Comparisons of Market Crash Risks Between SARS and Covid-19 in China

by

Pinyi Li

An honors thesis submitted in partial fulfillment

of the requirements for the degree of

Bachelor of Science

Business and Economics Honors Program

NYU Shanghai

May 2023

Professor Marti G. Subrahmanyam	Professor Jeffrey Wurgler
Professor Christina Wang	
Professor Wendy Jin	
Faculty Advisers	Thesis Adviser

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Abstract

This paper works on investigating whether SARS and COVID-19 outbreaks caused a market crash risk in China. As COVID-19 has significantly impacted most people's lives, this study analyzes the SSE Composite Index during the SARS outbreak from January 2000 to July 2005 and the COVID-19 outbreak from January 2017 to March 2023.

The research quantifies the market crash risk by constructing GARCH-s models for each period and using conditional skewness graphs. To better understand the effects brought about by the pandemic on the Chinese stock market, the study divides each period into three phases: pre-pandemic, pandemic, and post-pandemic.

The comparison between the two pandemics is based on the conditional skewness analysis and related market factors. This study finds that the COVID-19 pandemic caused a higher market crash risk than the SARS outbreak due to various factors, such as a longer duration and a more complicated international environment. However, timely and appropriate policy interventions helped the stock market recover more effectively and quickly during the COVID-19 pandemic. Overall, this study suggests that China has made significant progress in handling pandemics by improving policy responses and market interventions.

Key Words: *COVID-19, SARS, China Stock Market*

Preface

The reason behind this research on investment preferences during pandemics stems from my personal investment experiences during the COVID-19 outbreak. Observing continuously negative returns and high volatility in the investment market, along with the increasing risk aversion among investors, I became curious about whether there were increased risks in the Chinese stock market during this pandemic. Furthermore, considering the similar virus and shocks during the SARS outbreak, I was prompted to investigate whether there were also significant risks in the Chinese stock market during that time.

To compare the market risks between the two pandemics, I constructed GARCH-s models using the SSE Composite Index with the guidance of my advisor, Professor Wurgler from NYU. The conditional skewness generated through the GARCH-s models represents the market crash risks, allowing for a more direct and vivid comparison of the pandemic market risks. By comparing the resulting risks and possible reasons, I aim to identify any differences in the risks between the two pandemics.

1 Introduction

1.1 Background

A. SARS

Severe acute respiratory syndrome, known as SARS, was first identified in Guangdong, China at the end of November 2002. The outbreak resulted in over 8,000 confirmed cases from 29 countries and territories and caused at least 774 deaths worldwide ("2002-2004 SARS outbreak"). The World Health Organization, WHO, declared the major period of the SARS outbreak to have ended in July 2003. SARS is a relatively uncommon disease and this outbreak was the first time this particular strain was identified. It initially broke out in South China and subsequently spread to Singapore through a businessman, Hong Kong through an assisting doctor, and Canada through a traveler. The virus is known to be highly resilient, and it took researchers 14 years to identify the specific bat population responsible for the outbreak.

The case fatality rate of SARS in China was 6.55%, while its case fatality rate globally was 11%, which is considerably high. However, the virus was found to have a relatively low spread rate, identified as level two by Nanshan Zhong, an academician at the Chinese Academy of Engineering, when compared to other influenzas. Additionally, the main targets of the infection were young people aged 20 to 37, who are the main workforce and consumer base in China.

The SARS outbreak, which lasted for eight months and infected more than 8,000 people in twenty-nine different countries and territories, brought about many negative effects on the Chinese economy. This is evident in the GDP growth rate in 2003, which was relatively low compared to the growth trend after 2004, as shown in China's GDP graph from 2000 to 2021. According to the data from the National Bureau of Statistics of China, after the outbreak, GDP growth decreased from 11% to 9% in the second quarter, resulting in significant disruptions in economic activity.

The SARS outbreak also severely affected specific sectors such as tourism, retailing, and railways, leading to significant revenue losses. According to *The Short-Term Impact of SARS on the Chinese Economy*, the outbreak was predicted to lower China's economic growth rate in 2003 by 1 to 2 percentage points (Hai, Zhao, Wang 2004). The lockdown policies put in place to prevent the spread of the virus further affected both consumption and production. For instance, Beijing was locked down for 90 days in 2003. As reported in *4 charts show how SARS hit China's economy nearly 20 years ago*, growth in production slowed to 13.7% in May, and growth in the retail sales section also moderated to 4.3%, which is the slowest pace up till now. However, due to efficient treatments and the relatively low spread rate of SARS, the pandemic lasted only eight months in China, which may have had a shorter impact on the Chinese economy.

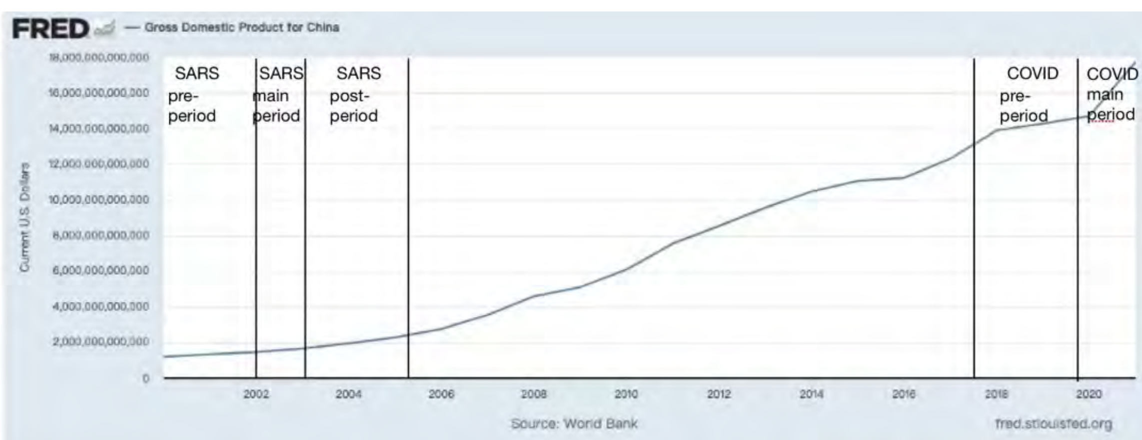

Figure 1: GDP growth rate in China

B. COVID-19

COVID-19, a new strain of coronavirus, was first identified in Wuhan in December 2019 and was announced to be a global pandemic by the WHO in March 2020. Unlike SARS, COVID-19 has more variants and is highly infectious, with a longer incubation

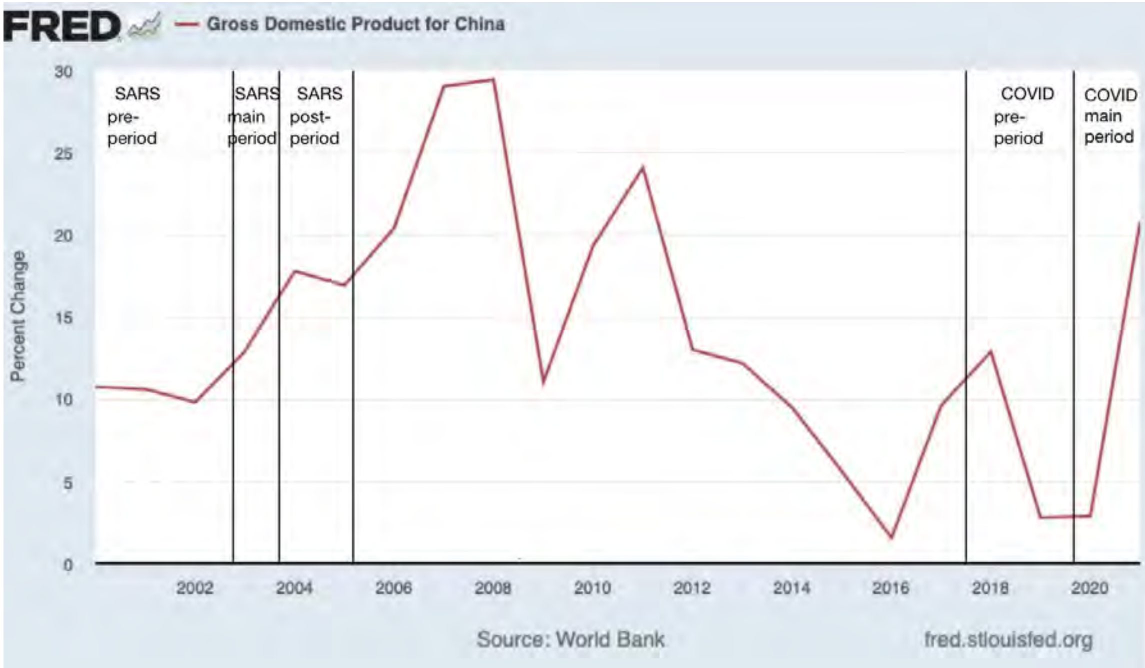

Figure 2: GDP in China

period, but a lower case fatality rate. As of 11 December 2022, there have been more than 650 million confirmed cases and 6.65 million deaths all over the world. The global case fatality rate is currently 1.03%, with a higher CFR of 5.6% in China. COVID-19 is highly infectious and can affect people of all ages, with a higher risk of mortality for the elderly. According to *Assessing the age specificity of infection fatality rates for COVID-19: systematic review, meta-analysis, and public policy implications*, a study on infection fatality rates specific to the age, "the IFR is very low for children and young adults (e.g., 0.002% at age 10 and 0.01% at age 25) but rises to 0.4% at age 55, 1.4% at age 65, 4.% at age 75, 15% at age 85, and exceeds 25% for ages 90 and above" (Levin 2020). Nanshan Zhong has identified COVID-19 as a level three spread rate disease, which is higher than SARS. The virus can infect people of all ages, with the elderly being more vulnerable to severe cases and higher mortality rates.

The COVID-19 pandemic has taken a heavy toll on the Chinese economy, per-

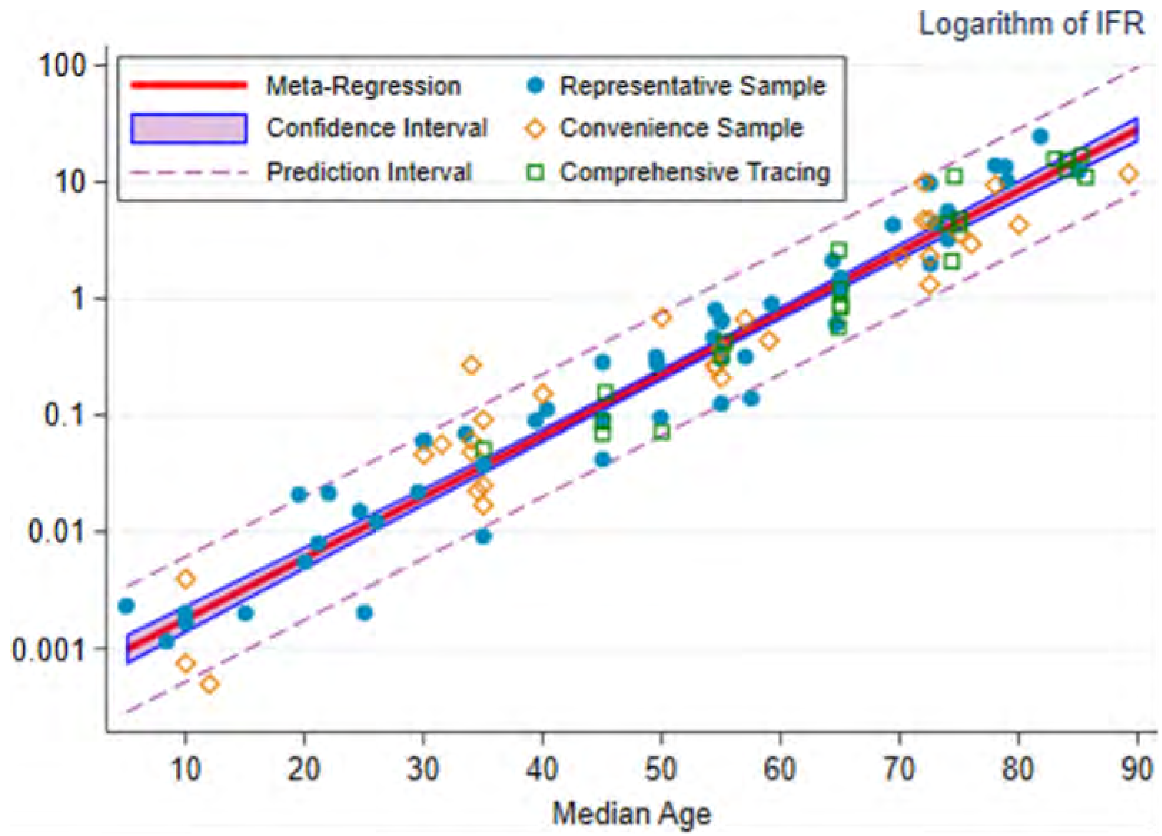

Figure 3: age specificity of infection fatality rates

sisting for over three years. The most apparent impact can be seen in China's GDP graph, which shows a sudden decrease in the GDP growth rate. FRED reports that in 2019, China's GDP was 14,279 billion yuan, but there was a 10% decline in growth rate in 2018. Additionally, the youth unemployment rate rose from 10% in 2018 to 12% in 2020. The pandemic's biggest impact on the Chinese economy stems from the lockdown policy implemented to control its spread, known as "Covid Zero". The lockdown first began in Wuhan in January 2020, where the entire city was isolated for 76 days. Due to repeated outbreaks, several other municipalities, including Shanghai and Beijing, also experienced multiple quarantine periods. According to *How China's lockdown policies are crippling the country's economy*, "Until May 30, China's official death toll from the pandemic stood at 5,226, compared with more than 1mn in the

US and 179,000 in the UK" (White 2022). Although this policy was successful in reducing the number of deaths, it had adverse effects on production and the global supply chain.

According to *China's Economy under COVID-19: Short-Term Shocks and Long-Term Changes*, there were three stages of negative effects. The first stage was weak consumption, resulting from home isolation, leading to a reduction in residents' outings and public contact across the country. The second stage was weak production because workers failed to return to work after the Spring Festival. The third stage was shrinking overseas demand due to the virus's spread worldwide. Liu and Hu reported that "during COVID-19, industrial value-added decreased by 13.5% YoY, service industry production index decreased by 13.0%, total retail sales of social consumer goods decreased by 20.5%, fixed asset investment decreased by 24.5%, and exports denominated in RMB fell by 15.9%" (2020). It is evident from these statistics that COVID-19 has led to a severe negative stagnant Chinese economy.

1.2 Motivation

This study works on investigating the impact of the pandemics including SARS and COVID-19 on the investment market in China. Specifically, it focuses on the market return volatility and crash risks to provide insights for future actions related to pandemics, not only from a market perspective but also from an investor's standpoint. By analyzing these effects, this research seeks to identify implications for both the investment market and investors, which can guide decision-making in similar situations in the future.

The remainder of the paper is organized as follows. Section 2 summarizes the literature. The data and methodology are discussed in Section 3 and Section 4.

Section 5 reports the results, and Section 6 concludes. Some of the proofs are relegated to the Appendix.

2 Literature

The negative impact of COVID-19 on the Chinese stock market has sparked widespread interest, prompting research on the topic. In their empirical study, *The Impact of COVID-19 Pandemic on Stock Markets: An Empirical Analysis of World Major Stock Indices*, Khan, Zhao et al. (2020) sought to investigate the impact of the pandemic on the sixteen countries' stock markets. By creating a weekly panel data set that tracks the number of COVID-19 cases and stock market returns, they find that once human-to-human transmission is confirmed by the government, all stock market indices react negatively in both the short- and long-term event windows. What's more, they mention that the Shanghai Composite Index experienced a severe decline during the short-term event window but bounced back during the long-term event window which may result from the Chinese government's aggressive measures to contain the pandemic restored investor confidence in the Shanghai Stock Market.

Researchers have developed various methods to quantify the impact of COVID-19 on the Chinese stock market. For instance, Zhu, Zhang, and Yang (2021) used the PCA method to construct a multiple-factor model to create a gambling preference index, which can predict stock returns. The model uses data from Chinese A-share listed companies from 2000 to 2018, based on four factors: price, return, volatility, and investor structure in China's stock market, each corresponding to the dimensions including stock price, skewness of stock returns, extreme stock returns, idiosyncratic volatility, turnover rate, and retail proportion.

The most common method is to construct GARCH models with varying emphasis. Wen, He, and Chen (2014) built the D-GARCH-M model, DR-GARCH-M model, and GARCHC-M model to connect investors' risk preference to the return values. The authors demonstrated that "investors' inherent risk preference displays risk-seeking behavior, and their risk preferences affect the conditional skewness; specifically, their risk aversion makes return skewness reduce while risk-seeking makes the skewness increase" (Wen, He, and Chen 2014).

This paper is closely related to Liu, Huynh, and Dai's (2021) research, *The impact of COVID-19 on the stock market crash risk in China*, in which they quantified the stock market crash risk and investigated the influence of investor sentiment using the Baidu Index with respect to COVID-19 infections and deaths in China. By using GARCH-s models and the China Stock Market & Accounting Research (CSMAR) database, they examined the return distribution of the Shanghai Stock Exchange using conditional skewness to indicate the equity market crash risk. They constructed a fear index based on the conditional skewness and the total confirmed cases, demonstrating that the pandemic increased stock market crash risk.

However, my study differs from Liu, Huynh, and Dai's (2021) research in two ways. First, I utilize a different dataset, specifically the SSE Composite Index, which represents the market crash risk due to Shanghai's unique lockdown policy and its status as an international trade city. Second, I analyze two pandemics, SARS and COVID-19, and conduct a detailed comparison of their negative impacts, providing a more nuanced understanding of the pandemics' effects.

3 Data

To divide SARS and COVID in China into different periods, I use data from Google Trends to show the topic's popularity in the US during the two pandemics. All data in Google Trend starts in 2004, therefore, some periods of SARS may be lost but the remains can still display the severity. From Figure 3, we can see that although ending in July 2003, the popularity of the topic of "SARS in China" doesn't decrease until July 2005. Therefore, I take 2003.7-2005.7 as the third period of SARS to show the response of people after SARS and how it differs from the pre-period. Besides this, we can see that people's interest in it rebounds at the beginning of 2020. It corresponds to the breakout of COVID in China since the essence of the two pandemics is similar viruses. Figure 4 shows "the popularity of Chinese COVID-19 in the US". The rapid increase corresponds to the overall breakout of COVID-19 in Jan 2020, similar to the trend of SARS in Figure 3. We can see three peaks for COVID-19 in 2020.3, 2022.3, and 2023.1. The first two stand for two main breakouts in China and the final one is special because it's the breakout caused by the all-around opening of China towards COVID-19. In other words, there won't be lockdowns or

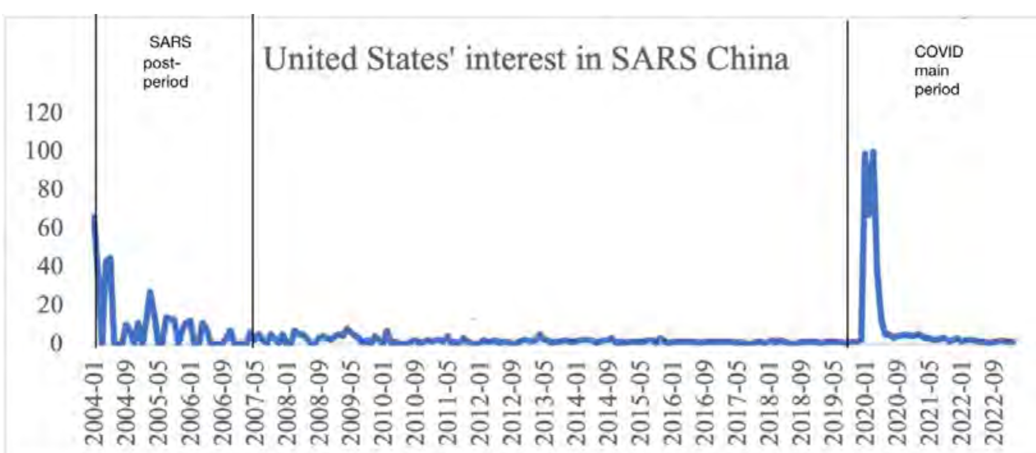

Figure 4: United States's interest in SARS China

quarantines anymore. Therefore, I take this as a separating point to show people's risk preference when facing such conditions compared with the previous breakouts under control.

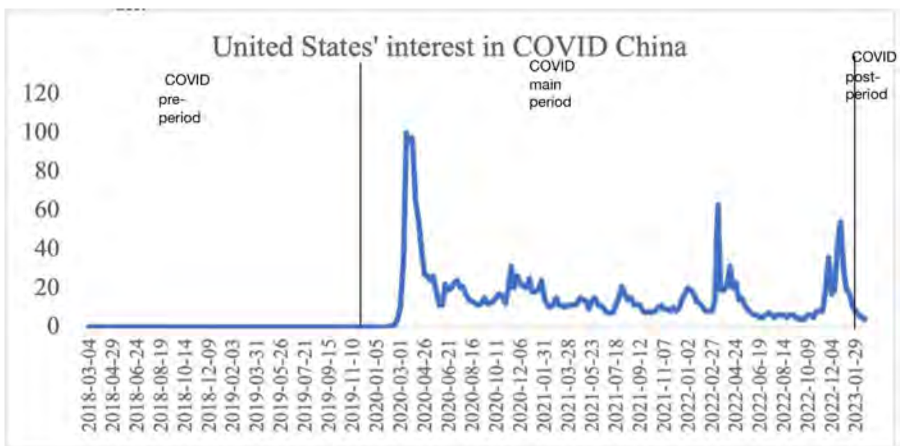

Figure 5: United States's interest in COVID China

To get a more accurate idea of Chinese stock market performance to calculate the conditional skewness, I choose the Shanghai Stock Exchange, namely the SSE Composite Index as the dataset, which is "a Paasche weighted composite price index of all stocks (A shares and B shares) that are traded at the Shanghai Stock Exchange" ("SSE Composite Index"). Regarded as a blue chip of the Mainland China stock exchange, it has enough significance and representation when encountering a crisis and risk. To calculate conditional skewness, I use the adjusted closing level price from 2000.1 to 2005.7 and from 2017.12 to 2023.3 on a daily basis. Figure 6 shows the time series data: the closing price trend since 2000.1.

From the stock price plot, I notice that there is level-dependent volatility, therefore, I take the first difference of the log adjusted closing price. After this action, I removed the level-dependent volatility as well as linearized the trend. I will work with the logged data to build GARCH-s models rather than the original price of the SSE Composite Index.

Figure 6: Stock Price of SSE Composite Index

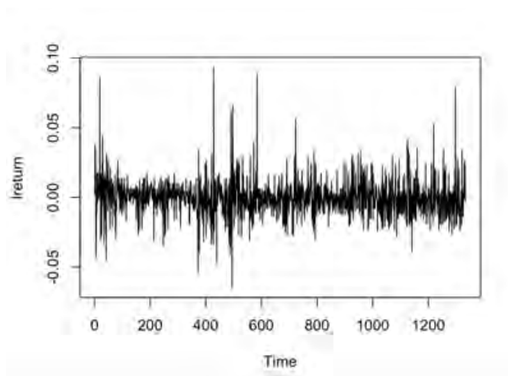

Figure 7: log Stock Price of SSE Composite Index during SARS

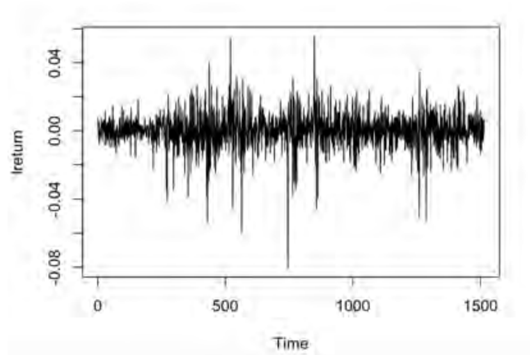

Figure 8: log Stock Price of SSE Composite Index during COVID

	SARS 2000.1-2005.7				COVID-19 2017.1-2023.3			
	2000.1 - 2005.7	**2000.1 - 2002.10**	**2002.11 - 2003.7**	**2003.8 - 2005.7**	**2017.1 - 2023.3**	**2017.1 - 2019.11**	**2019.12 - 2022.12**	**2022.12 - 2023.3**
Max	0.0940	0.0940	0.0565	0.0789	0.0555	0.0545	0.0555	0.0204
Min	-0.0654	-0.0654	-0.0309	-0.0396	-0.0804	-0.0601	-0.0804	-0.0194
Mean	-0.000196	0.000103	-0.000115	-0.000641	0.0000259	-0.000125	0.000146	0.000267
Std	0.0137	0.0144	0.0122	0.0133	0.0106	0.0104	0.0112	0.00694
Skew	0.844	0.820	0.517	0.960	-0.661	-0.450	-0.830	0.00364

Table 1: Properties of lreturn in 6 periods in SARS and COVID

Table 1 above shows the basic properties of the eight periods. We can see that the overall price during COVID-19 is much higher than during SARS because of the overall improved economic performance in China. What needs to be further noticed is the skewness. As we can see from the last row of the chart, the overall skewness of SARS is positive while the one of COVID is negative, which may indicate that COVID brings much more market crash risk than SARS in China.

4 Identification Strategy

The method is building GARCH-s models and drawing the conditional skewness graphs of each model. The model is built as follows:

$$r_t = \mu + \epsilon_t; \epsilon_t \sim (0, \sigma^2)$$

$$\epsilon_t = h_t^{0.5}\eta_t; \eta_t \sim (0, 1); \epsilon_t | I_t - 1 \sim (0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 h_{t-1}$$

$$s_t = \beta_0 + \beta_1 \eta_{t-1}^3 + \beta_2 s_{t-1}$$

Similar to Liu, Huynh and Dai(2021), in this GARCH-s model, r_t is the market returns of the SSE Composite Index, which is value-weighted; η_t is its standardized residual; ϵ_t is its residual; $I_t - 1$ is the available information at period t; h_t is the GARCH (1,1) model's conditional heteroscedasticity; s_t is the conditional skewness process, based on lagged return shocks. According to Leon', Rubio, and Serna (2005), I establish that $E(\eta_t) = 0; E({\eta_t}^2) = 1; E({\eta_t}^3) = s_t$ where s is by a GARCH (1,1) structure indicating that s_t represents the skewness corresponding to the conditional distribution of the normalized residual. Following Liu, Huynh, and Dai(2021), I use the Gram–Charlier series expansion at the third moment.

This model will be evaluated two times for two complete pandemics: SARS and COVID-19. However, during the analysis, I will compare the overall two complete periods and 6 subperiods (pre-, main, and post-periods of each pandemic) to fully show the differences between these two pandemics.

5 Results

5.1 Main Results

A. SARS

Here is the resulting model of the complete SARS period:

	params	**stderrors**	**tstats**
μ	0.000328	0.0194	0.0169
α_0	6.558	0.0208	0.000315
α_1	0.0418	0.0217	1.923
α_2	0.914	0.0217	41.980
β_0	0.0123	0.0194	0.633
β_1	0.00959	0.0216	0.443
β_2	0.809	0.0217	37.291
loglik	-5110.810	/	/
AIC	10235.619	/	/
BIC	10271.991	/	/

Table 2: Estimation results of the GARCH-S model for SARS in 2000.1-2005.7

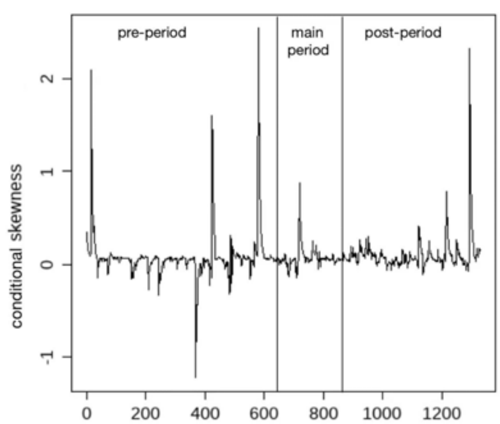

Figure 9: Conditional Skewness for SARS in 2000.1-2005.7

Table 2 represents the results of the GARCH-S model of SARS. From the data, it is clear that there presents significant conditional skewness during SARS. As we can see, the coefficient of lagged skewness is 0.809 with a t-statistic to be 37.291, which is positive and significant indicating the skewness is persistent during the period. What's more, the coefficient of the shock to skewness is 0.00959 with a t-statistic to be 0.443, which is positive and significant as well. With most coefficients being significant, this shows that the applying GARCH-S model is the appropriate method to estimate the Chinese stock market returns skewness for the SARS period.

From Figure 9, we can see that skewness is varying from time to time and there exists clustering skewness, especially a significant number of negative ones. This indicates that there exist crash risks at these points and the overall conditional skewness is quite volatile. I have divided the overall period into three parts.

Overall, we can see that during the main period of SARS, there are fewer negative conditional skewness and the extent is much less serious. From Figure 9, the largest negative value of skewness which is -1.2, occurred not during the SARS outbreak but during the pre-period which is on July 31, 2001. This extremely high negative conditional skewness corresponds to a big disaster in the Chinese stock market in July 2001, which is called "Black Monday". Here, I may briefly explain this incident.

In July 2001, the Shanghai Stock Exchange (SSE) was still in its early stages of development, having only been established in 1990. At that time, the Chinese stock market was still heavily regulated and restricted, with limited foreign investment allowed. The first problem happens on July 19, 2001. SSE suspended trading for half a day due to a technical glitch with its trading system. The system had experienced problems handling the large volume of trades, leading to a backlog of orders and a delay in the processing of transactions, which highlighted the challenges facing the relatively new and rapidly growing Chinese stock market, including the need for more robust technical infrastructure and risk management systems to handle large volumes of trades. Then starting on July 23, 2001, the regulation department published new law about the reduction of high-price state-owned shares in A shares, leading to a sharp decrease in stock market prices not only in Shanghai but also in Shenzhen. This also results in the Shanghai Composite Index receiving seven consecutive negative returns. After these seven-day consecutive negative returns, on July 30, SSE encountered "Black Monday" with the SSE index decreasing 109 points to 1956, which is 5.27%, leading to a permanent decrease in SSE. This incident causes a great influence on the Chinese stock market, however, this is a must in the overall improvement of Chinese welfare. Such reduction of high-price state-owned shares aims at improving the social security system, opening up new financing channels for social security funds, and supporting the reform and development of state-owned enterprises. Because of the continuous decreases in indexes and stock prices, the government urgently suspended this law in October 2001, leading to a sharp increase in SSE to 2.6. With this experience, the government gradually revises the law by collecting public suggestions, and the stock market became relatively stable.

Although not as serious as the incident in the pre-period, there is also a big clustering of negative skewness during the SARS. There are several economic influences brought about by SARS. First, the domestic GDP growth rate experienced a short-term decline during the SARS outbreak; in terms of industries, the transportation and catering, and accommodation industries experienced a significant decline during the SARS outbreak. According to the FRED, from the fourth quarter of 2002 to the fourth quarter of 2003, the domestic GDP growth rates were 9.1%, 11.1%, 9.1%, 10%, and 10%, respectively. Conversely, from January to June 2003, the Shanghai Composite Index rose by 16%. This has nothing to do with SARS but the easy monetary policy. In advance response to the possible negative effect brought about by SARS, in April 2003, the central government set up a fund with about 2 billion yuan to prevent and control SARS. The amount of the fund accounted for 0.13% 2003 central budgetary expenditure of 1,513.8 billion yuan. What's more, some industries directly affected by the SARS epidemic would also enjoy subsidies and preferential tax policies from May 1 to September 30, 2003. These actions greatly decrease the market crash risk resulting from SARS.

Therefore, thanks to the government's instantaneous action, the stock market has a much more positive performance. In this way, we can see that government intervention is very useful and vital for the stock market return since both the greatest decrease and relative stability are controlled by the government.

B. COVID-19

Here is the resulting model of the complete COVID period:

	params	**stderrors**	**tstats**
μ	-0.000141	0.0182	-0.00776
α_0	1.255	0.0257	4.883
α_1	0.0451	0.0227	1.986
α_2	0.940	0.0207	45.351
β_0	-0.0746	0.0182	-4.104
β_1	0.0197	0.0203	0.971
β_2	0.366	0.0205	17.881
loglik	-6247.538	/	/
AIC	12509.076	/	/
BIC	12546.334	/	/

Table 3: Estimation results of the GARCH-S model for COVID in 2017.1-2023.3

Table 3 presents the estimation results of the GARCH-S model of COVID-19. Similar to the case of SARS here, the coefficient of lagged skewness is 0.366 with a t-statistic to be 17.881 which is positive and significant indicating that the skewness is persistent. What's more, the coefficient of the shock to skewness is 0.0197 with a t-statistic to be 0.971, which is positive and significant as well. Overall, the majority of the coefficients were significant, implying that applying GARCH-S model to measure the conditional skewness is an appropriate method here. What's more, comparing Figure 10 and Figure 11, we can see that the first half of Figure 10 is the same as

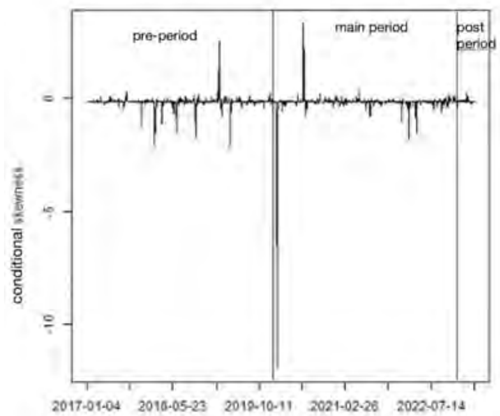

Figure 10: Conditional skewness for COVID in 2017.1-2023.3

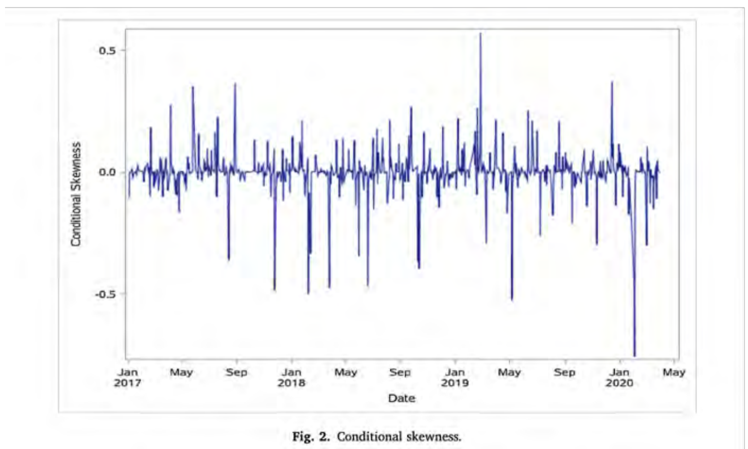

Figure 11: Conditional skewness for COVID from Liu, Huynh and Dai(2021)

Figure 11, indicating the correct applications of the data and model.

Regarding conditional skewness, there are more negative ones. There are several obvious characteristics. First, in the pre-period, which is from January 2017 to October 2019, there are frequent relatively large negative conditional skewnesses. The most important incident is the US-China trade war starting in 2018 when the US imposed tariffs on a wide range of Chinese goods, which were then met with retaliatory tariffs from China. The uncertainty and volatility caused by the trade war had a negative effect on the Chinese stock market, with SSE falling sharply in 2018 and

2019. During this period, many Chinese companies saw their share prices decline as investors became increasingly cautious about the potential impact of the trade war on the Chinese economy. However, the Chinese government also took steps to support the stock market, including cutting interest rates and reducing reserve requirements for banks. These measures helped to stabilize the market and decrease market crash risks as can see that the conditional skewness is about -1.5.

Second, there are two high positive conditional skewnesses, one is in February 2019 (2.5) and the other is in July 2020 (3.3). In February 2019, thanks to the government intervention during the US-China trade war, the Chinese stock market experienced a rebound after a period of significant volatility and decline in late 2018. The benchmark Shanghai Composite Index rose by around 4% over the course of the month. Actions like tax cuts and increased infrastructure spending helped to boost investor confidence and drive up share prices for many Chinese companies. Besides this, another factor was the progress made in trade negotiations between the US and China, which eased tensions and reduce uncertainty in the market, which in turn helped to drive up share prices. In July 2020, the Chinese stock market experienced a significant rally, with the SSE rising by more than 10%. One factor that contributed to the rally in the Chinese stock market was the positive economic data that had been released in the months leading up to July. Despite the pandemic, China's economy had shown signs of resilience, with growth returning and industrial production and retail sales rebounding. Another factor was the increased liquidity in the market, as the Chinese government had taken steps to support the economy by injecting capital and encouraging banks to lend more to small and medium-sized businesses. This helped to boost investor confidence and drove up share prices for many Chinese companies. Additionally, there was increased interest from foreign investors in the Chinese market, as the country continued to open up its financial markets and make it easier for overseas investors to participate. This helped to further drive up share prices and contributed to the overall bullish sentiment in the market. As we can see in both these two situations, government support that boosts investors' confidence is inevitable to decrease market crash risks.

Third, we can see an extremely negative value that occurred on February 4, 2020, with conditional skewness of -11.9. This corresponds directly to the outbreak and spread of COVID-19 on February 3, 2020. SSE fell by around % as investors became increasingly concerned about the potential impact of the virus on the Chinese economy and global markets. The most important factor that contributed to the decline in the stock market was the impact of the COVID-19 outbreak, which started in Wuhan, China, in late 2019 and had since spread rapidly to other parts of the world. The outbreak led to widespread disruptions in business activity and supply chains, which in turn caused concerns about the impact on global economic growth and corporate earnings. Besides the negative effect of COVID-19, another factor was the decline in oil prices, which had been driven lower by a combination of oversupply and weaker demand due to the pandemic. This had a negative impact on the energy sector and other related industries, which in turn weighed on the broader stock market. Despite the decline in February, as we can see the positive conditional skewness in July 2020, the Chinese government's timely steps including cutting the interest rates and increasing current liquidity successfully support the economy and stabilize the stock market.

C. Comparisons of the Two Pandemics

With the conditional skewness results from these two pandemics, we can compare the resulting market crash risks. The SARS outbreak in 2003 and the COVID-19 pandemic in 2020 both had significant effects on the Chinese stock market, although there were some notable differences in the way that these events impacted the market.

Simply, from Table 1, the overall skewness of SARS is positive while the one of COVID is negative, indicating that COVID brings much more severe overall market crash risks than SARS in China. And this can also be further shown in the conditional skewness graphs. There is less negative conditional skewness during the SARS compared with COVID-19. There are several possible explanations. First, the duration of COVID-19 is much longer lasting about three years. The viruses continuously updated and caused the repeated spread of the pandemics. Such several outbreaks increase the market crash risks during each outbreak. Compared to this, the lasting time of SARS is pretty short and the pandemic ends soon. Second, in 2003, the Chinese stock market is not so mature with various regulations and laws as can see above. Therefore, there are less foreign investors and involved international trade. The impacted economic activities are much less than now. With lock-down policies in important cities during COVID-19, international trade is disrupted and many small- and medium- size companies broke down: sectors like automobiles experienced a significant decline. This causes a decrease in investors' confidence as well.

However, one more important thing to notice is that although with greatly negative conditional skewness at the beginning of COVID-19, the stock market was able to recover fast from this crash. Focusing on the trend of conditional skewness change, we can even tell that the response and recovery were more rapid during COVID-19. This reflects the lessons learned from the earlier SARS outbreak. The Chinese government's proactive measures to stabilize the market and support the economy played a significant role in limiting the impact of the pandemic on the stock market. Therefore, one vital lesson to learn from these pandemics is the importance of appropriate government interventions.

5.2 Possible Improvements

This paper can be improved in several aspects. First, the stock market data can be more diverse. With different sectors influenced during each pandemic, to better examine the negative effects, analyzing certain industries can illustrate a more direct picture. Second, the compared markets can be more diverse. Not only the Chinese stock market but both SARS and COVID-19 also influence the whole world. Therefore, it's also necessary to compare different countries' actions and results to better learn the lesson and improve the solutions when facing similar situations in the future. Third, the investors' confidence is an important factor in stock market performances, therefore, based on the conditional skewness, if there are available data on investors' action during the pandemic, the analysis of investors' risk preferences can further improve the conclusion and give more suggestions for the government to comfort investors.

6 Conclusion

This study investigates the impact of two pandemics, SARS and COVID-19, on stock market crash risks, given the significant influence COVID-19 has had on people's lives. By analyzing the SSE Composite Index during SARS (2000.1-2005.7) and COVID-19 (2017.1-2023.3), this paper provides a better understanding of China's progress in managing similar pandemics. The study employs GARCH-s models and conditional skewness graphs to quantify market crash risk during each pandemic. The findings suggest that both SARS and COVID-19 increase stock market crash risk, which could result in a decline in stock market returns and exacerbate negative symmetry. Importantly, timely and appropriate government interventions can help minimize the market crash risks and negative effects of pandemics. In sum, the study highlights the need for clear and timely communication, supportive monetary policies, and cautiousness among investors and regulators to reduce stock market crash risks.

Overall, this study just wants to emphasize that justifying the situation and publishing certain monetary policies and supports towards the market are very vital to reduce stock market crash risk. Thus, in-time actions taken by the government regarding the pandemic, whether SARS or COVID-19, could bring about effective predictions in the market. Therefore, regulators should be more alert to stock market crash risks and take efficient actions while investors need to pay attention to such signs and regard this as a tool to invest during the pandemic.

References

[1] “2002–2004 SARS Outbreak.” Wikipedia, May 7, 2023. https://en.wikipedia.org/wiki/2002%E2%80%932004_SARS_outbreak.

[2] “Be a Global Citizen.” Subscribe to read | Financial Times. Accessed May 9, 2023. https://ig.ft.com/china-covid-economy/.

[3] “Covid-19 Map.” Johns Hopkins Coronavirus Resource Center. Accessed May 9, 2023. https://coronavirus.jhu.edu/map.html.

[4] Gross Domestic Product, Current Quarter (100 million yuan), National Bureau of Statistics of China, https://data.stats.gov.cn/english/easyquery.htm?cn=B01

[5] “Gross Domestic Product for China.” FRED, December 27, 2022. https://fred.stlouisfed.org/series/MKTGDPCNA646NWDB.

[6] Hai, Wen, Zhong Zhao, Jian Wang, and Zhen-Gang Hou. “The Short-Term Impact of SARS on the Chinese Economy.” Asian Economic Papers 3, no. 1 (2004): 57–61. https://doi.org/10.1162/1535351041747905.

[7] KHAN, Karamat, Huawei ZHAO, Han ZHANG, Huilin YANG, Muhammad Haroon SHAH, and Atif JAHANGER. “The Impact of Covid-19 Pandemic on Stock Markets: An Empirical Analysis of World Major Stock Indices.” The Journal of Asian Finance, Economics and Business 7, no. 7 (2020): 463–74. https://doi.org/10.13106/jafeb.2020.vol7.no7.463.

[8] León, Ángel, Gonzalo Rubio, and Gregorio Serna. “Autoregresive Conditional Volatility, Skewness and Kurtosis.” The Quarterly Review of Economics and Finance 45, no. 4–5 (2005): 599–618. https://doi.org/10.1016/j.qref.2004.12.020.

[9] Levin, Andrew, William Hanage, Nana Owusu-Boaitey, Kensington Cochran, Seamus Walsh, and Gideon Meyerowitz-Katz. Assessing the age specificity of infection fatality

rates for covid-19: Systematic review, meta-analysis, amp; public policy implications, 2020. https://doi.org/10.3386/w27597.

[10] Liu, Zhifeng, Toan Luu Huynh, and Peng-Fei Dai. “The Impact of Covid-19 on the Stock Market Crash Risk in China.” Research in International Business and Finance 57 (2021): 101419. https://doi.org/10.1016/j.ribaf.2021.101419.

[11] Liu, Zhiyi, and Biliang Hu. “China’s Economy under Covid-19: Short-Term Shocks and Long-Term Changes.” Modern Economy 11, no. 04 (2020): 908–19. https://doi.org/10.4236/me.2020.114068.

[12] Wen, Fenghua, Zhifang He, and Xiaohong Chen. “Investors’ Risk Preference Characteristics and Conditional Skewness.” Mathematical Problems in Engineering 2014 (2014): 1–14. https://doi.org/10.1155/2014/814965.

[13] YenNee_Lee. “4 Charts Show How SARS Hit China’s Economy Nearly 20 Years Ago.” CNBC, February 11, 2020. https://www.cnbc.com/2020/02/11/coronavirus-4-charts-show-how-sars-hit-chinas-economy-in-2003.html.

[14] “Youth Unemployment Rate for China.” FRED, March 7, 2023. https://fred.stlouisfed.org/series/SLUEM1524ZSCHN.

[15] Zhu, Hong-bing, Bing Zhang, and Li-hua Yang. “The Gambling Preference and Stock Price: Evidence from China’s Stock Market.” Emerging Markets Review 49 (2021): 100803. https://doi.org/10.1016/j.ememar.2021.100803.

Appendix A   STATA Code

if(!require(GARCHSK)) install.packages("GARCHSK")

library(GARCHSK)

my.garchsk$_{l}ik < -function(params, data)nT < -length(data)$

t <- 2:nT

likelihoods <- numeric(0)

GARCHSK <- my.garchsk$_{c}onstruct(params, data)$

h = GARCHSK$h[t]$

sk = GARCHSK$sk[t]$

std <- (data[t] - params[1])/sqrt(h) nt

f <- log((1 + (sk/6) * (std$^{3} - 3 * std))^{2})$

g <- log(1 + (sk^{2})/6)

likelihoods <- -0.5 * (log(h) + std$^{2}) + f - g$

likelihoods <- -likelihoods

LLF <- sum(likelihoods)

if (is.nan(LLF)) LLF <- 1e+06 return(LLF)

my.garchsk$_{c}onstruct < -function(params, data)nT < -length(data)$

h <- rep(stats::var(data), nT)

sk <- rep(skewness(data), nT)

para$_{m} < -params[1]$

para$_{h} < -params[2:4]$

para$_{s}k < -params[5:7]$

for (t in 2:nT)

h[t] <- para$_{h}$

sk[t] <- para$_{s}k$

return(list(h = h, sk = sk))

my.garchsk$_{e}st < -function(data)X < -data[-length(data)]$

Y <- data[-1]

a1 <- stats::cov(Y, X)/stats::var(X)

b1 <- 0.01

b2 <- 0.9

b0 <- (1 - (b1 + b2)) * stats::var(data)

c1 <- 0.01

c2 <- 0.7

c0 <- (1 - (c1 + c2)) * skewness(data)

init <- c(a1, b0, b1, b2, c0, c1, c2)

aLB <- c(-1)

bLB <- c(0, rep(0, length(b1)), rep(0, length(b2)))

cLB <- c(rep(-1, length(c1)), rep(-1, length(c2)))

sumbLB <- c(0)

sumcLB <- c(-1)

ineqLB <- c(aLB, bLB, cLB, sumbLB, sumcLB)

aUB <- c(1)

bUB <- c(Inf, rep(1, length(b1)), rep(1, length(b2)))

cUB <- c(rep(1, length(c1)), rep(1, length(c2)))

sumbUB <- c(1)

sumcUB <- c(1)

ineqUB <- c(aUB, bUB, cUB, sumbUB, sumcUB)

sol <- Rsolnp::solnp(pars = init, fun = my.garchsk$_{l}ik, ineqfun = my.garchsk_{i}neqfun, ineqLB = ineqLB, ineqUB = ineqUB, data = data)$

params <- solpar

loglik <- sol$values$

loglik <- loglik[length(loglik)]

hessian <- sol$hessian[1:length(params), 1:length(params)]$

stderrors <- sqrt(1/length(data) * diag(hessian))

tstats <- params/stderrors

AIC <- -2 * loglik + 2 * length(params)

BIC <- -2 * loglik + length(params) * log(length(data)) return(list(params = params, stderrors = stderrors, tstats = tstats, loglik = loglik, AIC = AIC, BIC = BIC))

my.garchsk$_ineqfun < -function(params, data)para_m < -params[1]$

para$_h < -params[2:4]$

para$_sk < -params[5:7]$

return(c(para$_m, para_h, para_sk[-1], sum(para_h[-1]), sum(para_sk[-1])))$

plot(sk[-seq(1,100)],type = "l",xlab="",ylab="skewness")

Acknowledgement

I'm honored that I have finished this research. Getting to know GARCH models from one of my DURF projects, I decided to apply this method to the topic I'm interested in – stock market changes. It's been a really hard time for me to write and debug all the codes for the GARCH-s models since there is little information about coding on the Internet. But I'm very proud that I have figured it out and completed the conclusion.

I want to thank Professor Jeffrey Wurgler for his helpful comments and suggestions for my overall research, and Professor Wendy Wang for her help in finding the data. Especially, I also want to thank myself and my parents who are always with me.

Thank you all.