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CORONAVIRUS AND THE CHINESE STOCK MARKET: PANDEMIC VERSUS FINANCIAL CRISIS

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ABSTRACT

This paper explores the impact of the COVID-19 pandemic on the Shanghai Stock Exchange (SSE) index returns and volatility from October 2019 to March 2020. The GARCH results show that the pandemic negatively affected the SSE stock returns during the spread of the virus, and the conditional variance showed increased variation at the time. However, the increased volatility did not cause a market crash as Patel & Sarkar (1998) and Mishkin & White (2002) reported. The negative effect on stock returns and the increased volatility might be justified because well-diversified markets can alter the wealth effects on composite stock markets, and they can make a quick recovery after crises. When comparing the effects of the pandemic to those of the 2008 financial crisis on SSE returns, the results show higher risk values and much thicker tails of probability distribution during the pandemic. Both the Covid-19 pandemic and the 2008 financial crisis negatively affected stock returns, but the effect on volatility was stronger during the pandemic.

Contribution/Originality: This study is one of very few studies which have investigated the effects of the Covid-19 pandemic on the Shanghai Stock Exchange and compared it with the effects of the 2008 financial crisis.

1. INTRODUCTION

Financial crises are often caused by unexpected fundamental changes fueled by overreaction, irrationalities, and other human activities. The recent eruption of the coronavirus caused worldwide turbulence. More than 210 countries and territories have been affected, with major outbreaks in China, the United States, Spain, Italy, Germany, the United Kingdom, France, Turkey, and Iran, among others. The first Covid-19 case was identified in Wuhan, China, and on January 30, 2020, the World Health Organization (WHO) declared the outbreak a public health emergency of international concern. The WHO then followed this with an announcement on February 11, 2020, that the name for this new disease is officially known as Covid-19, which has killed more than 174 thousand people worldwide. There have been more than 2.5 million confirmed cases worldwide, and this figure is still rising.

In 2020, the Organization for Economic Co-operation and Development (OECD) projected a worldwide slowdown of economic growth. The projections are as follows: China's economy is expected to grow by 4.9% in 2020 compared to 6.1% in 2019; the Euro area economies are expected to grow by 0.8% in 2020 compared to 1.2% in 2019; Japan's is expected to grow by 0.2% in 2020 compared to 0.7% in 2019; the United Kingdom's is expected to grow by

0.8% in 2020 compared to 1.4% in 2019; and the United States economy is expected to grow by 1.9% in 2020 compared to 2.3% in 2019[1]. The coronavirus pandemic has also affected global supply and demand due to the worldwide containment measures. For example, quarantine measurements have led to factory closures and a loss of confidence in supply and demand channels. Travel bans and restrictions have forced cutbacks in service provisions and caused lower business and tourism in supply and demand channels. The closure of public places has caused supply chain disruption and a decreased demand for education and entertainment services.[2] There is also a loss of confidence that might magnify financial stress. The implied oil price volatility, the Chicago Board Options Exchange Market Volatility Index (VIX), and the Merrill Lynch Option Volatility Estimate Index (MOVE) increased toward the end of 2019–2020 (Celik, Demirtaş, & Isaksson, 2019).

As the second-largest economy globally, China is incurring huge losses due to trade disruptions and output delays. The virus spread has also caused huge losses in the stock market; China's Shanghai Composite Index dropped by approximately 12.5%, from 3,119 on January 14 to 2,728 on February 03, 2020. However, the announcement by the G7 Financial Ministers and major Central Bankers to offer a stimulus plan to ease the impact of the outbreak caused the index to bounce back to 2993 as of March 03, 2020, with a 4% decline compared to its value on January 14, 2020. Recently, due to Covid-19, the oil demand has dropped significantly, with more than 30% worldwide in a market swamped by supply. In April 2020, Brent Crude fell below $19 per barrel for the first time since February 2002, while West Texas Intermediate settled at $11.57 per barrel (43% lower) for June. Prices have crashed below zero for the first time in history, forcing producers to pay buyers to take the barrels they could not store.

This paper examines the effects of the pandemic on the stock returns and volatility of China's Shanghai Composite Index (SSE) and compares the results to the effects of the 2008 financial crisis on the SSE returns. The rest of the paper is organized as follows: Section 2 summarizes the major theoretical arguments linking stock returns and volatility to epidemic diseases; Section 3 discusses the data and methodology; Section 4 summarizes the empirical results; Section 5 compares the effects of the pandemic to the financial crisis of 2008, and Section 6 concludes.

2. LITERATURE REVIEW

Covid-19 has severely affected the Chinese economy and stock market. However, the 12.5% decline cannot be defined as a financial crisis because it is lower than the threshold specified in related literature. For example, Patel & Sarkar (1998) used a 35% or more fall from its historical maximum to define a stock market crash, whereas Mishkin & White (2002) defined a stock market crash as a 20% decline in the stock market. The drop in the Shanghai Index can develop into a crash if Covid-19 continues to spread with no major signs of recovery.

The volume of literature relating to financial crises and their effects on stock returns and volatility is considerable, but literature that considers fear and panic caused by epidemic/pandemic diseases as a major cause of financial stress is rare. In theory, panic causes an increase in volatility and negatively affects stock returns. Gertler, Kiyotaki, & Prestipino (2017) expressed that panic was most intense in October 2008. All the major investment banks effectively failed, the commercial paper market froze, and the primary reserve fund experienced a run. The distress rapidly spilled over to the real sector without any apparent large exogenous disturbance to the economy.

Gertler et al. (2017) incorporated banks and banking panic in a conventional New Keynesian model with capital accumulation to characterize the sudden and discrete nature of bank-related panic and the circumstances that make the economy vulnerable to such panics in some instances but not in others. They found that waves of panic led to a gradual decline in banks' net worth that closely matches the observed decline in financial sector equity. The model also predicted a relatively slow recovery following the financial crisis. Worthington (2008) examined the impact of natural events and disasters in Australia on Australian stock market returns. The data employed consisted of the

[1] Source: OECD Economic Outlook database, March 02, 2020.

[2] Source: OECD Economic Outlook database, March 02, 2020.

daily price and accumulation returns for the market index from January 01, 1980, to June 30, 2003. The complete timing and duration of all severe storms, floods, cyclones, earthquakes, and bushfires were documented during this period. The GARCH-M(1,1) specification results show that natural events and disasters have no significant impact on returns at the market level, regardless of how they are defined.

Westerhoff (2004) developed a deterministic behavioral stock market model in which agents are influenced by their emotions (greed and fear) in their trading activities. Agents optimistically believe in booming markets but panic if prices change too abruptly. In addition, the agents switch between two activity levels. If historical market volatility is low, they are rather calm, and vice versa. His model suggests that emotions such as greed and fear may play a role in determining stock prices. The existence of herd behavior exaggerates panic, and it has been argued that panic is just as, if not more, contagious as Covid-19. Cont & Bouchaud (2000) presented a simple model of a stock market in which a random communication structure between agents generically gives rise to heavy tails in the distribution of stock price variations in the form of an exponentially truncated power law. They suggested a relation between the excess kurtosis observed in asset returns, the market order flow, and the tendency of market participants to imitate each other. The heavy tails observed in these distributions correspond to large fluctuations in prices, causing an outbreak of volatility that is difficult to explain only in terms of variations in fundamental economic variables (Shiller, 1989). Other studies have shown that simulating behavior has often been associated with excessive volatility observed in the market prices of financial assets (see, for example, Banerjee (1993); Orléan (1995); Topol (1991)).

Banerjee (1993) studied a class of information (rumors) transmission processes. The distinctive feature of these processes is that the information transmission occurs in such a way that the recipient does not know whether to believe the information. The probability of someone receiving the information depends on how many people already have it. Banerjee (1993) shows that, for a wide class of alternative specifications, the optimal Bayesian decision rule, which states that a positive fraction of those who observe the rumor, will not invest.

Chen & Siems (2002) used the event study methodology to assess the capital markets' response to cataclysmic events. They examined the U.S. capital market's response to fifteen cataclysmic events dating back to the 1929 stock market crash, and the global capital markets' response to three major cataclysmic events, namely the 1987 stock market crash, Iraq's invasion of Kuwait in 1990, and the September 11 terrorist attacks in the United States. They concluded that global capital markets are tightly interlinked and that news spreads rapidly with strong contagion effects. They also reported that the U.S. markets are now more resilient and recover faster than in the past from cataclysmic events compared to other global capital markets. This faster recovery can be partially explained by the abundance of liquidity provided by the banking and financial sector.

Wang & Kutan (2013) investigated the impact of natural disasters on the insurance sector and the stock markets in Japan and the U.S. They employed GARCH models to capture the wealth and risk effects of natural disasters. They found that well-diversified markets can affect the wealth of composite stock markets. According to Poterba (2000), the wealth theory suggests that rising stock prices increase consumption pressures. In contrast, a decline in stock market wealth may contribute to economic activity slowing down, or speeding up an existing slowdown (Poterba, 2000). Recently, due to the COVID-19 breakout, research on the pandemic's potential economic and financial consequences has started to increase rapidly. Zhang, Hu, & Ji (2020), for example, showed that, in response to the pandemic, the risks of financial markets have increased significantly; this stock market reaction depends on the intensity of the outbreak, which results in a more volatile and unpredictable market. Ashraf (2020) found that the returns of 64 stock markets declined due to Covid-19. However, the negative response to the stock market reacted more proactive to the increase in the number of confirmed cases than to the growth in the number of deaths. More specifically, early stock prices reflected the risks related to Covid-19 as the number of confirmed cases increased and they reacted less to the number of confirmed deaths later on. Along the same line, Heyden & Heyden (2021) examined the short-term reaction of stock at a cross-country level at the beginning of the pandemic. They showed that stocks in the U.S. and European markets showed different significant negative responses to the announcement of the first death and the announcement of the fiscal policy measures. Their results imply that monetary policy measures can ease the market in contrast to fiscal policy measures. Baig, Butt, Haroon, & Rizvi (2021) examined the impact of the Covid-19 pandemic on stock-level liquidity and volatility. Their results showed that market illiquidity and volatility increased significantly as confirmed cases and deaths increased.

Similarly, it was found that mandatory government measures (i.e., restrictions and lockdowns) and public fear contributed to illiquidity and volatility. Finally, Akhtaruzzaman, Boubaker, & Sensoy (2021) found that financial contagion occurred between China and G7 countries during the pandemic. Specifically, they found that dynamic conditional correlation increased significantly between financial and non-financial firms and was higher for the former. This financial contagion implies that financial firms play an important role in the transition of financial contagion. Although we can conclude that cataclysmic events, rumors, emotions (greed and fear), natural events and disasters, and panic can affect economies and stock markets majorly, in this paper, we believe that the Covid-19 pandemic can cause most of the abovementioned effects and can influence decisions and the behavior of market investors. For this purpose, we studied the effects of the epidemic in China on the SSE stock returns, and we further extended the empirical analysis to compare the effects of the pandemic versus those of the 2008 financial crisis.

3. DATA AND METHODOLOGY

The data consists of daily closing prices for the Shanghai Stock Exchange (SSE), which tracks the performance of all A-shares and B-shares listed on the SSE in China. The Shanghai Composite Index is a capitalization-weighted index. The sample period covers the period of the Covid-19 spread with a longer window to study how returns behave. Therefore, we examine the period of the first hit between October 01, 2019, and March 05, 2020. Additionally, to compare the pandemic effects with those of the 2008 financial crisis, our sample also consists of 1,793 daily price observations spanning from July 01, 2005, to November 01, 2012.

Table 1 presents the descriptive properties of the SSE returns and the logarithm of trading volume (Lvol). The results show that the average return during the study sample is -0.0016 for the SSE. The variables' distributional properties show that the series distribution is far from normal, with excess kurtosis in the SSE returns of approximately 38.2.

Table 1. Summary statistics.

Descriptive Statistics	SSE Returns	Lvol
Mean	-0.002	2.375
Median	0.000	0.000
Maximum	3.146	13.007
Minimum	-7.725	0.000
Std. Dev.	0.835	4.961
Skewness	-3.767	1.607
Kurtosis	38.208	3.583
Jarque–Bera	14152.370 (0.000)	116.404 (0.000)
Sum	-0.412	622.118
Sum Sq. Dev.	182.039	6423.362
Observations	262	262

Note: This table reports the following summary statistics of the return of SSE and the logarithm of trading volume (Lvol) for the entire sample period, from October 01, 2019, to March 05, 2020: Mean, Variance, Maximum, Minimum, Skewness, Kurtosis, and the Jarque–Bera test statistic. Parentheses correspond to top values.

On the other hand, the volatility of the SSE returns is high and equal to 0.84% during the study period. The Jarque–Bera probability is highly significant, indicating non-normality in the data, and further justifies using the GARCH model to capture time-variant risk premia.

The period was extended to cover one year of index returns history to better understand how SSE returns behaved before and during the pandemic. The returns of the SSE index from April 22, 2019, to April 21, 2020, are shown in Figure 1, which shows an increase in volatility of SSE index returns at the end of December 2020 (M12) (the coronavirus spread date) until the second half of April 2020, with many of the fluctuations occurring between February and March.

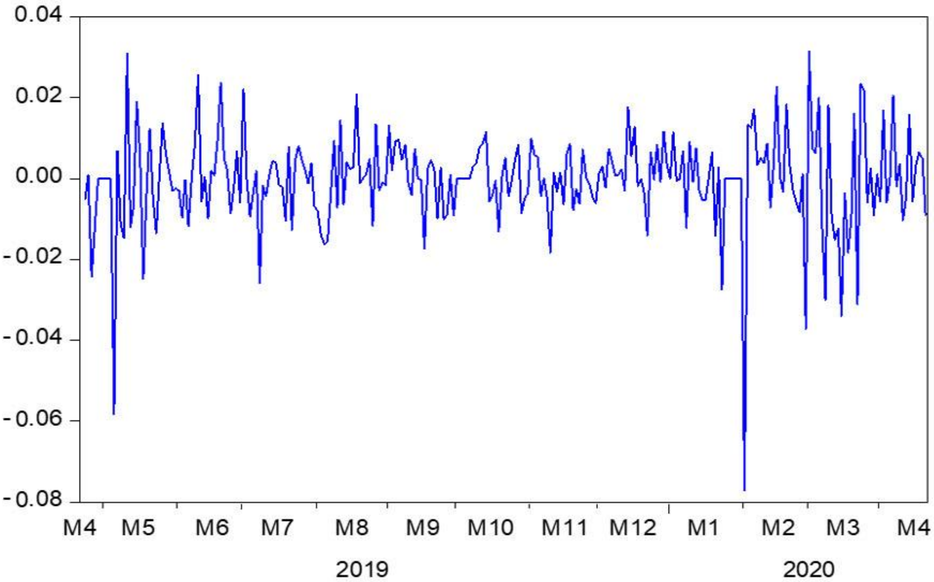

Figure 1. SSE returns.

3.1. GARCH Model

The main objective of this study is to examine the behavior and volatility of the stock returns on the SSE during the period when Covid-19 was spreading. For this purpose, the GARCH(1,2) model was used because it fits a wide variety of financial data and has proven to be useful in estimating conditional volatility in developed and emerging markets. Engle (1982) first developed the ARCH model and then it was generalized to form the GARCH model by Bollerslev (1986). The ARCH family of models is mainly designed to model conditional variances. These models are extensively used in financial time series analyses, where the variance of the dependent variable is postulated to be a function of past values of the dependent and independent variables. Under the ARCH model, the time-varying conditional variance of the present error term is assumed to be a linear function of the variance of the prior periods' error terms. The GARCH(1,2) specification was confirmed to be the most suitable for the regressions after preliminary tests, including the ARCH-LM test and other diagnostics. We introduced dummy variables to measure stock returns and volatility during the epidemic and added the logarithm of trading volume as an explanatory variable. The resulting model is as follows:

$$R_t = X_t' \theta + \epsilon_t \qquad (1)$$

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\sigma_{t-2}^2 \qquad (2)$$

Equation 1 presents the mean, and Equation 2 presents the conditional variance. Where R_t represents stock returns at time t; X_t' represents a vector of independent variables including a dummy variable (D), which takes the values 0 and 1 to indicate the absence or presence of the Covid-19 pandemic, respectively; $Lvol$ is the logarithm of trading volume; and σ_t^2 represents the volatility of the SSE.

4. EMPIRICAL RESULTS

This study examines the impact of the coronavirus pandemic on the SSE stock returns and volatility during the period from March 2019 to March 2020, and the GARCH(1,2) specification is used for this purpose. The results presented in Table 2 show that the spread of Covid-19 negatively affected the SSE stock returns during the study period. The estimated coefficient of the dummy variable is negative and statistically significant at a 5% level of significance.

The coefficient of news about volatility from the previous period (ϵ_{t-1}^{2}) causes the conditional volatility of stock returns to increase by 0.12, which is statistically significant at a 1% significance level. The forecasted variances from the last two periods (the GARCH terms) show that traders changed their predictions regarding stock volatility. This result could potentially be explained by the high uncertainty surrounding Covid-19. The conditional variance in Figure 2 shows increased variation when China announced that Covid-19 is an epidemic and spreading fast.

Our results align with Wang & Kutan (2013), who stated that well-diversified markets can diversify away the wealth effects on composite stock markets, such as in the U.S. and Japan, and they also align with those of Kong, Morales, & Coughlan (2014), who found that the Chinese stock market made a quick recovery after the global financial crisis. This quick recovery implies that markets, including the Chinese market, can diversify the impact of natural disasters (in this case an epidemic/pandemic) on stock returns.

Table 2. GARCH results.

Mean Equation	Coefficient	P-value
D	-0.084	0.023
$Lvol$	1.015	0.027
Variance Equation		
ω	-0.089	0.11
ϵ_{t-1}^{2}	0.120	0.000
σ_{t-1}^{2}	-0.075	0.000
σ_{t-2}^{2}	0.950	0.000
R-squared	0.020	
Adjusted R-squared	0.002	
Akaike information criterion	3.3	
Schwarz information criterion	3.4	
Durbin–Watson stat	2.002	
No. of observations	263	
Convergence achieved after	85	

Note: This table reports the maximum likelihood estimates from equations 1 and 2 for the full sample period, from October 01, 2019, to March 05, 2020.

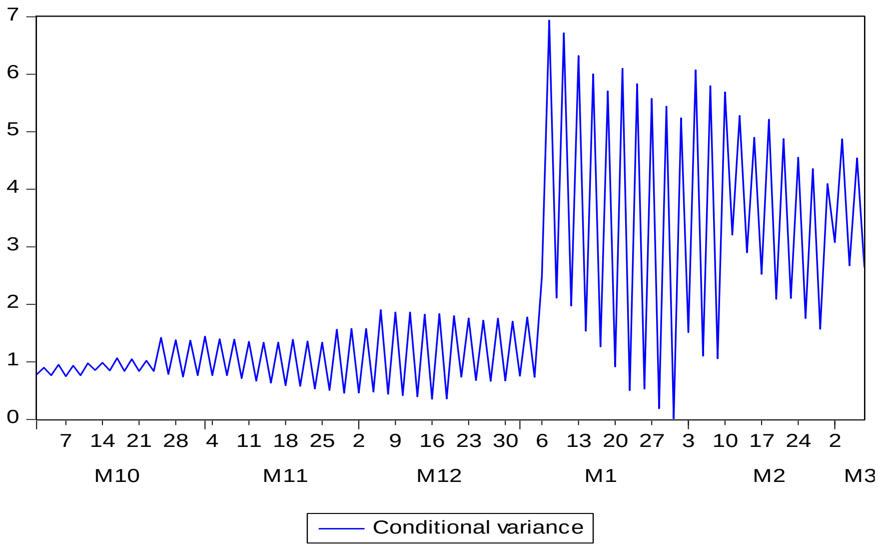

Figure 2. Conditional variance from the GARCH equation.

5. CORONAVIRUS VERSUS THE FINANCIAL CRISIS OF 2008

Pessimism is everywhere, fueled by high uncertainty and fears surrounding the Covid-19 crisis. Business leaders believe that the pandemic will signal a deep recession that will underprice assets, which will far exceed the effects of the 2008 financial crisis. The analysis was extended to reexamine the effect of the 2008 financial crisis on SSE returns and compare the effects to those caused by the pandemic. To conduct such a comparison, another GARCH(p,q) test was run on the SSE returns to study the behavior of stock returns during the crisis. The GARCH(1,1) specification was found to be the most suitable for the regressions after preliminary tests, including the ARCH-LM test and other diagnostics. Dummy variables were introduced to measure stock returns and volatility during the 2008 financial crisis, and the logarithm of trading volume was added as an explanatory variable. The resulting model is as follows:

$$R_t = X_t' \theta + \epsilon_t \quad (3)$$

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (4)$$

Where R_t represents stock return at time t, X_t' represents a vector of independent variables including a dummy variable (D), which takes the values 0 and 1 to indicate the absence or presence of the 2008 financial crisis, respectively, and the logarithm of trading volume ($Lvol$). The dummy variable range is from October 08, 2007 (the start of the price falls) to October 06, 2008. σ_t^2 represents the volatility of the SSE. SSE returns during the financial crisis are presented in Figure 3, and the descriptive statistics are shown in Table 3. The returns data in Figure 3 exhibit behavior of volatility clustering where the volatility changes over time, and its degree shows a tendency to persist. Excess volatility and volatility clustering during the 2008 financial crisis are persistent due to high uncertainty and panic during the crisis. The standard deviation statistic shows excessive risk during the financial crisis of 1.013% compared to 83% during the current pandemic. On the other hand, the kurtosis statistic is very high during the pandemic (38.21) compared to that during the 2008 crisis (30.32). The kurtosis in both return series is large, thereby indicating leptokurtic distribution. The distribution is far from normal and further justifies the use of the GARCH model.

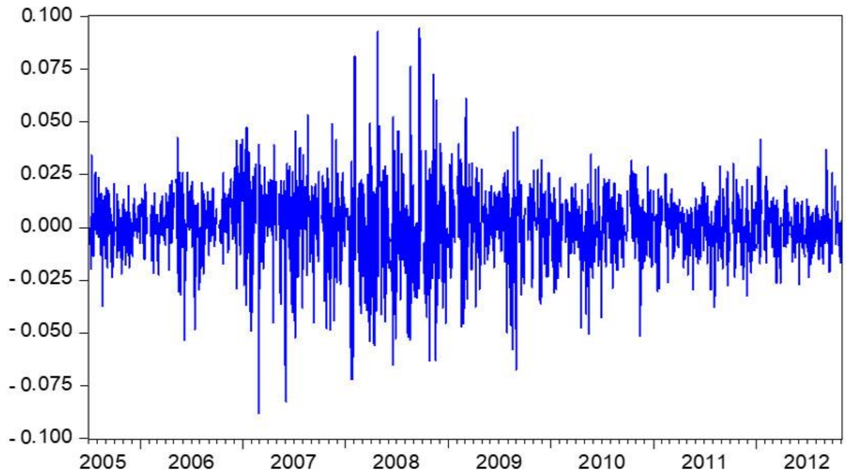

Figure 3. SSE returns during financial crises.

Table 3. Summary statistics during the 2008 financial crisis.

Descriptive Statistics	SSE	Lvol
Mean	-0.047	1.493
Median	0.000	0.000
Maximum	9.455	11.864
Minimum	-7.729	0.000
Std. Dev.	1.013	3.763
Skewness	0.081	2.126
Kurtosis	30.316	5.528
Jarque–Bera	55714.560 (0.000)	1826.847 (0.000)
Sum	-84.550	2675.287
Sum Sq. Dev.	1837.823	25362.610
Observations	1792	1792

Note: This table reports the following summary statistics of the returns of the SSE and the logarithm of trading volume (Lvol) during the financial crisis, from October 08, 2007, to October 06, 2008: Mean, Variance, Maximum, Minimum, Skewness, Kurtosis, and the Jarque–Bera test statistic. Parentheses correspond to the top values.

Table 4. GARCH results during the 2008 financial crisis.

Mean equation	Coefficient	P-value
Constant	-1.000	0.050
D	-0.380	0.003
$Lvol$	0.100	0.029
Variance Equation		
ω	0.019	0.040
ϵ_{t-1}^2	0.048	0.000
σ_{t-1}^2	0.948	0.000
R-squared	0.010	
Adjusted R-squared	0.009	
Akaike information criterion	3.75	
Schwarz information criterion	3.77	
Durbin–Watson stat.	2.01	
No. of observations	263	
Convergence achieved after	17	

Note: This table reports the maximum likelihood estimates from equations 3 and 4 for the full sample period, from October 08, 2007, to October 06, 2008.

The GARCH(1,1) results of the mean and variance Equations 3 and 4, respectively, show similar results to the Covid-19 equations. Table 4 shows that the 2008 crisis negatively affected the stock returns of the SSE during the study period. The effect is strong and significant but less than that of the pandemic. The dummy variable coefficient during the 2008 financial crisis is -0.38, which is statistically significant at a 1% level of significance compared to -0.84 during the pandemic. The volatility news coefficient from the previous period (ϵ_{t-1}^2) caused the conditional volatility of stock returns to increase by 0.048, which is significant at a 1% significance level. The forecast variance from the last period (the GARCH terms) shows that traders did not change their stock volatility predictions contrary to those reported during the examined Covid-19 period. This result might be explained by less uncertainty surrounding the recent pandemic compared to the 2008 financial crisis.

6. CONCLUSIONS

This paper explores the impact of the coronavirus crisis on the Shanghai Stock Exchange (SSE) Index returns from October 2019 to March 2020. The GARCH results show that the pandemic negatively affected the SSE stock returns during the period of disease spread. Volatility also increased due to high uncertainty and fear surrounding the pandemic. The conditional variance shows increased variation at the time when China announced that Covid-19 was an epidemic and spreading fast. At this stage, the virus did not ignite a market crash, as defined in the related literature, but it might do if Covid-19 continued to spread with no real signs of improving. When comparing the effects of the pandemic to those of the 2008 financial crisis, the results showed higher risk values during the financial crisis. The probability of extreme negative outcomes is very high during the pandemic compared to the 2008 financial crisis based on the respective kurtosis values of 38.21 and 30.32. The heavy tails observed in these distributions correspond to large fluctuations in prices, causing an outbreak of volatility that is difficult to explain only in terms of variations in fundamental economic variables (Shiller, 1989). Consequently, both Covid-19 and the 2008 financial crisis negatively affected stock returns, but the effects were found to be stronger during the pandemic.

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REFERENCES

Akhtaruzzaman, M., Boubaker, S., & Sensoy, A. (2021). Financial contagion during COVID–19 crisis. *Finance Research Letters, 38*, 1-20.Available at: https://doi.org/10.1016/j.frl.2020.101604.

Ashraf, B. N. (2020). Stock markets' reaction to COVID-19: Cases or fatalities? *Research in International Business and Finance, 54*, 1-7.Available at: https://doi.org/10.1016/j.ribaf.2020.101249.

Baig, A. S., Butt, H. A., Haroon, O., & Rizvi, S. A. R. (2021). Deaths, panic, lockdowns and US equity markets: The case of COVID-19 pandemic. *Finance Research Letters, 38*, 1-9.Available at: https://doi.org/10.1016/j.frl.2020.101701.

Banerjee, A. V. (1993). The economics of rumours. *The Review of Economic Studies, 60*(2), 309-327.Available at: https://doi.org/10.2307/2298059.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 987-1007.Available at: https://doi.org/10.1016/0304-4076(86)90063-1.

Celik, S., Demirtaş, G., & Isaksson, M. (2019). *Corporate bond markets in a time of unconventional monetary policy*. Paris: OECD Capital Market Series.

Chen, A. H., & Siems, T. F. (2002). *An empirical analysis of the capital markets' response to cataclysmic events*. Paper presented at the Working Paper, The DIW Economic Consequences of Global Terrorism Workshop, Berlin, 14-15 June.

Cont, R., & Bouchaud, J.-P. (2000). Herd behavior and aggregate fluctuations in financial markets. *Macroeconomic Dynamics, 4*(2), 170-196.Available at: https://doi.org/10.1017/S1365100500015029.

Engle, R., F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom Inflation. *Econometrica, 50*(4), 987-1007.Available at: https://doi.org/10.2307/1912773.

Gertler, M., Kiyotaki, N., & Prestipino, A. (2017). A macroeconomic model with financial panics. National Bureau of Economic Research (NBER), Working Paper No. 24126.

Heyden, K. J., & Heyden, T. (2021). Market reactions to the arrival and containment of COVID-19: An event study. *Finance Research Letters, 38*, 1-8.Available at: https://doi.org/10.1016/j.frl.2020.101745.

Kong, S. Q., Morales, L., & Coughlan, J. (2014). The effects of the global financial crisis on the Shanghai stock market. *The Globalization of Chinese Business*, 169-188.Available at: https://doi.org/10.1533/9781780634494.2.169.

Mishkin, F., & White, E. (2002). U.S. stock market crashes and their aftermath: Implications for monetary policy. NBER Working Papers, No. 8992.

Orléan, A. (1995). Bayesian interactions and collective dynamics of opinion: Herd behavior and mimetic contagion. *Journal of Economic Behavior & Organization, 28*(2), 257-274.Available at: https://doi.org/10.1016/0167-2681(95)00035-6.

Patel, S., & Sarkar, A. (1998). Stock market crises in developed and emerging markets. The Federal Reserve Bank of New York, Research Paper, No. 9809.

Poterba, J. M. (2000). Stock market wealth and consumption. *The Journal of Economic Perspectives, 14*(2), 99–118.Available at: https://www.jstor.org/stable/2647097.

Shiller, R. J. (1989). *Market volatility*. Cambridge Mass: MIT Press.

Topol, R. (1991). Bubbles and volatility of stock prices: Effect of mimetic contagion. *The Economic Journal, 101*(407), 786-800.Available at: https://doi.org/10.2307/2233855.

Wang, L., & Kutan, A. M. (2013). The impact of natural disasters on stock markets: Evidence from Japan and the US. *Comparative Economic Studies, 55*(4), 672-686.Available at: https://doi.org/10.1057/ces.2013.16.

Westerhoff, F. H. (2004). Greed, fear and stock market dynamics. *Physica A: Statistical Mechanics and its Applications, 343*, 635-642.Available at: https://doi.org/10.1016/s0378-4371(04)00848-9.

Worthington, A. C. (2008). The impact of natural events and disasters on the Australian stock market: A GARCH-M analysis of storms, floods, cyclones, earthquakes and bushfires. *Global Business and Economics Review, 10*(1), 1-10.Available at: https://doi.org/10.1504/gber.2008.016824.

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters, 36*, 1-6.Available at: https://doi.org/10.1016/j.frl.2020.101528.