5}$$

d is a dummy variable. ε_{i-1} bigger than zero is good news. ε_{i-1} smaller than zero is bad news. γ term coefficients, if γ is not zero then there is an asymmetry in volatility (Lim, 2013).

3.2.4. VaR

The full name of the VaR model is Value at Risk. The model is a method of risk. It is defined as the maximum possible loss in the value of an asset that occurs with a certain probability over a certain period of time. Therefore, the magnitude of risk can be effectively assessed by calculating VaR (Chen, 2014). The formula for VaR calculation is follows:

$$\text{Prob}\ (\Delta P \leq \text{VaR}) = \alpha \tag{6}$$

ΔP represents the value of the actual loss of an asset. α denotes the confidence level, which can reflect the degree of risk manager's appetite for risk. The confidence level is usually 95% or 99% in practice. VaR value represents the value of the maximum loss to which an asset is exposed at a confidence level of $1 - \alpha$.

The formula for the VaR model based on the GARCH model is s follows:

$$VaR = -(\mu_p + Z_\alpha \sigma_p) \tag{7}$$

μ_p is the mean of the returns. σ_p is the standard deviation. Z_α refers to the critical value value, which depends on the confidence level. larger values of VaR represent larger losses.

4. Results

Based on the descriptive statistics, the average return of the American stock market is the highest, and the average return of the Chinese stock market is the lowest. According to the standard deviation, the standard deviation of the China is higher than that of the United States, Korea and Japan. This indicates that the Chinese stock market is the most volatile. This may be because China is not a developed country and the Chinese stock market was created the latest. Compared to the other three developed countries, the Chinese stock market is not mature enough (Su, 2022). As can be seen in **Table 1**, the normality tests for all four countries are significant at the 1% level. This indicates that the logarithmic returns of the stock markets of all four countries do not follow a normal distribution. The Kurtosis of the stock markets of the four countries is higher than 3 and the Skewness is less than 0. This indicates that the logarithmic returns conform to the characteristics of the sharp peaks and thick tails, so we use the t distribution to construct the GARCH.

Table 1. Descriptive statistics for logarithmic returns.

	China	**US**	**Korea**	**Japan**
Mean	0.0012	0.0051	0.0034	0.0033
Median	0.0172	0.0051	0.0270	0.0198
Maximum	4.0830	4.4500	4.9007	5.7477
Minimun	−4.0199	−5.5439	−5.3711	−5.2598
Sum	5.9725	26.2982	17.5344	17.1906
Std. Dev	0.6470	0.5370	0.6235	0.6354
Skewness	−0.3170	−0.5390	−0.5271	−0.3607
Kurtosis	5.5876	9.8490	6.7030	6.5222
Jarque−Bera	6833.5	21209.0	9948.3	9304.0
Probability	0.0000	0.0000	0.0000	0.000

Table 2 shows the smoothness test and autocorrelation test for the four countries. The results of the ADF test were significant at the significance level of 5%, it shows that the log returns of the four countries are stationary. The results of the autocorrelation test show that the log returns of the stock markets of China, the United States and Japan are autocorrelated. The log returns of the Korean are not autocorrelated.

Table 2. ADF test and autocorrelation test.

	China	US	Korea	Japan
ADF test	−15.521	−17.861	−16.477	−17.151
Probability	0.010	0.010	0.010	0.010
Ljung-Box test	13.168	69.068	0.8255	15.393
Probability	0.040	0.000	0.220	0.017

Because the Chinese, US, and South Korean stock markets have autocorrelation, an ARMA model is constructed to eliminate the autocorrelation of log returns (Dana, 2016). Based on the results of the **Table A1** in Appendix, ARMA (3,2) is used for the SSE index. ARMA (1,1) is used for the S&P 500 and Nikkei 225 index. Since the Korean stock market does not have autocorrelation, a constant mean model is used. The residuals of the mean model are tested for ARCH effect. The results in **Table 3** for all four countries are significant at the 1% level, indicating that they all have ARCH effects and can be modeled using the GARCH model.

Table 3. Autocorrelation test and ARCH test for residuals.

	China	US	Korea	Japan
Ljung-Box test	2.993	10.154	8.255	7.315
Probability	0.810	0.118	0.220	0.293
ARCH effect	382.0	1310.3	848.8	1017.1
Probability	0.000	0.000	0.000	0.000

4.1. Result of GARCH

GARCH is symmetric GARCH model, EGARCH and TGARCH models are asymmetric GARCH models (Lim, 2013). Because the return rate of the stock market is usually asymmetric, it is necessary to compare the return rate with the symmetric GARCH model and the asymmetric GARCH model. Three GARCH models are constructed separately and the best fit is selected according to the AIC criterion. According to the AIC criterion, the smaller the AIC indicates a better fit (Endri, 2020). Based on the results of the **Table 4,** EGARCH model fits the volatility of log returns of the four countries best. The γ coefficients in the EGARCH model for all four countries are significant at the 1% level, indicating that there is an asymmetry in the volatility of the log returns.

Table 4. Results of the GARCH.

		China	US	Korea	Japan
GARCH	α	0.067***	0.124***	0.082***	0.087***
	β	0.929***	0.874***	0.913***	0.896***
	AIC	1.574	1.060	1.452	1.663
EGARCH	α	−0.027***	−0.143***	-0.079***	-0.104***
	β	0.989***	0.978***	0.983***	0.364***
	γ	0.158***	0.163***	0.171***	0.176***
	AIC	1.569	1.033	1.438	1.643

Table 4. (*Continued*).

		China	US	Korea	Japan
TGARCH	α	0.052***	0.007	0.034***	0.023**
	β	0.926***	0.880***	0.904***	0.877***
	γ	0.033**	0.187***	0.103***	0.136***
	AIC	1.573	1.038	1.441	1.647

4.2. Result of stock market volatility

Figure 1 shows the volatility fitted by EGARCH model. In **Figure 1**, the volatility of all four countries increased significantly during the subprime crisis, the Chinese stock market crash crisis, and the COVID-19 crisis. China's stock market has a significant increase in volatility during the subprime crisis and the Chinese stock market crash crisis. The U.S. stock market has a significant increase during the subprime crisis and the COVID-19 crisis. The Korean stock market has more significant volatility during the subprime crisis and the COVID-19 crisis. The Japanese stock market has more pronounced volatility during all three crisis events. This provides evidence that crisis events elevate the risk of the stock market.

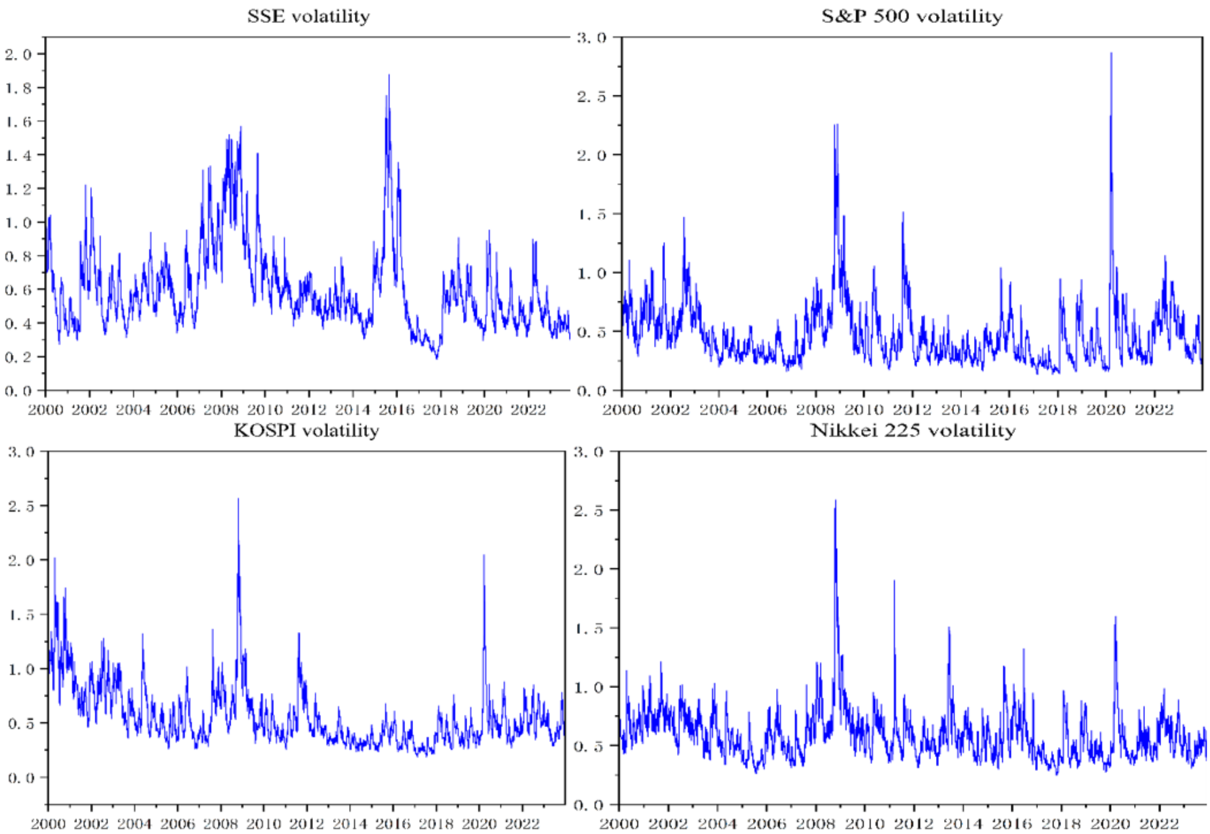

Figure 1. Volatility of the stock markets.

4.3. Result of stock market risk

We use the EGARCH-VaR to further investigate the influence of crisis events on stock market risk. **Table 5** shows the risk of the stock markets of China, the US, South Korea and Japan at 95% confidence level. According to **Figure 2**, it can be seen that the Chinese stock market has the highest level of risk during the Chinese stock market crash crisis. During the subprime crisis, the risk of Chinese stock market is also higher than the risk of the full phase. The risk during COVID-19 is lower than the full-stage period. This indicates that COVID-19 does not have a significant influence on the risk of Chinese stock market.

Table 5. Descriptive statistics of the risk of SSE composite index.

	Whole stage	Crisis 1	Crisis 2	Crisis 3
Mean	0.9399	1.6848	2.1324	0.7904
Maximum	2.9323	2.4467	2.9323	1.4838
Minimum	0.2851	0.9446	1.2292	0.4944
Std. Dev	0.3963	0.3543	0.4206	0.2071

Notes: Crisis 1 is the subprime crisis. Crisis 2 is the crash of the Chinese stock market. Crisis 3 is the COVID-19 crisis.

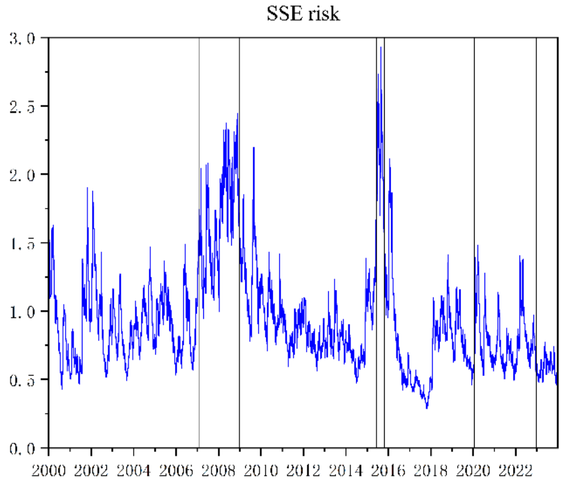

Figure 2. Risks of SSE composite index.

According to the **Table 6** and **Figure 3** that the US stock market has the highest average level of risk during the subprime crisis. However, during the early part of the COVID-19 crisis, the S&P 500 has the highest level of risk on record. Although the average level of the S&P 500 during COVID-19 crisis is lower than during subprime crisis. But COVID-19 initially has a higher impact on US stock market risk than the other two crisis events. S&P 500 volatility during the Chinese stock market crash is similarly higher than the risk during the full period. But the impact is the smallest of the crisis events.

Table 6. Descriptive statistics of the risk of S&P 500 Index.

	Whole stage	Crisis 1	Crisis 2	Crisis 3
Mean	0.7318	1.0729	0.7795	0.8733
Maximum	4.4753	3.5267	1.6249	4.4753
Minimum	0.2102	0.2832	0.4752	0.2535
Std. Dev	0.4074	0.6574	0.3012	0.5354

Notes: Crisis 1 is the subprime crisis. Crisis 2 is the crash of the Chinese stock market. Crisis 3 is the COVID-19 crisis.

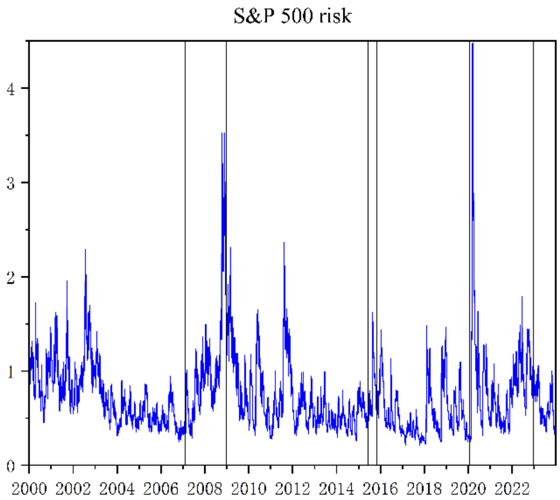

Figure 3. Risks of S&P 500 index.

According to the **Table 7** and **Figure 4,** KOSPI Index has the highest level of risk during subprime crisis. The COVID-19 crisis has the second highest impact on KOSPI Index among these crises. The impact of COVID-19 on KOSPI Index is similar to that of S&P 500 Index. Both have high risk level in the early period, but the average level during the crisis is similar to the risk level in the full period. However, the Chinese stock market crash crisis has no effect on KOSPI Index and the average risk level during the period is much lower than during the full period.

Table 7. Descriptive statistics of the risk of KOSPI index.

	Whole stage	**Crisis 1**	**Crisis 2**	**Crisis 3**
Mean	0.8683	1.1856	0.6884	0.8668
Maximum	4.0096	4.0096	1.0547	3.1917
Minimum	0.2858	0.4400	0.4458	0.4216
Std. Dev	0.4284	0.6248	0.1427	0.3591

Notes: Crisis 1 is the subprime crisis. Crisis 2 is the crash of the Chinese stock market. Crisis 3 is the COVID-19 crisis.

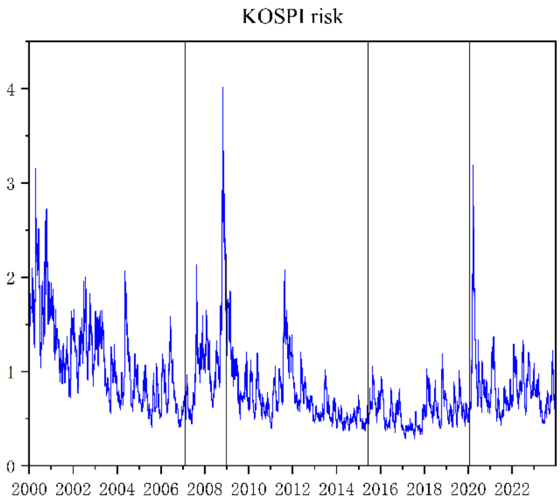

Figure 4. Risks of KOSPI index.

According to the **Table 8** and **Figure 5**, Nikkei 225 Index has the highest average risk during the subprime crisis. Similar to the U.S. and South Korea, the difference between the risk in Japan during COVID-19 and the risk in the full period is not significant. But the beginning phase of the COVID-19 crisis has a high level of risk in Nikkei 225 Index. The average risk of Nikkei 225 Index during the Chinese stock market crash crisis is higher than during the full-phase period, and the risk level is only lower than during the subprime crisis.

Table 8. Descriptive statistics of the risk of Nikkei 225 index.

	Whole stage	**Crisis 1**	**Crisis 2**	**Crisis 3**
Mean	0.917235	1.21798	1.058865	0.906422
Maximum	4.040391	4.040391	1.83445	2.497952
Minimun	0.390773	0.506513	0.563376	0.51931
Std. Dev	0.335077	0.644609	0.384807	0.296478

Notes: Crisis 1 is the subprime crisis. Crisis 2 is the crash of the Chinese stock market. Crisis 3 is the COVID-19 crisis.

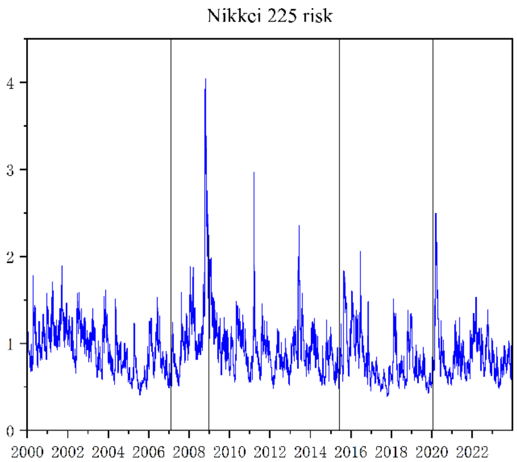

Figure 5. Risks of nikkei 225 index.

Subsequently, this paper uses the VaR Failure test to test whether the results of the VaR are accurate. The number of days in which the actual loss is higher than the VaR value is divided by the total number of days to determine the probability of loss occurrence. One minus the confidence level is the expected failure rate. If the probability of occurrence of actual loss exceeds the expected failure rate, the model is unreliable. In the **Table 9**, it can be seen that the probability of the actual loss rate occurring is lower than the expected failure rate for all four countries at the 95% confidence level. This means that the results of VaR are reliable.

Table 9. VaR failure test result.

	Failure rate
China	0.0455
US	0.0447
Korea	0.0471
Japan	0.0474

5. Conclusion

The volatility of stock indexes of four countries is firstly fitted using different GARCH models. It is found that the EGARCH has a better and better fit to the volatility compared to the GARCH and TGARCH. The gamma coefficients of the EGARCH model are significant, meaning that the volatility of the stock index of the four countries has an asymmetric effect. After that, the volatility of the stock index is calculated using the EGARCH model. The volatility of the stock markets of the four countries increases during subprime crisis, Chinese stock market crash crisis and COVID-19 crisis.

Based on the volatility calculated by EGARCH, the risk level of stock indexes is further calculated by VaR model. The Chinese stock market has the highest risk during the Chinese stock market crash crisis, followed by the subprime crisis. The COVID-19 crisis has little impact on the risk of the Chinese stock market. The US stock market has the highest average risk during the subprime crisis, but the Chinese stock market crash crisis has no impact on the risk of the US stock market. The COVID-19 crisis has a large negative impact on the US stock market in the early stage of the crisis, and the value of risk tended to normalize in the late stage of the crisis. The Korean stock market has the highest risk during the subprime crisis, followed by the COVID-19 crisis. The impact of the Chinese stock market collapse crisis on the Korean stock market is insignificant. The Japanese stock market has a significant increase in the level of risk during the subprime crisis and the Chinese stock market crash crisis. the impact of the COVID-19 crisis on the risk of the Japanese stock market is more pronounced in the early part of the crisis, and has no significant impact in the later part of the crisis.

This shows that the subprime crisis is the crisis event that has the most pronounced impact on the stock markets of the countries. The risk of the stock markets of all four countries increases significantly during the subprime crisis. The impact of the COVID-19 crisis on the risk of the stock markets of each country is more pronounced in the early part of the crisis and normalized in the later part of the crisis. In contrast, the Chinese stock market crash crisis has a limited impact on stock market risk in countries other than China.

In summary, global crises tend to increase the risk of the stock market significantly. During a crisis, risk averse individuals need to adjust their portfolios to avoid losses. Policymakers need to formulate timely policies to reduce stock market volatility and prevent financial risks from spreading from the stock market to the rest of the financial system. In the early stages of a crisis event, stock market volatility and risk are higher. Policymakers need to adopt monetary policies such as lowering interest rates or reducing reserve requirements as early as possible to prevent the further spread of a crisis event. Company decision makers also need to pay attention to the volatility of stock prices during a crisis and avoid stock-related operations such as equity pledges and IPOs during a crisis.

Author contributions: Conceptualization, YZ and SIT; methodology, YZ and SIT; software, YZ and AD; validation, YZ, SIT, AD and JC; formal analysis, YZ; data curation, YZ and JC; writing—original draft preparation, YZ; writing— review and editing, YZ; supervision, SIT and AD; project administration, SIT; funding acquisition, YZ. All authors have read and agreed to the published version of the manuscript.

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References

Ahmed, A. E. M., & Suliman, S. Z. (2011). Modeling stock market volatility using GARCH models evidence from Sudan. International journal of business and social science, 2(23).

Altig, D., Baker, S., Barrero, J. M., Bloom, N., Bunn, P., Chen, S., ... & Thwaites, G. (2020). Economic uncertainty before and during the COVID-19 pandemic. Journal of public economics, 191, 104274.

Bordo, M. D., & Meissner, C. M. (2016). Fiscal and financial crises. In Handbook of macroeconomics (Vol. 2, pp. 355-412). Elsevier.

Borges, M. R. (2010). Efficient market hypothesis in European stock markets. The European Journal of Finance, 16(7), 711-726.

Bressan, S., & Weissensteiner, A. (2024). On the time-varying relationship between coskewness and returns of banks. Review of Financial Economics, 42(1), 21-38.

Chen, D. H., Chen, C. D., & Wu, S. C. (2014). VaR and the cross-section of expected stock returns: An emerging market evidence. Journal of Business Economics and Management, 15(3), 441-459.

Chen, M. H. (2010). The economy, tourism growth and corporate performance in the Taiwanese hotel industry. Tourism Management, 31(5), 665-675.

Chong, C. W., Ahmad, M. I., & Abdullah, M. Y. (1999). Performance of GARCH models in forecasting stock market volatility. Journal of forecasting, 18(5), 333-343.

Chuang, W. I., Liu, H. H., & Susmel, R. (2012). The bivariate GARCH approach to investigating the relation between stock returns, trading volume, and return volatility. Global Finance Journal, 23(1), 1-15.

Cui, Y., Li, L., & Tang, Z. (2021). Risk Analysis of China Stock Market During Economic Downturns–Based on GARCH-VaR and Wavelet Transformation Approaches. Asian Economic and Financial Review, 11(4), 322.

Dana, A. N. (2016). Modelling and estimation of volatility using ARCH/GARCH models in Jordan's stock market. Asian Journal of Finance & Accounting, 8(1), 152-167.

Degiannakis, S., Floros, C., & Livada, A. (2012). Evaluating value-at-risk models before and after the financial crisis of 2008: International evidence. Managerial Finance, 38(4), 436-452.

Ding, D., Guan, C., Chan, C. M., & Liu, W. (2020). Building stock market resilience through digital transformation: using Google trends to analyze the impact of COVID-19 pandemic. Frontiers of Business Research in China, 14(1), 21.

Endri, E., Abidin, Z., Simanjuntak, T. P., & Nurhayati, I. (2020). Indonesian stock market volatility: GARCH model. Montenegrin Journal of Economics, 16(2), 7-17.

Grout, P. A., & Zalewska, A. (2016). Stock market risk in the financial crisis. International Review of Financial Analysis, 46, 326-345.

Gunnigle, P., Lavelle, J., & Monaghan, S. (2013). Weathering the storm? Multinational companies and human resource management through the global financial crisis. International Journal of Manpower, 34(3), 214-231.

Kestens, K., Van Cauwenberge, P., & Bauwhede, H. V. (2012). Trade credit and company performance during the 2008 financial crisis. Accounting & Finance, 52(4), 1125-1151.

Li, Y., Wang, S., & Zhao, Q. (2021). When does the stock market recover from a crisis? Finance Research Letters, 39, 101642.

Lim, C. M., & Sek, S. K. (2013). Comparing the performances of GARCH-type models in capturing the stock market volatility in Malaysia. Procedia Economics and Finance, 5, 478-487.

Lin, Z. (2018). Modelling and forecasting the stock market volatility of SSE Composite Index using GARCH models. Future Generation Computer Systems, 79, 960-972.

Maital, S., & Barzani, E. (2020). The global economic impact of COVID-19: A summary of research. Samuel Neaman Institute for National Policy Research, 2020(2020), 1-12.

Masoud, N. M. (2013). The impact of stock market performance upon economic growth. International Journal of Economics and Financial Issues, 3(4), 788-798.

Mathur, S., Chotia, V., & Rao, N. V. M. (2016). Modelling the impact of Global Financial Crisis on the Indian stock market through GARCH models. Asia-Pacific Journal of Management Research and Innovation, 12(1), 11-22.

Mazur, M., Dang, M., & Vega, M. (2021). COVID-19 and the march 2020 stock market crash. Evidence from S&P1500. Finance research letters, 38, 101690.

Miletic, M., & Miletic, S. (2015). Performance of Value at Risk models in the midst of the global financial crisis in selected CEE emerging capital markets. Economic research-Ekonomska istraživanja, 28(1), 132-166.

Nguyen, Q. T. T., Anh, D. L. T., & Gan, C. (2021). Epidemics and Chinese firms' stock returns: is COVID-19 different? China Finance Review International, 11(3), 302-321.

Ozili, P. (2020). COVID-19 in Africa: socio-economic impact, policy response and opportunities. International Journal of Sociology and Social Policy, 42(3/4), 177-200.

Rahman, M. L., Amin, A., & Al Mamun, M. A. (2021). The COVID-19 outbreak and stock market reactions: Evidence from Australia. Finance Research Letters, 38, 101832.

Rehman, M. Z. (2023). Black swan events and stock market behavior in Gulf countries: a comparative analysis of financial crisis (2008) and COVID-19 pandemic. Arab Gulf Journal of Scientific Research.

Rossi, M., & Gunardi, A. (2018). Efficient market hypothesis and stock market anomalies: Empirical evidence in four European countries. Journal of Applied Business Research, 34(1).

Sengupta, I. (2020). An Exhaustive Study of the'BLACK SWAN'Events in the Financial Markets. Adhyayan: A Journal of Management Sciences, 10(02), 22-35.

Setiawan, B., Ben Abdallah, M., Fekete-Farkas, M., Nathan, R. J., & Zeman, Z. (2021). GARCH (1, 1) models and analysis of stock market turmoil during COVID-19 outbreak in an emerging and developed economy. Journal of Risk and Financial Management, 14(12), 576.

Silva, T. C., Muniz, F. J., & Tabak, B. M. (2022). Indirect and direct effects of the subprime crisis on the real sector: labor market migration. Empirical Economics, 62(3), 1407-1438.

Stracca, L. (2015). Our currency, your problem? The global effects of the euro debt crisis. European Economic Review, 74, 1-13.

Su, C., Liu, Y., Liu, C., & Tao, R. (2022). The Impact of Medical and Health Fiscal Expenditures on Pharmaceutical Industry Stock Index in China. International Journal of Environmental Research and Public Health, 19(18), 11730.

Wang, Y. C., Tsai, J. J., & Li, X. (2019). What drives China's 2015 stock market surges and turmoil? Asia-Pacific Journal of Financial Studies, 48(3), 410-436.

Xu, W., Wu, J., & Cao, L. (2020). COVID-19 pandemic in China: Context, experience and lessons. Health policy and technology, 9(4), 639-648.

Zakoian, J. M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and control*, *18*(5), 931-955.

Zhu, Y., Taasim, S. I., Daud, A., & Cai, J. (2024). Government policies and their impact on the China securities index 300 stock market: Insights from the COVID-19 crisis. Journal of Infrastructure, Policy and Development, 8(10), 7737.

Zouaoui, M., Nouyrigat, G., & Beer, F. (2011). How does investor sentiment affect stock market crises? Evidence from panel data. Financial review, 46(4), 723-747.

Appendix

Table A1. AIC results of SSE's ARMA model.

	ARMA (,1)	ARMA (,2)	ARMA (,3)
ARMA (1,)	10196.40	10197.51	10195.99
ARMA (2,)	10197.56	10200.18	10174.18
ARMA (3,)	10196.43	10174.18	10176.21