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The impact of COVID-19 on value-at-risk estimations for US and China stock markets

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Abstract

This study seeks to assess the influence of the COVID-19 pandemic on market risk in two global financial stock markets. Employing four value-at-risk methodologies, we analyze and compare market risks before and during the pandemic. These methodologies encompass the normal distribution assumption method, historical simulation, exponential weighted moving average (EWMA) method, and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) approach. The GARCH approach incorporates auto-selection procedures to identify the optimal ARIMA-GARCH model. The quantified value-at-risk serves as a measure of the pandemic's impact severity on both financial stock markets.

Subject Classification: *91B25, 37M10.*

Keywords: *COVID-19, GARCH, Value-at-Risk.*

1.0 Introduction

Prior to the onset of the COVID-19 pandemic, a majority of countries around the world were undergoing positive economic growth. Nevertheless, the repercussions of this pandemic extended to global financial markets, with many experiencing a substantial decline beginning in March 2020, coupled with abnormally high volatility. Numerous studies

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have investigated the volatility behaviours of global financial markets due to the impact of the pandemic [1, 2]. Tissaoui et. al. [3] reported a significant effect of market volatility on the illiquidity of the Saudi stock market during the COVID-19 outbreak. Eduardo Eduardo Vera-Valdes [4] investigated the behaviour of long-memory volatility of VIX and several global markets using the GPH and exact local Whittle methods. The results showed that most selected countries experienced increases in the degrees of memory following the pandemic. In general, this study indicated that the pandemic marked the beginning of a period of higher and more persistent financial volatility for the selected global markets.

In another study by Nammouri et. al. [5], they examined the co-movement between each sector index in the United States during the COVID-19 crisis period by testing for multivariate cointegration and bivariate cointegration. The study concluded that the pandemic has a significant impact on the cointegration of sector indexes, and there was co-movement during the COVID-19 period. Additionally, they identified that sectoral contagion during this pandemic is important for portfolio diversification. Matthias Scherf et. al. [6] investigated the stock market reactions to governments' response to COVID-19, such as lockdown restriction for OECD and BRICS countries. The results showed that stock market reactions appeared to have a delayed response. Consequently, they reported a typical pattern of a delayed and then excessively strong response to a surprising exogenous event.

In a study conducted by Curto and Serrasqueiro [7], the impact of COVID-19 on the volatility of eleven SP500 sector indices and six American stocks was analyzed using the APARCH(1,1) model. Their findings revealed that the increase in volatility primarily favored the FATANG (Facebook, Amazon, Tesla, Apple, Netflix, and Google) sector, as well as the Information Technology, Consumer Discretionary, Telecom Services, Industrial, and Consumer Staple sectors. Conversely, the Energy sector experienced the most significant negative impact. Meanwhile, Wael Rouatbi et al. [8] reported that the COVID-19 vaccination program contributed to a decrease in stock market volatility, particularly stabilizing equity markets. The study also noted a relatively stronger impact of vaccinations on volatility in developed markets compared to emerging markets. Vijander et al. [9] conducted another study, focusing on predicting confirmed, deceased, and recovered cases of COVID-19. The results of their predictions played a crucial role in resource planning, guiding government policies, and issuing immunity passports to survivors.

Claudiu Tiberiu Albulescu [10] explored the influence of the coronavirus pandemic on financial market volatility, revealing that the crisis amplified volatility in US financial markets, consequently affecting the global financial cycle. Sónia R. Bentes [11] investigated changes in the persistence of G7 stock market volatility following the pandemic, utilizing the FIGARCH (1,d,1) model to capture volatility dynamics. The study concluded that stock market price behavior in developed economies undergoes changes over time, leading to clusters of varying intensities in volatility and persistence post-pandemic outbreaks.

In a global analysis, Md. Bokhtiar Hasan et al. [12] examined the impact of the COVID-19 pandemic on both Islamic and traditional stock markets. Employing continuous wavelet transform for wavelet decomposition and analyzing wavelet coherences, the study explored the relative volatility and interactions between global COVID-19 death counts and selected market indices. The findings challenged the decoupling hypothesis between Islamic and conventional stock markets, cautioning investors that the conservative attributes of Islamic stocks may not provide hedging opportunities or superior investment alternatives, especially during crisis periods.

As a result, COVID-19 has had severe negative impacts on global trade, tourism, food production, as well as stock markets. In this study, we aim to contribute to the new strand of the COVID-19 financial-related literature by investigating the effect of news impact and volatility clustering during this pandemic period.

2.0 Methodology

2.1 *Value-at-risk Estimation*

Under normal circumstances, Value-at-Risk (VaR) is primarily used to discuss market risk. From the perspective of financial institutions, VaR can be defined as the maximum loss of a financial position in a given period with a given confidence level. It aims to provide a single number that summarizes the total risk in a portfolio of financial assets. Assuming a normal distribution of return with long position of investment with a capital amount of \$*Capital*, VaR can be expressed as follows:

$$VaR = Capital \times (\mu + Z\sigma)$$

where Z represents the normal critical value, μ and σ are the mean and standard deviation of the return, respectively. If we assume the returns follow a Student's-t distribution, VaR can be calculated as:

$$VaR = Capital \times (\mu + T(\upsilon, c)\sigma)$$

where T (v, c) represents the critical value with an adjusted degree of freedom v at confidence level c. Additionally, we have:

$$p = \Pr[L(l) \geq VaR] = \Pr[L(l) \leq VaR]$$

where l denotes the holding period, and $L(l)$ represents the loss of the portfolio.This implies that during the entire holding period l, the probability that the holder will experience a loss greater than or equal to VaR is p. Alternatively, it can be interpreted as the probability that the potential loss of the holder will be less than or equal to the VaR during the entire holding period l is ($1-p$). Assuming there are N days in the holding period l, the VaR can be calculated as:

$$VaR(N - day) = VaR(1 - day) \times \sqrt{N}.$$

As a comparison, we have selected four commonly used VaR methods for our empirical study. Each method is described as follows:

2.1.1 Variance-Covariance Method

The variance-covariance approach is another term for the normal distribution method. The advantage of this method is its simplicity. However, it has the disadvantage that all calculations are performed on the assumption that both the profit and loss of the portfolio are normally distributed. Under this assumption, the general idea of calculating VaR is to multiply the standard deviation of returns by the z-score at different confidence levels.

2.1.2 Historical Simulation

In comparison to the normal distribution method, the historical simulation method has the obvious advantage of requiring no distribution assumptions and no parameter adjustment. This method assumes that prior profits and losses can serve as a good guide for determining the distribution of returns in the subsequent payback period. The general concept is to order historical returns from lowest to highest. After sorting the returns, the VaR is calculated using a confidence level multiplied by the sample size of the returns. In this case, past data on daily returns is used to obtain the VaR value and deduced the risk factors from historical observations. However, this method has certain potential flaws, such as a slow response to changes in volatility because the quantile does not alter within a few days of an extreme event.

2.1.3 Exponential Weighted Moving Average (EWMA)

The weighted moving average method involves assigning different weights to observed values, calculating the moving average based on the weights, and predicting the value based on the final moving average. This method is utilized because recent observations within the observation period have a stronger influence on the predicted value, allowing for a more accurate capture the pattern of recent changes. Consequently, the weighting coefficient of returns decreases exponentially with time, with the weighting coefficient being greater the closer the return is to the current moment. The formula for the EWMA variance can be expressed as:

$$\sigma_t^2 = \frac{1}{c}\sum_{i=1}^{n} \lambda_{i-1} y_{t-i}^2$$

where n is the size of an estimation window, λ is the decay fact, and c is a normalizing constant with $c = \sum_{i=1}^{n} \lambda_{i-1} = \frac{1-\lambda^n}{1-\lambda} \rightarrow \frac{1}{1-\lambda}$ as $n \rightarrow \infty$. In GARCH, it is written as

$$\sigma_t^2 \approx (1-\lambda)\left(y_{n-1}^2 + \sum_{i=2}^{\infty} \lambda_{i-1} y_{t-i}^2 \right) = (1-\lambda) y_{n-1}^2 + \lambda \sigma_{t-1}^2$$

It is worth noting that a commonly used value for the decay factor λ practical applications is 0.94.

2.1.4 ARMA-GJR Approach

If the variance is represented by the Autoregressive Conditional Heteroskedasticity (ARCH) model, then the extension of the ARCH model is the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The ARMA(m,n)-GARCH(p,q) model has the following form:

$$\text{ARMA}: \qquad \mu_t = \theta_0 + \sum_{i=1}^{n} \theta_i r_{t-i} + \sum_{j=1}^{m} \phi_j \varepsilon_{t-j}$$

$$\text{GARCH}: \qquad \sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

It is common to observe that stock returns are negatively correlated with changes in volatility. This means that when stock returns are lower than expected, volatility tends to increase, and when stock returns are higher than expected, volatility tends to decrease. If a company uses both debt and equity financing, its debt-to-equity ratio increases as its share price falls, leading to higher volatility in equity returns. Therefore, lower-than-expected stock returns result in higher future volatility, while higher-than-expected stock returns result in lower future volatility. The GJR-GARCH model, proposed by Glosten, Jagannathan and Runkle [13], is one model that captures this leverage effect. The GJR-GARCH(1,1) can be expressed as

$$\sigma_t^2 = \alpha_0 + (\alpha_1 + \delta I_{t-1})\varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

where

$$I_t = \begin{cases} 0, & \text{if} \quad r_{t-1} \geq \mu \\ 1, & \text{if} \quad r_{t-1} < \mu \end{cases}.$$

For δ > 0, it implies that the residual of today is negative, indicating that a negative shock today will have a larger impact on future volatility compared to a positive shock.

In this study, diagnostic evaluations for the VaR are conducted using several backtesting methods, including the binomial test, traffic light test, Kupiec's test, CCI test and TBFI test [14].

3.0 Empirical Study

3.1 *Data Selection*

Since the United States and China represent the two largest economies in the world, researchers can gain valuable insights into the state of the global economy by examining their respective stock markets. For this study, we have selected two key index datasets: the S&P500 index, which reflects the performance of the U.S. stock market, and the Shanghai Stock Index, which represents the Chinese stock market. The main objective of the study is to evaluate the impact of the COVID-19 pandemic on global financial markets. To achieve this, we analyzed two distinct periods: one without COVID-19, spanning from 2nd January 2018 to 31st January 2020, and one encompassing the period affected by COVID-19, ranging from 2nd January 2018 to 31st December 2021. By comparing these two time periods, we aimed to gain insights into how the pandemic influenced the performance and behavior of the global financial markets, as reflected by the selected stock market indexes.

3.2 *Value-at-Risk Estimation and Back-testing Result*

In this section, the VaR results are generated by fitting an ARIMA-GJR model to the returns before the onset of COVID-19 pandemic. For the data that includes the COVID-19 period, VaR calculations were performed using four different methods: the normal distribution method, the historical simulation method, EWMA and ARIMA-GJR. To assess the accuracy and effectiveness of the VaR results, a series of back-testing methods were employed. These methods evaluate the VaR outcomes in different time periods and using different calculation methods. By conducting these backtests, the study ensures that the chosen VaR model is appropriate and accurate, which is crucial for future analysis and forecasting purposes. This comprehensive evaluation allows for a comparison of VaR outcomes across different periods and methods, aiding in the selection of the most suitable and reliable model for further analysis and forecasting.

3.2.1 The S&P500

Before COVID-19, the dataset includes 525 trading days of data from 2018 to February 2020. As the sequence of closing prices is non-stationary, the first-order difference is taken to convert the closing prices into continuously compounded returns. To determine the optimal lags for the ARIMA-GJR model, a heat map based on the Akaike Information Criterion (AIC) is used. The heat map visually represents the AIC values, with squares becoming whiter as the AIC value decreases. By iterating through the generated heat map, the maximum lag for the ARIMA model is set to

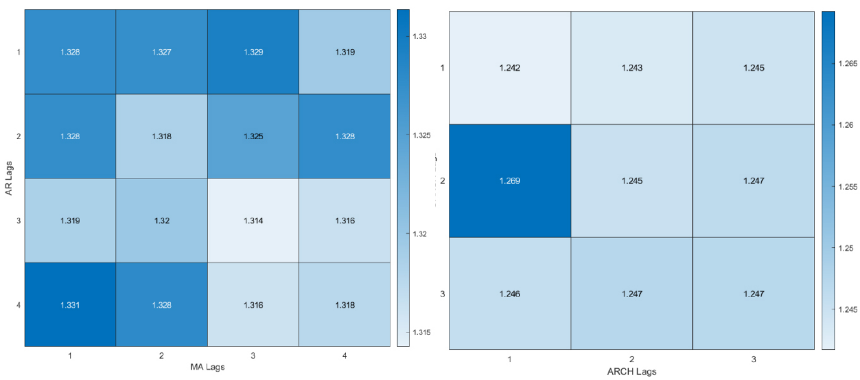

Figure 1

Heat map for ARIMA-GJR model

Table 1

ARIMA(3,1,3) - GJR(1,1) model for S&P500 without COVID-19 period

Parameter	Coefficient	Standard Error	T-statistic	P-value
		Mean Equation		
Constant	0.11782	0.050089	2.3522	0.018662
AR(3)	-0.65208	0.2403	-2.7136	0.0066557
MA(3)	0.66537	0.23547	2.8257	0.028404
Variance Equation				
Constant	0.036736	0.016734	3.1456	0.0016573
GARCH(1)	0.7934	0.048363	14.051	1.7526×10^{-60}
ARCH(1)	0.11194	0.036039	2.0302	0.0226204
Leverage(1)	0.31811	0.079668	3.9929	6.5265×10^{-5}
DoF	5.9479	1.5296	3.8885	0.00010086

4, while for the GJR model, it is set to 3. Based on the analysis, the ARIMA(3,1,3) - GJR(1,1) model is chosen as the best fit for the S&P500 before the onset of COVID-19. This model selection is supported by Figure 1, which presumably displays the results of the analysis.

Table 1 presents the parameters of the ARIMA(3,1,3) - GJR(1,1) model. A p-value smaller than 0.05 indicates that all parameters are statistically significant and deemed appropriate for the model. It is important to note that the assumption of student-t distribution is chosen due to the characteristics of the returns, which exhibit sharp peaks and thick tails. Figure 2 displays the VaR results before the onset of COVID-19. Under the 95% confidence level, the average VaR value is approximately 1.5% with the highest VaR occurring on October 10, 2018, at around 4%. When considering 99% confidence level, the overall fluctuation of VaR becomes more pronounced, with the maximum value reaching 7.3%. This indicates that there is higher potential risk associated with extreme events when using a higher confidence level.

For the S&P500 data that includes the COVID-19 period, there are a total of 1008 observations spanning from 1 January 2018 to 31 December 2021. To capture the impact of COVID-19 more accurately, an ARIMA(3,1,3) - GJR(1,1) model is fitted to this dataset. Table 2 presents the result of the results of ARIMA(3,1,3) - GJR(1,1) model for the S&P500 with COVID-19.

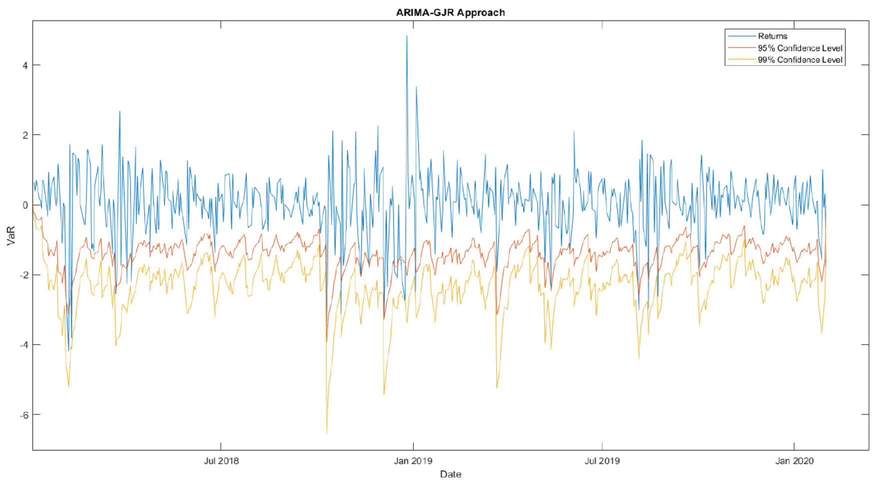

Figure 2

VaR Result for S&P 500 Using ARIMA-GARCH Approach

By comparing the fitted models under two different periods of time, it is observed that the absolute values of the parameters in the mean function increase. The increase in the absolute values of the mean function's parameters indicates a change in the average level of the S&P500 index. This could be attributed to the impact of COVID-19 on the global economy and financial markets. Additionally, the difference between the constants in the variance equation is positive, specifically 0.010291 (0.047027-0.036736). This suggests that COVID-19 has a positive impact on the volatility of the S&P500 index. This suggests that the market experienced higher fluctuations and increased risk during this time, likely due to the uncertainty and economic disruptions caused by the pandemic. Overall, the comparison of the fitted models indicates that COVID-19 had a positive impact on the volatility of the S&P500 index, leading to increased fluctuations and higher risk in the market.

For volatility impact, based on the analysis, it is concluded that the GARCH terms, both before and during COVID-19, are statistically significant and higher than the ARCH terms. This indicates that volatility is highly persistent and clustered, meaning that periods of high volatility are followed by more periods of high volatility. Furthermore, the model exhibits a lower ARCH value and a higher GARCH value during the COVID-19 period compared to before. This implies that volatility is sharper and more pronounced during the COVID-19 period, reflecting the

Table 2
ARIMA(3,1,3) - GJR(1,1) model for S&P500 with COVID-19 period

Parameter	Coefficient	Standard Error	T-statistic	P-value
		Mean Equation		
Constant	0.15295	0.042861	3.5685	0.00035901
AR(3)	-0.70953	0.18578	-3.8193	0.00013384
MA(3)	0.73073	0.17835	4.0972	4.1816×10^{-5}
Variance Equation				
Constant	0.047027	0.011756	4.0002	6.3295×10^{-5}
GARCH(1)	0.75771	0.035268	21.484	2.1819×10^{-102}
ARCH(1)	0.038072	0.037957	1.003	0.31584
Leverage(1)	0.35536	0.074289	4.7835	$1.7228\mathrm{e}\times10^{-6}$
DoF	5.4659	0.87345	6.2578	3.9038×10^{-6}

increased market uncertainty and heightened fluctuations caused by the pandemic. The presence of a leverage effect is also indicated by the positive and statistically significant leverage parameters. The positive leverage value suggests that bad news or negative shocks are more likely to lead to increased volatility in the S&P500 index than good news or positive shocks. This asymmetry in the response of volatility to different types of news or events is a characteristic of the leverage effect. Overall, the analysis highlights the persistence and clustering of volatility, the sharper volatility during COVID-19, and the presence of a leverage effect where bad news has a stronger impact on volatility compared to good news in the S&P500 index.

Figure 2 and Figure 3 present the results of VaR (Value at Risk) under different methodologies. It is evident from the figures that the EWMA and ARIMA-GJR models exhibit a better fitting effect, with the ARIMA-GJR model capturing the changes in returns more accurately. The maximum VaR value of 10.03% is observed on 13 March 2020, with a confidence level of 95%. This indicates that there was a high potential for loss in the S&P500 index on that day. When considering a higher confidence level of 99%, the maximum VaR value reaches 16.47%. This value is significantly higher than the maximum VaR value before the onset of COVID-19, indicating the increased risk and volatility during the pandemic. It is worth noting that the VaR result remained at around 2% for an extended period after the COVID-19 period. This value is slightly higher than the average VaR (1.5%) calculated before the pandemic, suggesting that the market continued to exhibit heightened risk and volatility even after the initial impact of COVID-19. Overall, the figures demonstrate the effectiveness of the EWMA and ARIMA-GJR models in estimating VaR, with the ARIMA-GJR model providing a more precise capture of return changes. The VaR results show a significant increase in risk and volatility during the COVID-19 period compared to before, emphasizing the impact of the pandemic on the financial markets.

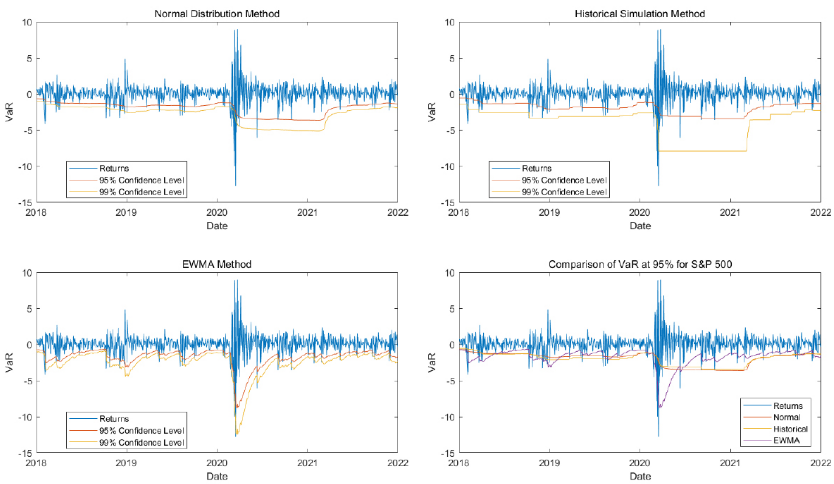

Figure 2

VaR Result for S&P 500 Using Three Basic Approach

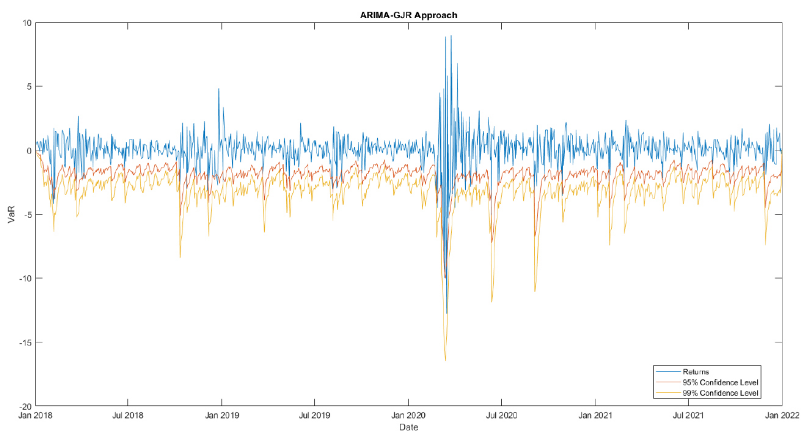

Figure 3

VaR Result for S&P 500 Using ARIMA-GJR Approach

In Table 3, the back-testing results for VaR at different confidence levels and methods are presented. The ARIMA(3,1,3) - GJR(1,1) model, at a 95% confidence level, observed 52 failures, and the observed level is 94.836%, which is close to the expected level. This indicates that the model performs well in capturing the expected level of VaR. The historical simulation method provides the closest observed number of failures under the 99% confidence level. However, it is noted that this method exhibits a specific over-fitting behavior, as shown in Fig. 2, which is considered unacceptable. The majority of VaR test outcomes at the 95% confidence level passed the frequency test, binomial test, and proportion of failure test, demonstrating their acceptability. The results of the traffic light test for all three methods are green, indicating that they are appropriate, except for the normal distribution method. At the 99% confidence level, both the normal distribution method and the EWMA method show a red traffic light signal, indicating that the results are inappropriate. Furthermore, both the ARIMA-GJR and EWMA methods fail to reject the conditional coverage independence test (CCI). Overall, the back-testing results indicate that the ARIMA(3,1,3) - GJR(1,1) model performs well in capturing the expected level of VaR at a 95% confidence level. However, certain methods and confidence levels exhibit limitations and inconsistencies, highlighting the importance of selecting an appropriate method for accurate risk assessment.

Furthermore, the time between failures independence test (TBFI) results indicate that almost all methods reject the assumption of independence between failures. At a 95% confidence level, it is expected that failures occur once every twenty days on average. However, the median time between failures for the four approaches ranged from 4 to 10 days, which is significantly shorter than the expected 20 days. This suggests a higher frequency of failures than anticipated.

Taking the ARIMA-GJR approach as an example, the results show that two consecutive failures occur within ten days approximately 50% of the time, which is much more frequent than the expected 20 days. This implies an increased number of test failures compared to the expected pattern. Additionally, the third quartile value of 25.5 indicates that 75% of failures occur within nearly 26 consecutive days. The maximum duration between failures is 134 days, highlighting the variability in the occurrence of failures.

These findings indicate that the assumption of independence between failures is not met, and the actual time between failures deviates significantly from the expected average. This suggests that the risk of failures is more clustered and unpredictable than originally anticipated.

Table 3

VaR summary for S&P500

VaR ID	VaR Level	Observed Level	Observations	Failures	Expected	Ratio	TL Test	Bin Test	POF Test	TUFF Test
Normal-95	0.95	0.9375	1008	63	50.4	1.25	Yellow	Accept	Accept	Accept
Historical-95	0.95	0.94048	1008	60	50.4	1.1905	Green	Accept	Accept	Accept
EWMA-95	0.95	0.94643	1008	54	50.4	1.0714	Green	Accept	Accept	Accept
GJR-95	0.95	0.94841	1008	52	50.4	1.0317	Green	Accept	Accept	Accept
Normal-99	0.99	0.96329	1008	37	10.08	3.6706	Red	Reject	Reject	Accept
Historical-99	0.99	0.98611	1008	14	10.08	1.3889	Green	Accept	Accept	Accept
EWMA-99	0.99	0.96726	1008	33	10.08	3.2738	Red	Reject	Reject	Accept
GJR-99	0.99	0.99007	1008	10	10.08	0.9921	Green	Accept	Accept	Accept

VaR ID	VaR Level	CC Test	CCI Test	TBF Test	TBFI Test	TBF Min	TBF Q1	TBF Q2	TBF Q3	TBF Max
Normal-95	0.95	Reject	Reject	Reject	Reject	1	2	4	14.25	134
Historical-95	0.95	Reject	Reject	Reject	Reject	1	2	4	12.5	134
EWMA-95	0.95	Accept	Accept	Reject	Reject	1	3	10	28	71
GJR-95	0.95	Accept	Accept	Reject	Reject	1	4	9	25.5	134
Normal-99	0.99	Reject	Reject	Reject	Reject	1	2	3	22	327
Historical-99	0.99	Reject	Reject	Reject	Reject	1	2	2.5	29	430
EWMA-99	0.99	Reject	Accept	Reject	Reject	1	3.75	23	54.25	127
GJR-99	0.99	Accept	Accept	Accept	Accept	10	27	87	180	211

3.2.2 The ShangHai Index

The pre-pandemic data for the Shanghai index consists of 501 trading days, whereas the entire dataset including COVID-19 comprises 970 trading days. Table 4 and Table 5 display the results of fitting the same ARIMA(4,1,4) - GJR(1,1) model to different time periods.

Table 4

ARIMA(4,1,4) - GJR(1,1) model for ShangHai Index without COVID-19 period

Parameter	Coefficient	Standard Error	T-statistic	P-value
		Mean Equation		
Constant	-0.0014551	0.010207	-0.13248	0.8946
AR(4)	0.71938	0.2369	3.0366	0.0023926
MA(4)	-0.75271	0.22435	-3.3551	0.00079345
Variance Equation				
Constant	0.051021	0.021042	2.424	0.01573
GARCH(1)	0.89843	0.04802	18.71	4.1384×10^{-78}
ARCH(1)	0.045791	0.033712	1.3583	0.17437
Leverage(1)	0.039347	0.044991	0.87455	0.38182
DoF	3.9871	0.8508	4.6863	2.7819×10^{-6}

Table 5

ARIMA(4,1,4) - GJR(1,1) model for ShangHai Index with COVID-19 period

Parameter	Coefficient	Standard Error	T-statistic	P-value
		Mean Equation		
Constant	0.0081773	0.010207	0.80112	0.42306
AR(4)	0.69956	0.20247	3.4551	0.00055003
MA(4)	-0.73954	0.18969	-3.8986	9.6744×10^{-5}
Variance Equation				
Constant	0.067548	0.028042	2.4088	0.016004
GARCH(1)	0.87588	0.036127	24.245	7.5061×10^{-130}
ARCH(1)	0.053588	0.025333	2.1154	0.034399
Leverage(1)	0.043791	0.03449	1.2697	0.20421
DoF	4.592	0.71207	6.4487	1.1278×10^{-10}

Similarly to the performance of the S&P500, the coefficients of the variance equation for the Shanghai index also show a positive difference, indicating a volatility shift under the influence of COVID-19. However, in contrast to the S&P500 model, the p-values of the leverage coefficient and the ARCH coefficient in the model for the Shanghai index are both greater than 0.05. This suggests that these coefficients may not be statistically significant at the 95% confidence level. This observation is related to the inherent high volatility of the Shanghai index itself. This can be seen in Figure 4, where the fitted VaR results capture most of the changes in volatility, but fail to accurately predict sudden unexpected spikes in returns, resulting in a higher number of "failure" observations.

According to Figure 5, both the Normal Distribution Method and the Historical Simulation method with a 95% confidence interval appear as straight lines, in contrast to the return series that exhibits significant fluctuations. Although the observed levels obtained by these two methods are close to 0.95 and the failure ratio is close to 1, the rejection of the CCI test indicates that the VaR violations are not independent. On the other hand, the figures generated by the EWMA and ARIMA-GJR methods are much more accurate and closely resemble the original data. Comparing the two, the modified ARIMA(4,1,4) - GJR(1,1) model performs slightly better as illustrated in Figure 6. According to Table 6, at a confidence level of 95%, the number of failures is 46 with an observed level of 0.95253. Not

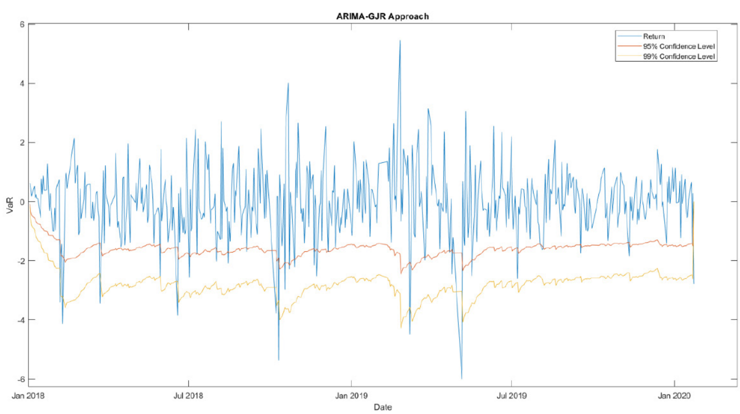

Figure 4

VaR Result for Shanghai Index Using ARIMA-GJR Approach without COVID-19

only does the traffic light test show green, but the frequency tests, including the Bin test, POF test, and CCI test, also produce acceptable results.

It is worth noting that all the methods reject the TBFI test, which is consistent with the result obtained for the S&P500 index. This suggests that there are likely periods with multiple failures occurring in a short time span, and a single failure may increase the likelihood of subsequent failures in the following days. This is one of the characteristics of the impact of COVID-19.

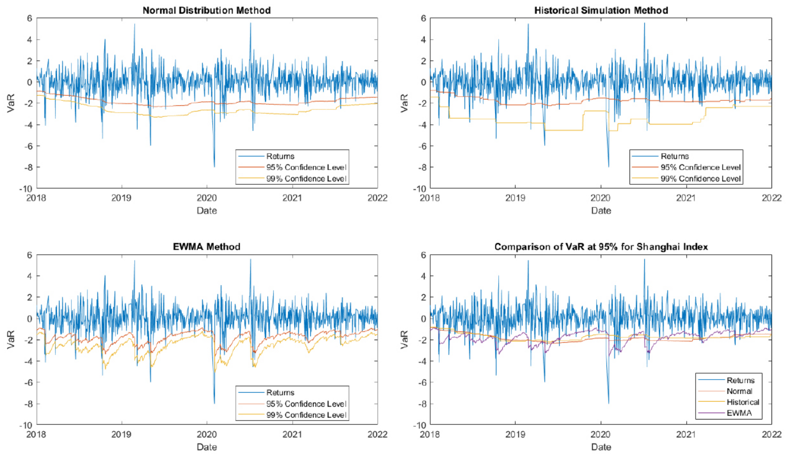

Figure 5

VaR Result for Shanghai Index Using Three Basic Approach

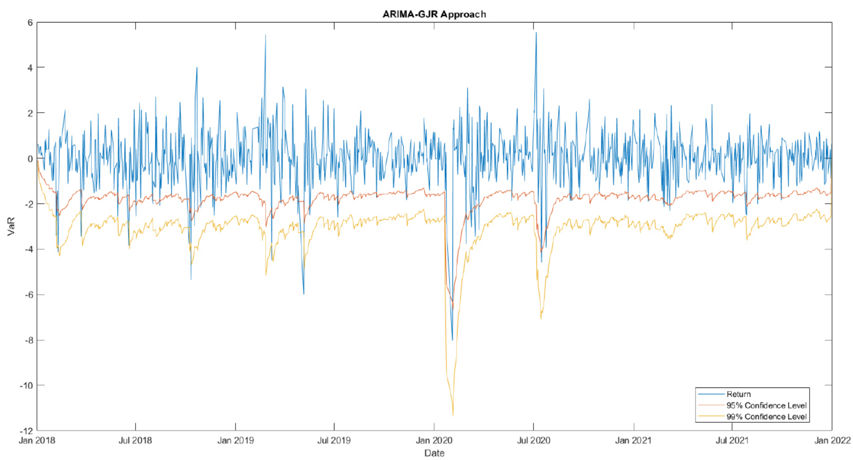

Figure 6

VaR Result for Shanghai Index Using ARIMA-GJR Approach with COVID-19

Table 6

VaR summary for ShangHai Index

VaR ID	VaR Level	Observed Level	Observations	Failures	Expected	Ratio	TL Test	Bin Test	POF Test	TUFF Test
Normal-95	0.95	0.94421	968	54	48.4	1.1157	Green	Accept	Accept	Accept
Historical-95	0.95	0.93698	968	61	48.4	1.2603	Yellow	Accept	Accept	Accept
EWMA-95	0.95	0.94938	968	49	48.4	1.0124	Green	Accept	Accept	Accept
GJR-95	0.95	0.95253	968	46	48.4	0.9494	Green	Accept	Accept	Accept
Normal-99	0.99	0.97624	968	23	9.68	2.376	Red	Reject	Reject	Accept
Historical-99	0.99	0.9845	968	15	9.68	1.5496	Yellow	Accept	Accept	Accept
EWMA-99	0.99	0.98037	968	19	9.68	1.9628	Yellow	Reject	Reject	Accept
GJR-99	0.99	0.99174	968	8	9.68	0.8256	Green	Accept	Accept	Accept

VaR ID	VaR Level	CC Test	CCI Test	TBF Test	TBFI Test	TBF Min	TBF Q1	TBF Q2	TBF Q3	TBF Max
Normal-95	0.95	Reject	Reject	Reject	Reject	1	3	6	17	141
Historical-95	0.95	Reject	Reject	Reject	Reject	1	2.75	6	17	84
EWMA-95	0.95	Accept	Accept	Accept	Accept	1	5	16	30	78
GJR-95	0.95	Accept	Accept	Accept	Accept	1	5	14.5	29	79
Normal-99	0.99	Reject	Reject	Reject	Reject	1	3.5	9	41.75	243
Historical-99	0.99	Reject	Reject	Reject	Reject	1	2.25	26	92.5	243
EWMA-99	0.99	Reject	Accept	Reject	Reject	1	13.75	35	81.25	126
GJR-99	0.99	Accept	Accept	Accept	Accept	3	14	30	65	99

3.3 *Value-at-Risk Determination*

The calculations are based on the ARIMA-GJR Approach With a \$100,000 invested capital amount and considering a 95% and 99% confidence levels, the VaR for the next trading day is determined as follows:

For the S&P500, using ARIMA(3,1,3)-GJR(1,1) model, the one-day ahead quantiles are calculated as follows:

$$95\%\,\text{Quantile} = -0.000539 + (-1.5749 \times \sqrt{1.0122 \times 10^{-4}}) = -0.0163838$$

$$99\%\,\text{Quantile} = -0.000539 + (-2.5866 \times \sqrt{1.0122 \times 10^{-4}}) = -0.0265623$$

The VaRs at the 95% and 99% confidence levels are:

$$V\,aR_{95\%} = \$100,\,000 \times 1.63838\% = -\ \$1638.38$$

$$V\,aR_{99\%} = \$100,\,000 \times 2.65623\% = -\ \$2656.23$$

The negative values indicate the potential losses. These results indicate that with a 95% confidence level, there is a potential loss up to \$1638.38 on the next trading day. With a 99% confidence level, the potential loss could be up to \$2656.23.

For ShangHai Index, using the ARMA(4,1,4)-GJR(1,1) model, the one-day ahead VaR is calculated as:

$$VaR_{95\%} = \$100,000 \times (-0.000147 + (1.5441 \times \sqrt{1.385 \times 10^{-4}}) = -\$1831.89$$

$$VaR_{95\%} = \$100,000 \times (-0.000147 + (2.6248 \times \sqrt{1.385 \times 10^{-4}}) = -\$3103.72$$

Again, the negative values indicate potential losses. These results indicate that with a 95% confidence level, there is a potential loss of up to \$1832.89 on the next trading day for the Shanghai Index. With a 99% confidence level, the potential loss could be up to \$3103.72.

4.0 Conclusion

VaR values have indeed increased significantly during the COVID-19 period, reaching their peak in March 2020. The S&P500 index has shown greater resilience compared to the Shanghai index, as it has returned to normal levels by the end of 2020 and maintained a steady upward momentum thereafter. The impact of COVID-19 is diminishing over time for both markets.

The variance-covariance method, using VaR, measures stock risk. With a total investment of $100,000 in the S&P500, there is a 99% confidence that the position will not lose more than $2656.23 over the next trading day. Similarly, with a total investment of $100,000 in the Shanghai index, there is a 99% confidence that the position will not lose more than $3103.72 in the coming trading day. These results indicate that the stock market was highly volatile during the COVID-19 period, and investors faced a significant risk of loss. Comparatively, investors in the Shanghai index would have a higher probability of loss.

Among the four fitting methods, the historical simulation method reacts slowly to changes in data and has a larger error. The normal distribution method shows a close result to 95% confidence but has some lag. The EWMA method responds to data changes more promptly but still requires improvement. The modified ARIMA-GJR model, developed in this study, demonstrates the ability to reflect data changes in a timely manner and ensures the flexibility and timeliness of VaR. It can be considered a more reference-worthy method compared to others.

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