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MARKET RISK DATA ANALYTICS FOR SELECTED ASIAN STOCK MARKETS DURING THE PANDEMIC COVID-19

(Analitik Data Risiko Pasaran untuk Pasaran Saham Asia Terpilih Semasa Pandemik COVID-19)

LENG JING TENG, CHIN WEN CHEONG* & LIM MIN

ABSTRACT

This study investigates various conditional mean and variance models to account for the impact of COVID-19 on the selected Asian markets, specifically the Japanese and Singaporean stock markets. The research period (24 August 2012 to 24 August 2022) is split into two periods, from 24 August 2012 to 31 March 2020 and from 24 August 2012 to 24 August 2022, to analyse the effect of COVID-19 on both stock returns. We found that both returns exhibit non-normality. The best-fitted models for the Japanese and Singaporean stock markets are Student-t ARMA(1,1)-EGARCH(1,1) and ARMA(2,1)-GJR(1,1), respectively. The presence of the pandemic period indicates positive shifts in volatility intensity in both the Japanese and Singaporean stock markets. The 5% Value-at-Risk under the GARCH estimations is $3568.20 for Japan and $2050.40 for Singapore. Meanwhile, the 5% expected shortfall based on historical simulation for both countries is $3214.00 for Japan and $2196.26 for Singapore. From the results of Value-at-Risk and expected shortfall, the Japanese stock returns showed more significant maximum losses than Singaporean stock returns, which further indicates that the Japanese stock market was more volatile than the Singaporean stock market before and during the pandemic period.

Keywords: conditional variance; volatility analysis; COVID-19

ABSTRAK

Kajian ini mengkaji pelbagai model min dan varians bersyarat untuk mengambil kira kesan COVID-19 terhadap pasaran Asia terpilih, khususnya pasaran saham Jepun dan Singapura. Tempoh kajian (24 Ogos 2012 hingga 24 Ogos 2022) dibahagikan kepada dua tempoh, dari 24 Ogos 2012 hingga 31 Mac 2020 dan dari 24 Ogos 2012 hingga 24 Ogos 2022, untuk menganalisis kesan COVID-19 terhadap kedua-dua pulangan saham. Kami mendapati bahawa kedua-dua pulangan tidak menurut taburan normal. Model terbaik yang bersesuaian untuk pasaran saham Jepun dan Singapura adalah Student-t ARMA(1,1)-EGARCH(1,1) dan ARMA(2,1)-GJR(1,1) masing-masing. Kehadiran tempoh pandemik menunjukkan pergeseran positif dalam intensiti ketidistabilan dalam kedua-dua pasaran saham Jepun dan Singapura. Nilai Risiko pada 5% di bawah anggaran GARCH adalah $3568.20 untuk Jepun dan $2050.40 untuk Singapura. Sementara itu, kekurangan dijangka pada 5% berdasarkan simulasi sejarah untuk kedua-dua negara adalah $3214.00 untuk Jepun dan $2196.26 untuk Singapura. Daripada hasil Nilai Risiko dan kekurangan dijangka, pulangan saham Jepun menunjukkan kerugian maksimum yang lebih ketara daripada pulangan saham Singapura, yang menunjukkan bahawa pasaran saham Jepun lebih tidak stabil daripada pasaran saham Singapura sebelum dan semasa tempoh pandemik.

Kata kunci: varians bersyarat; analisis kemeruapan; COVID-19

1. Introduction

The World Health Organization (WHO) identified the first case of COVID-19 on December 31, 2019, in Wuhan, China. The virus spread quickly and caused the WHO to announce that the

COVID-19 pandemic had evolved into a global crisis on March 11, 2020. Due to the COVID-19 outbreak, the global financial markets, derivative markets, and economic activities have been affected (Sheth *et al.* 2022). The Asian financial market volatility has been studied extensively since the Asian Financial Market responded swiftly to the financial crisis in 2008, and the stock return has been significantly impacted (Singhania & Anchalia 2013). Therefore, the COVID-19 pandemic significantly impacted financial markets in 2020, including the Asian financial market, with travel restrictions, lockdowns, and enormous unemployment.

The main objective of this study is to estimate and assess the Japanese and Singaporean financial stock market volatilities before the pandemic and during the pandemic by using multiple combined ARMA-GARCH models. Japan and Singapore have been chosen as priority countries since they are rapidly growing and developing in Southeast and East Asia. Japan is the third-largest economy in the world by nominal Gross Domestic Product (GDP) and the fourth-largest national economy in the world by purchasing power parity (PPP) (Lah 2011). It is the world's second-largest developed economy that has become a leading exporter of transport equipment, machinery, and electrical machinery. Meanwhile, Singapore is ranked first among 39 countries in the Asia-Pacific region. It is the second-highest per-capita GDP in the world in terms of PPP. Singapore provides one of the world's most business-friendly regulatory environments for local entrepreneurs. It is ranked among the world's most competitive economies that exports chemicals, electronics, and business services. Therefore, this study focused on the volatilities of Japan and Singapore's financial stock markets. Furthermore, this study aims to help investors understand and forecast market volatility. Volatility acts as a proxy for investment risk. Therefore, investors can use volatility forecasting to generate consistent returns. Investors may adjust their investing strategy by using financial derivatives or hedge their investments.

Due to the influences of COVID-19 pandemic to the uncertainty of global financial markets, the studies of the market risk are closely related to market volatility which can be quantified as a statistical measure of the dispersion of a security's or market index's return distribution. Financial stock market volatility is a significant factor in determining whether investors' fortunes improve or deteriorate. Rastogi (2014) summarised the study of volatility becomes more critical during extreme conditions such as the financial crisis. This article analyses and compares volatility before and after the 2008 financial crisis using GARCH, TGARCH, and EGARCH models. The research focused on emerging economies and produced some surprising findings. It indicates that although the crisis significantly influenced the volatility and leverage effect of stock markets in several countries, the direction of the impact was uneven. The random walk hypothesis is a financial model that believes the stock market moves unpredictably. For over half a century, financial experts have regarded the movements of markets as a random walk, and this hypothesis has become a cornerstone of modern financial economics and many investment strategies. According to the random walk hypothesis, stock price fluctuations have the same distribution and are unrelated. As a result, it is assumed that a stock price or market's historical movement or trend cannot be utilised to forecast its future behaviour. In contrast to the Random Walk Theory, other economists, professors, and investors believe that future price movements may be forecasted using trends, patterns, and historical price activity, and the market is somewhat predictable. These people think that the prices follow patterns and that analysing historical data may be utilized to forecast future price direction. Lo and MacKinlay (1999) provided evidence that the random walk hypothesis is incorrect in their book "A Non-Random Walk Down Wall Street". The book contains various tests and research that reportedly support the concept that the stock market exhibits tendencies and is somewhat predictable. In this study, the past prices of the stock are used to forecast the future price direction, which applies the non-random walk hypothesis.

The remaining of this paper is structured as follows: in Section 2 some literature reviews are summarised, then in Section 3 we provide the methodology used in the study, followed by the empirical results in Section 4, and we conclude in Section 5.

2. Literature Review

A large and growing body of literature has investigated the circumstance of financial markets during the global pandemic of COVID-19. Apergis *et al.* (2023), Ha (2023), Nguyen *et al.* (2023) and Zhang *et al.* (2022) have analysed the influence of the COVID-19 pandemic on stock market risk statistically. Zhang *et al.* (2020) established that the financial markets have seen unprecedentedly extreme activity during the COVID-19 pandemic. The current findings demonstrate that the pandemic has significantly raised the risks associated with the world's financial markets. There is a clear relation between individual stock market responses and each country's severity of the pandemic. The pandemic's high level of uncertainty and the resulting economic losses have made markets volatile and unpredictable.

There are numerous studies worked on the volatility and market risk analysis. Wang *et al.* (2022) used a generalised autoregressive conditional heteroskedasticity (GARCH)- type model to perform an empirical analysis on data from the Shanghai Composite Index and Shenzhen Component Index returns. The authors created the autoregressive moving average (ARMA)-GARCH model with t-distribution for the sample series to examine model effects under various distributions and orders. To capture the characteristics of the index, the authors instead suggested threshold-GARCH (TGARCH) and exponential- GARCH (EGARCH) models. Additionally, mean squared error (MSE), mean absolute error (MAE), and root-mean-squared error (RMSE) were used to analyse the error level and prediction outcomes of various models. The findings show that when predicting the Shanghai Composite Index return series using Student's *t*-distribution, the ARMA (4,4)-GARCH (1,1) model performs better than other models. ARMA(1,1)-TGARCH(1,1) provides the best predicting performance for the return series of the Shenzhen Component Index across all models. However, the authors have not evaluated the impact of the COVID-19 pandemic on the Chinese stock markets.

Chaudhary *et al.* (2020) had analysed the effect of COVID-19 on the return and volatility of the stock market indexes of the world's top ten economies by GDP, using the GARCH model, which is a widely used econometric model. Daily returns on market indexes from January 2019 to June 2020 were considered. The authors found that the data indicate that daily mean returns in all market indexes were negative throughout the COVID period (January 2020 to June 2020). While the second quarter of the COVID period demonstrates a recovery for all market indexes with changed strengths, volatility remains higher than the normal period, indicating a negative market trend. The COVID variable is positive and significant for all market indexes when used as an exogenous variance regressor in GARCH modelling. Additionally, the data indicated that all market indexes follow a mean-reverting trend.

Onali (2020) investigated the impact of COVID-19 cases and fatalities on the U.S. stock markets (Dow Jones and S&P 500 indexes), considering changes in trading volume and volatility expectations, as well as weekday impacts. He suggests that changes in the number of cases and deaths in the U.S. and six other countries severely impacted by the COVID-19 crisis do not affect U.S. stock market return, with the expectation of China's reported cases. However, the author found evidence of a beneficial effect on the conditional heteroscedasticity of the Dow Jones and S&P 500 returns in several notions. According to VAR models, the reported death rate in Italy and France has an adverse but favourable effect on the VIX returns. Finally, he found that Markov-Switching models indicate that the VIX's negative effect on stock market returns would have tripled by the end of February 2020. Sharma (2020) provided a note on commodity volatility for five developed Asian economies, namely Hong Kong, Japan, Russia, Singapore, and South Korea. Additionally, the author examined of COVID-19 changed the Asian region's commonality of volatility. The author found that Singapore's volatility is more prominent than the other four economies during COVID-19.

Endri *et al.* 2021 analysed the reaction of the stock price on the Indonesian Stock Exchange (IDX) to COVID-19 using an event research technique and the GARCH model. In their article, the research sample consists of the closing price of the Composite Stock Price Index (JCI) and companies that are a member of LQ-45 for the 40 days preceding the COVID-19 incident, for one day during the COVID-19 incident (March 20, 2020), and for ten days following the COVID-19 incident, January 6, 2020- March 16, 2020. The empirical evidence demonstrates that abnormal returns are negatively correlated with COVID-19, that JCI volatility fluctuates significantly during the COVID-19 event, and that the GARCH(1,2) model can assess volatility and forecast stock abnormal returns in IDX during COVID-19 market conditions. The authors found the results have a practical consequence for investors in that the COVID-19 incident increased stock price volatility, which impacts abnormal returns. As a result, various risk management is required to manage a stock portfolio in the future under circumstances of uncertainty and heightened volatility. Additionally, it enables speculators to benefit from an inefficient market environment. This research is based on the emerging empirical literature on stock price volatility behaviour during COVID-19 on the IDX. The GARCH model demonstrates that stock market volatility increases during the COVID-19 epidemic, resulting in a fall in anomalous returns. Additionally, the empirical results confirm the efficient market hypothesis theory in terms of event analysis and the theory of financial behaviour regarding uncertainty.

3. Methodology

This study used the daily historical data of the financial stock market for Japan (Nikkie 225) and Singapore (STI index). The observations of the financial stock market for Japan were sourced from Yahoo Finance, while Singapore were sourced from Wall Street Journal. The data sets for this study are started from 24 August 2012 to 24 August 2022. There are 2443 and 2506 observations for Nikkei 225 and STI index, respectively. The data was divided into two parts that are pre-COVID-19 pandemic (24 August 2012 to 31 March 2020) and during the COVID-19 pandemic (24 August 2012 to 24 August 2022) to capture the impact of the COVID-19 pandemic on the return of the financial stock market. In this study, the Box-Jenkins Methodology was used to find the best models for the financial stock market of Japan and Singapore.

The studies started with descriptive statistics. Descriptive statistics were used to determine the distribution properties of the pre-pandemic and during the pandemic. Additionally, the data was divided into two data sets: the training set and the validation set. The training set was utilised to fit the model. After the stationary and heteroscedasticity tests were performed, a combined ARMA-GARCH model was estimated. The stock market returns must be stationary to estimate a GARCH model, and the heteroscedasticity test evaluates for the presence of ARCH effects in the stock return residual. After the data is fitted, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) will be used to choose the best-fitting model and analyse the model's parameters. After the best fit model is found, the model is then used to make a 200-step-ahead forecast. The validation set is then used to assess forecast accuracy using Mean Absolute Error (MAE) and Mean Square Error (MSE). Furthermore, the Value-at-Risk (VaR) and Expected Shortfall (ES) were evaluated to determine the risk of investment loss for the Japanese and Singaporean stock markets.

3.1. *Model specification*

The conditional mean, r_t follows a stationary ARMA(p, q) model where its equation is given by

$$r_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i r_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{1}$$

where φ_0, φ_i and θ_j representing a constant term, coefficients of AR terms of order p and coefficients of MA terms of order q respectively. The ε_t are residuals that are identically distributed with mean zero and subject to conditional heteroscedasticity. If ε_t is assumed to be following a standard normal distribution, then ε_t can be further expressed as

$$\varepsilon_t = \sigma_t z_t \tag{2}$$

The σ_t in the equation represent the conditional standard deviation at time t and $z_t \sim N(0,1)$ which is identical independent distribution equipped with mean 0 and variance 1. On the other hand, if ε_t is assumed to be following a student-t distribution, then ε_t is

$$\varepsilon_t = \sigma_t T_t \tag{3}$$

where T_t ~ Student-t T(v) with v is the degrees of freedom.

For volatility model, the exponential GARCH model is estimated to capture the asymmetric impacts of stock such as news and incidents. By using the EGARCH model, the logarithms of volatility are calculated. It makes the asymmetric impact exponential rather than quadratic and provides positive parameter estimations. A symmetric model is indicated by a parameter that is statistically equal to zero, whereas a negative suggests that negative shocks cause larger volatility than positive shocks. Equation of EGARCH(p,q) conditional variance process has the form

$$\log \sigma_t^2 = \omega + \sum_{i=1}^{p} \gamma_i \log \sigma_{t-i}^2 + \sum_{j=1}^{q} \alpha_j \left[\frac{|\varepsilon_{t-j}|}{\sigma_{t-j}} - E\left\{ \frac{|\varepsilon_{t-j}|}{\sigma_{t-j}} \right\} \right] + \sum_{j=1}^{q} \xi_j \left(\frac{\varepsilon_{t-j}}{\sigma_{t-j}} \right) \tag{4}$$

where the ω is the conditional mean model constant, γ_i is the coefficients of GARCH component, α_j is ARCH component coefficients and ξ_j is the leverage component coefficients. Another model namely the Glosten, Jagannathan, and Runkle (GJR) model was used to estimate the conditional heteroscedasticity in the innovation process. When an innovation process does not have significant autocorrelations, but the variance of the process increases with time, volatility clustering arises. The GJR model is a generalisation of the GARCH model that is suitable for modelling asymmetric volatility clustering. The GJR(p,q) conditional variance process has the form

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \gamma_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \xi_j I[\varepsilon_{t-j} < 0] \varepsilon_{t-j}^2 \tag{5}$$

where the ω is a positive conditional variance model constant, γ_i , α_j , ξ_j are the GARCH, ARCH and leverage component coefficients respectively.

3.2. *Market risk*

VaR is a financial metric that estimates the risk of an investment. VaR is a statistical technique that was used to forecast the greatest possible losses over a certain period of time. The magnitude and likelihood of possible losses in portfolios may be calculated using VaR. VaR is a tool used by risk managers to measure and manage the amount of risk exposure. There are three methods of calculating VaR including the historical method, the variance- covariance method, and the Monte Carlo simulation. The VaR model is quantified as

$$N - \text{day VaR} = 1 - \text{day VaR} \times \sqrt{N} \tag{6}$$

The historical method is the simplest method for calculating VaR. This technique's basis is that the pattern of past returns predicts the pattern of future returns. For variance-covariance technique relies on the characteristics of the probability distribution of price changes or returns and uses the variances and covariances of assets for VaR computation. The variance-covariance technique assumed that asset returns are normally distributed, with the mean located at the centre of the probability distribution with a bell shape. Assets may have the propensity to rise and fall together or oppose one another. This strategy makes the assumption that both the correlations between asset returns and the standard deviation of asset returns are constant throughout time. If the return series is expected to be normally distributed, then the 1-day VaR will be expressed as

$$\text{VaR} = \mu + \sigma N^{-1}(X) \tag{7}$$

where μ and σ denote the mean of the returns and the standard deviation of the return series with $N^{-1}(X)$ is the inverse of the one-tail standard normal distribution function with confidence level X. For a general ARMA-GARCH method, the a one-day ahead forecast conditional mean and variance models can be written as

$$\hat{r}_t(1) = \varphi_0 + \sum_{i=1}^{p} \varphi_i r_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{8}$$

$$\hat{\sigma}_{t+1}^2(1) = \omega + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \tag{9}$$

Using the forecasted conditional volatility, the VaR can be further determined. Another measurement of risk is computed in ES. It has the advantage to capture the tail behaviour of the measuring risk. This method extended the VaR by computing the average portfolio's tail distribution returns at selected confidence level. Similar to *N*-day VaR, the calculation of *N*-day ES is as below:

$$N - \text{day ES} = 1 - \text{day ES} \times \sqrt{N} \tag{10}$$

4. Empirical Results

The analysis started with the distributional features of stock market returns. The Japan and Singapore stock indexes were plotted in Figure 1. The Japanese stock market clearly showed an upward trend before the COVID-19 pandemic, but the Singaporean stock market has an upward and downward trend before the pandemic. The price index of Japan and Singapore dropped as the COVID-19 pandemic began in April 2020. However, both of the stock markets recovered slowly afterward. The descriptive statistics were based on sample observations made before the COVID-19 pandemic (24 August 2012 to 31 March 2020) and during the COVID-19 pandemic (24 August 2012 to 24 August 2022). The descriptive statistics for Japan and Singapore Stock Markets are shown in Table 1.

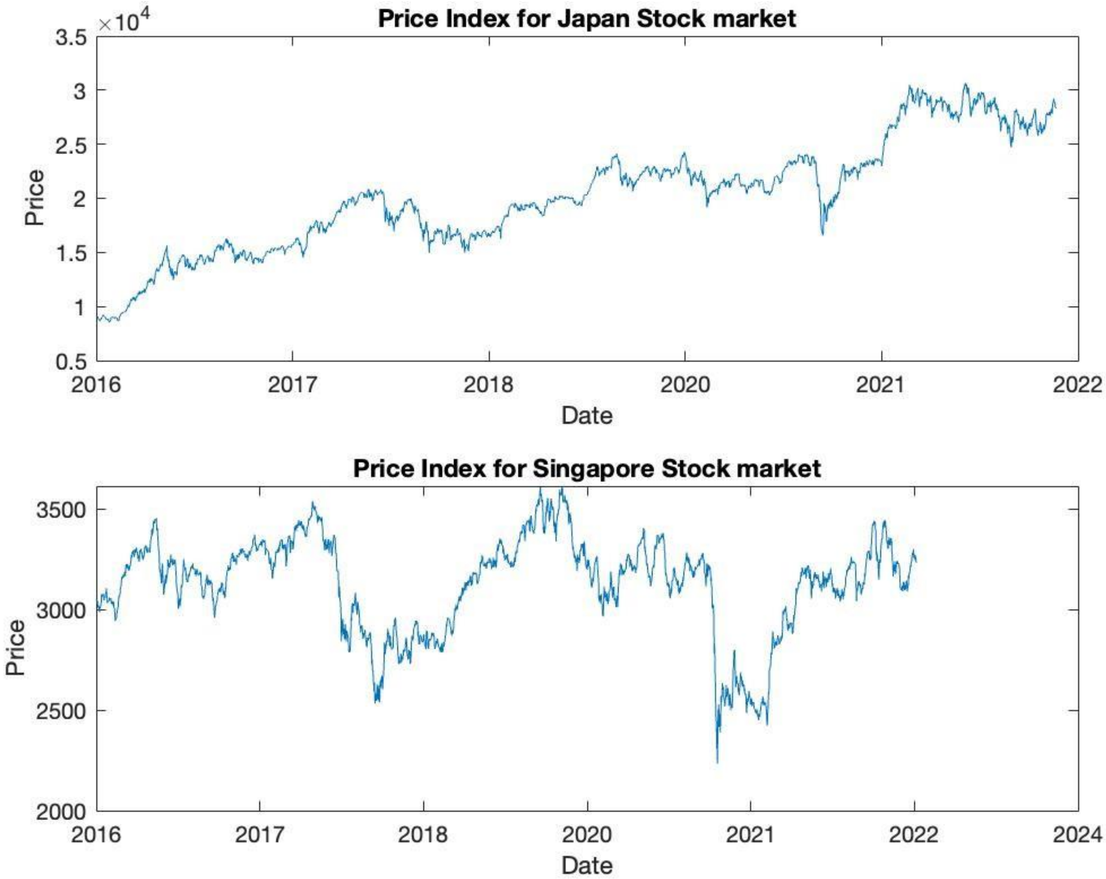

Figure 1: Price index for Japan and Singapore stock markets

From Table 1, the daily mean returns of Japan were both positive before and during the COVID-19 pandemic, and this indicates that the Japan Stock Market is not experiencing a significant loss for pre- and during the pandemic. However, the daily mean returns of Singapore before the pandemic were negative while positive during the COVID-19 pandemic indicating that Singapore Stock Market experienced a gain during the pandemic. Moreover, the maximum and minimum returns for Japan and Singapore Stock Market are the same before and during COVID-19, respectively. This suggests that the Japanese and Singaporean Stock Market do not experience high fluctuation in a single day before and during the pandemic. However, it can be claimed that the Japanese Stock Market is more volatile than the Singaporean Stock

Market since it has a higher value of the maximum and minimum value than the Singaporean Stock Market.

Table 1: Descriptive statistics of Japan and Singapore stock returns

	Japan Stock Market		Singapore Stock Market	
	Before pandemic	During pandemic	Before pandemic	During pandemic
Mean	0.0396	0.0466	-0.0109	0.0023
Median	0.0770	0.0793	-0.0029	0.0110
Maximum	7.7314	7.7314	5.8946	5.8946
Minimum	-8.2529	-8.2529	-7.6373	-7.6373
S.D	1.3484	1.3265	0.8068	0.8221
Skewness	-0.3010	-0.2524	-0.8161	-0.5317
Kurtosis	7.8748	7.1127	14.8487	12.1885

Japanese Stock Market has shown a higher standard deviation than the Singapore Stock Market for both periods. A higher standard deviation indicates higher volatility in the stock returns. For Japan Stock Market, the return price before COVID-19 had higher variability than during COVID-19, while there was higher variability in the price changes for the returns during the COVID-19 for Singapore Stock Market. Furthermore, the skewness of Japan and Singapore Stock Markets was shown to be negative before and during the COVID-19 pandemic. This implies that the distributions for both stock markets are skewed to the left or negatively skewed. Besides, the kurtosis values of the Japan and Singapore Stock Markets are greater than three for both periods suggesting that the returns have a heavier tail than the normal distribution. Furthermore, the return series for both stock markets were plotted in Figure 2.

The daily price series was transformed into a return series to achieve stationarity. Figure 2 shows that both time series have achieved stationarity with no trend. In Figure 2, there is a substantial adverse fluctuation after 2020 in the daily returns plot for both stock markets, indicating that there are considerable price drops in the price series. The return plots for both stocks also showed the occurrence of volatility clustering. For the return plots of Japan and Singapore stocks, there were some obvious volatility clustering for specific periods, such as 2015 to 2017 and after 2020. The reason for the presence of volatility clustering for specific periods is that high returns are often accompanied by significant changes, while low returns are frequently associated with small changes.

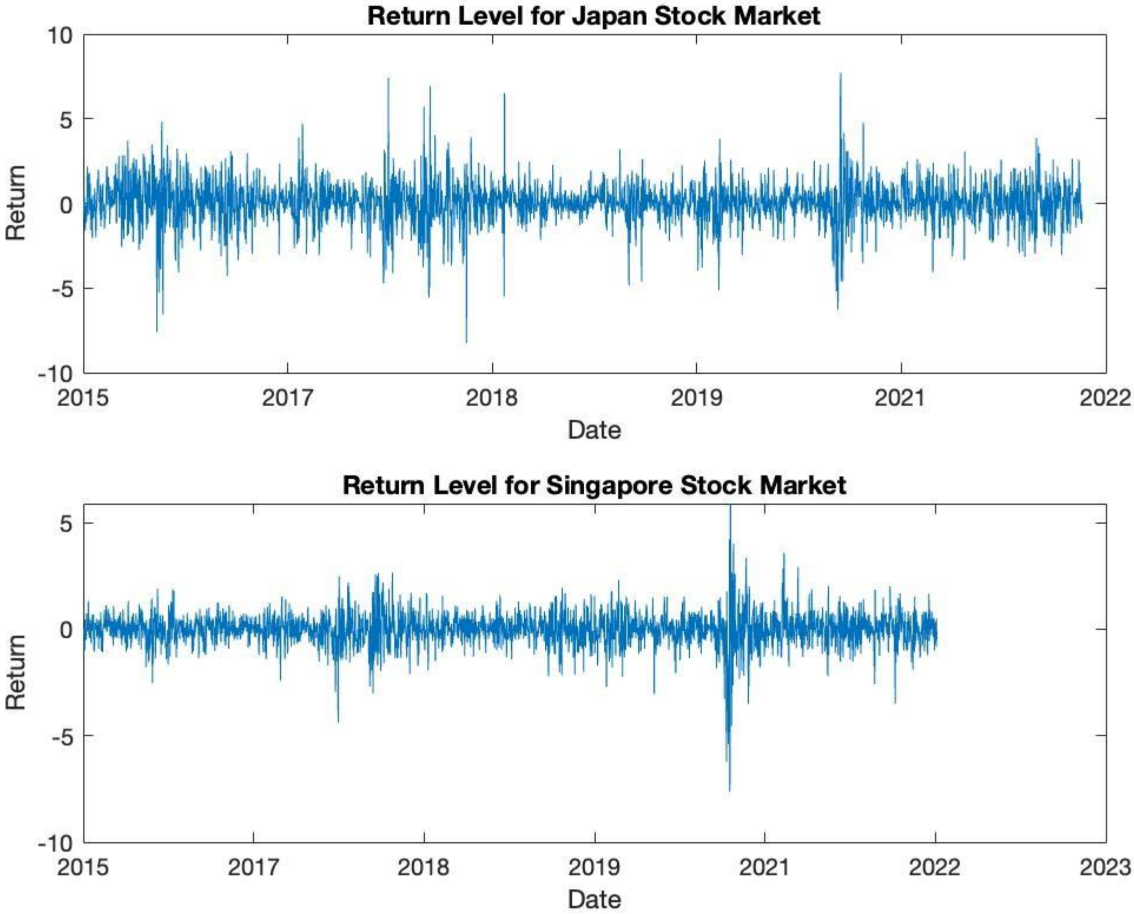

Figure 2: Japan and Singapore stock returns level

4.1. *Estimation and model selections*

Some ARMA-GARCH models were built up and simulated the return series and conditional volatility for both Japan and Singapore stock markets. A trial and error method was undertaken to discover satisfactory parameters for the ARMA-GARCH model to fit well with the return series and conditional volatility. Based on the diagnostic test, four models that fit well with the return series of both Japan and Singapore Stock Market were constructed, and the optimized parameters were estimated. However, choosing a model based on how well it performs on a hold-out test data set or estimating model performance using a resampling approach is typical. Table 2 shows the results of the AIC and BIC values for the models of the Japan Stock Market.

Table 2: Results of AIC and BIC for 4 models for Japan stock market

No	Models	AIC	BIC
1	ARMA(1,1)-GJR(1,1)	7284.4	7330.4
2	ARMA(1,1)-EGARCH(1,1)	7266.1	7312.2
3	ARMA(2,2)-GARCH(1,1)	7336.1	7387.9
4	GARCH(1,1)	7336.8	7365.6

According to the results in Table 2 above, ARMA(1,1)-EGARCH(1,1) shows relatively small AIC and BIC values compared to the other three models. Consequently, it can be reported that ARMA(1,1)-EGARCH(1,1) best matches the return series and conditional volatility of the Japan Stock Market.

Table 3: Results of forecast evaluation for Japan stock market

No	Models	MAE	MSE	Ranking
1	ARMA(1,1)-GJR(1,1)	0.0674	0.0045	2
2	ARMA(1,1)-EGARCH(1,1)	0.0625	0.0039	1
3	ARMA(2,2)-GARCH(1,1)	0.0875	0.0079	3
4	GARCH(1,1)	0.0907	0.0082	4

By referring to Table 3, the values for MAE and MSE for ARMA(1,1)-EGARCH(1,1) are smaller than the three other models. Hence, there is enough evidence to suggest ARMA(1,1)-EGARCH(1,1) is a better forecasting model that fits well with the conditional variance of the Japan Stock Market. This is merely because the lower the value of MAE and MSE, the higher the prediction accuracy, as there would be an excellent match between the actual value and the predicted data set. Since the best model was chosen, then the estimated parameters for the best model will be discussed in detail for two periods in this section.

Table 4: Fitted parameters for ARMA(1,1)-EGARCH(1,1) model with Student's *t* distribution before COVID-19 for Japan stock market

Student's t ARMA(1,1)-EGARCH(1,1) Model				
Parameter	Coefficient	Std.Error	T -statistics	P -value
Mean Equation				
Constant	0.097358	0.089853	1.0835	0.27857
AR{1}	-0.44997	1.2603	-0.35702	0.72108
MA{1}	0.43683	1.2694	0.34413	0.73075
DoF	5.0482	0.63105	7.9996	1.2482×10^{-17}
Conditional Variance Equation				
Constant	0.01387	0.0075829	1.8291	0.06739
GARCH {1}	0.95082	0.0097474	97.546	0
ARCH {1}	0.22388	0.031577	7.0901	1.3398×10^{-15}
Leverage {1}	-0.15647	0.020797	-7.5237	5.3233×10^{-16}
DoF	5.0482	0.63105	7.9996	1.2482×10^{-17}

From Table 4, the estimated ARMA(1,1)-EGARCH(1,1) before COVID-19 pandemic for Japan stock markets are as follows:

$$\hat{r}_t = 0.097358 - 0.44997 r_{t-1} + 0.43683 \varepsilon_{t-1}$$

$$\log \hat{\sigma}_t^2 = 0.01387 + 0.95082 \log \sigma_{t-1}^2 + 0.22388 \left[\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - E\left\{ \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} \right\} \right] - 0.15647 \left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right)$$

Table 5: Fitted parameters for ARMA(1,1)-EGARCH(1,1) model with Student's *t* distribution during COVID-19 for Japan stock market

Student's t ARMA(1,1)-EGARCH(1,1) Model				
Parameter	Coefficient	Std.Error	T -statistics	P -value
Mean Equation				
Constant	0.099838	0.04597	2.1718	0.029871
AR{1}	-0.59956	0.53095	-1.1292	0.2588
MA{1}	0.57921	0.54077	1.0711	0.28413
DoF	5.5791	0.67122	8.3119	9.4215×10^{-17}
Conditional Variance Equation				
Constant	0.015909	0.0067665	2.3511	0.018716
GARCH {1}	0.94779	0.0093317	101.57	0
ARCH {1}	0.22038	0.028014	7.8668	3.6393×10^{-15}
Leverage {1}	-0.14832	0.018231	-8.1356	4.0982×10^{-16}
DoF	5.5791	0.67122	8.3119	9.4215×10^{-17}

From Table 5, the estimated ARMA(1,1)-EGARCH(1,1) during COVID-19 pandemic for Japan stock markets are as follows:

$$\hat{r}_t = 0.099838 - 0.59956 r_{t-1} + 0.57921\varepsilon_{t-1}$$

$$\log\hat{\sigma}_t^2 = 0.015909 + 0.94779\log\sigma_{t-1}^2 + 0.22038\left[\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - E\left\{\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}}\right\}\right] - 0.14832\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right)$$

From the estimated conditional mean equation of Japan stock market before and during COVID-19 pandemic, the estimated parameter coefficients in the mean equations are 0.097358 and 0.099838, respectively are statistically significant at the 5% significance level, which indicates that the use of ARMA mean models are necessary. The difference between the constant coefficient in the variance equation before (0.01387) and during (0.015909) the COVID-19 is 0.002039, indicating that COVID-19 has a positive impact on Japan stock returns. Furthermore, since the GARCH terms before and during COVID-19 which is 0.95082 and 0.94779, respectively are statistically significant and higher than the ARCH terms which are 0.22388 and 0.22038. Therefore, it is concluded that volatility is highly persistent, and volatility is clustered. The leverage parameters for both equations are negative. Negative leverage value suggests that the good news is more likely to lead to volatility in Japan stock price than bad news.

Similar procedures have been implemented on Singapore stock market. The best model ARMA(2,1)-GJR(1,1) was chosen as it shows a relatively small AIC and BIC values. The estimated parameters for the best model of Singapore stock market will be discussed in detail for two periods since the best model was chosen.

Table 6: Fitted parameters for ARMA(2,1)-GJR(1,1) model with Student's *t* distribution before COVID-19 for Singapore stock market

Student's t ARMA(2,1)-GJR(1,1) Model				
Parameter	Coefficient	Std.Error	T -statistics	P -value
Mean Equation				
Constant	0.0020716	0.0044382	0.46675	0.64068
AR{1}	0.75989	0.25189	3.0167	0.0025554
AR{2}	0.013772	0.027539	0.50008	0.61702
MA{1}	–0.7455	0.25067	–2.974	0.0029394
DoF	8.1879	1.3305	6.154	7.5552×10^{-14}
Conditional Variance Equation				
Constant	0.0087284	0.0026201	3.3314	0.00086418
GARCH {1}	0.92974	0.013695	67.888	0
ARCH {1}	2×10^{-12}	0.014341	1.3946×10^{-10}	1
Leverage {1}	0.10711	0.019753	5.4224	5.8808×10^{-8}
DoF	8.1879	1.3305	6.154	7.5552×10^{-14}

Table 7: Fitted parameters for ARMA(2,1)-GJR(1,1) model with Student's *t* distribution during COVID-19 for Singapore stock market

Student's t ARMA(2,1)-GJR(1,1) Model with				
Parameter	Coefficient	Std.Error	T -statistics	P -value
Mean Equation				
Constant	0.0036604	0.0047296	0.77394	0.43897
AR{1}	0.72901	0.19573	3.7246	0.0001956
AR{2}	0.032173	0.022775	1.4126	0.15777
MA{1}	–0.73147	0.19479	–3.7551	0.00017324
DoF	7.1125	0.9441	7.5336	4.9365×10^{-14}
Conditional Variance Equation				
Constant	0.012224	0.0029718	4.1136	3.8962×10^{-5}
GARCH {1}	0.91268	0.0127	71.867	0
ARCH {1}	0.015723	0.010613	1.4815	0.13849
Leverage {1}	0.10047	0.017928	5.6037	2.0981×10^{-8}
DoF	7.1125	0.9441	7.5336	4.9365×10^{-14}

The estimated ARMA(2,1)-GJR(1,1) before COVID-19 pandemic:

$$\hat{r}_t = 0.0020716 + 0.75989 r_{t-1} + 0.013772 r_{t-2} - 0.7455\varepsilon_{t-1}$$
$$\sigma_t^2 = 0.0087284 + 0.92974\sigma_{t-1}^2 + 2\times10^{-12}\varepsilon_{t-1}^2 + 0.10711 I[\varepsilon_{t-1} < 0]\varepsilon_{t-1}^2$$

The estimated ARMA(2,1)-GJR(1,1) during COVID-19 pandemic

$$\hat{r}_t = 0.036604 - 0.72901 r_{t-1} + 0.032173 r_{t-2} - 0.73147\varepsilon_{t-1}$$

$$\sigma_t^2 = 0.012224 + 0.91268\sigma_{t-1}^2 + 0.015723\varepsilon_{t-1}^2 + 0.10047I[\varepsilon_{t-1} < 0]\varepsilon_{t-1}^2$$

From the estimated conditional mean equations before and during COVID-19 of Singapore stock market, the estimated parameter coefficients which are 0.0020716 and 0.0036604 in the mean equations of Singapore stock return before and during COVID-19, respectively are not statistically significant at the 5% significance level, which indicates that the use of ARMA mean models may not be necessary. However, the ARMA(2,1)-GJR(1,1) model have passed the diagnostic test of no serial correlation and no additional ARCH effect in the standardised residuals at the 5% significance level. Therefore, ARMA(2,1)-GJR(1,1) was still considered as the best model for Singapore Stock Market. Moreover, the difference between the constant coefficient in the variance equation before and during the COVID-19 is 0.0034956, indicating COVID-19 has only positive impact on Singapore stock return. Since 0.92974 and 0.91268 which are the GARCH terms before and during COVID-19, respectively are statistically significant and higher than the ARCH terms which are 2×10^{-12} and 0.015723, respectively. Thus, it is concluded that the volatility is highly persistent, and volatility is clustered. According to the model before COVID-19, it has lower ARCH value before COVID-19. This implies that volatility with relatively high ARCH value and low GARCH value is more intense during COVID-19. In addition, the presence of leverage effects is indicated by positive and statistically significant leverage parameter values of 0.10711 and 0.10047 before and during COVID-19, respectively. Likewise, positive leverage value suggests that the bad news is more likely to lead to volatility in Singapore stock price than good news.

4.2. *Market risk determination*

The calculations of VaR and ES are based on the scenario that an investor has an investment capital amount of $100,000 with risk calculated for the next trading day at 95% and 99% confidence levels. Note that the risk was computed based on the training data from 24 August 2012 till 6 March 2022. Hence the forecast was based on the risk on 7 March 2022, which is the next trading day for both Japan and Singapore Stock Markets.

4.2.1. *Historical simulation method*

To compute the quantiles of VaR, we need to sort the returns for both stock markets. In an ascending order of the returns, the quantile of VaR for the Japan Stock Market at the 95% confidence interval and 99% confidence level are computed. Therefore, the quantile of VaR at the 95% confidence interval for the Japan stock Market is 116th, with losses of 2.1525%, while the quantile of VaR at the 99% confidence level is 23rd, with losses of 3.0123%.

$$95\%: 1 - \text{day VaR} = \$100{,}000 \times 2.1525\% = \$2152.50$$

$$99\%: 1 - \text{day VaR} = \$100{,}000 \times 3.0123\% = \$3012.30$$

Similarly, for the Singapore Stock Market, the quantile of VaR at the 95% confidence level is 120th with losses of 2.1409% while the quantile of VaR at the 99% confidence level is 24th, with losses of 3.9095%.

$$95\%: 1 - \text{day VaR} = \$100{,}000 \times 1.25607\% = \$1256.07$$

$$99\%: 1 - \text{day VaR} = \$100{,}000 \times 1.91140\% = \$1911.40$$

According to the calculations, there is a 95% confidence that with $100,000 investment in Japan Stock Market will experience losses of not more than $2152.50, and $1256.07 in the Singapore Stock Market on the following trading day, respectively when using historical simulation. Furthermore, there is a 99% confidence that with $100,000 investment in Japan Stock Market will be lost of at most $3012.30, and $1911.40 in the Singapore Stock Market on the next trading day.

4.2.2. *Variance-covariance method*

The VaR at the 95% and 99% confidence levels for Japan Stock market are:

$$95\%: 1 - \text{day VaR} = \$100{,}000 \times 2.8065\% = \$2806.50$$

$$99\%: 1 - \text{day VaR} = \$100{,}000 \times 4.0110\% = \$4011.00$$

The VaR at the 95% and 99% confidence levels for Singapore Stock market are:

$$95\%: 1 - \text{day VaR} = \$100{,}000 \times 1.1244\% = \$1124.40$$

$$99\%: 1 - \text{day VaR} = \$100{,}000 \times 1.5913\% = \$1591.30$$

Utilizing variance-covariance might result in underestimating the VaR since it relies on the normality assumption. The models with student's *t* distribution have a better fit to returns, according to the modelling result. Therefore, the VaR calculated using the variance-covariance method is not a reliable predictor of risk for investor in both the stock markets.

4.2.3. *VaR using ARMA-GARCH method*

Using the estimated ARMA(1,1)-EGARCH(1,1) model, the VaR at the 95% and 99% confidence levels for Japan Stock market are:

$$95\%: 1 - \text{day VaR} = \$100{,}000 \times 3.5682\% = \$3568.20$$

$$99\%: 1 - \text{day VaR} = \$100{,}000 \times 5.8956\% = \$5895.60$$

For Singapore stock market, the estimated is ARMA(1,1)-GJR(1,1) model, The VaR at the 95% and 99% confidence levels are:

$$95\%: 1 - \text{day VaR} = \$100{,}000 \times 2.0504\% = \$2050.40$$

$$99\%: 1 - \text{day VaR} = \$100{,}000 \times 3.2042\% = \$3204.20$$

According to the calculations, there is a 95% confidence that $100,000 invested in the Japan Stock Market will experience losses of not more than $3568.20, and $2050.40 in the Singapore Stock Market on the following trading day, respectively when using ARMA-GARCH method. Furthermore, there is a 99% confidence that $100,000 invested in Japan Stock Market will be lost of not more than $5895.60, and $3204.20 in the Singapore Stock Market on the next trading day.

4.2.4. *Expected shortfall*

The ES on a \$100,000 capital investment in Japan and Singapore stock markets at 95% and 99% confidence levels were discussed in this section. The quantile of VaR for the Japan stock market at 95% confidence level of Historical Simulation is 116th while the quantile of VaR at the 99% confidence level is 23rd. The ES for Singapore stock market of 95% confidence level was calculated by averaging the 1 to 120th worst returns, while the ES of 99% confidence level was calculated by averaging the 1 to 24th worst returns.

The ES for Japan Stock Market at 95% and 99% confidence level are:

$$95\%: 1-\text{day ES} = \$100{,}000 \times 3.2140\% = \$3214.00$$

$$99\%: 1-\text{day ES} = \$100{,}000 \times 5.0743\% = \$5074.30$$

The ES for Singapore Stock Market at 95% and 99% confidence level are:

$$95\%: 1-\text{day ES} = \$100{,}000 \times 2.19626\% = \$2196.26$$

$$99\%: 1-\text{day ES} = \$100{,}000 \times 3.42562\% = \$3425.62$$

From the above results, there is a 95% confidence that the expected loss on a \$100,000 investment in Japan Stock Market will be \$3214.00, and \$2196.26 in Singapore Stock Market on the next trading day. Moreover, there is a 99% confidence that the expected loss on a \$100,000 investment in Japan Stock Market will be \$5074.30, and \$3425.62 in Singapore Stock Market.

5. Conclusion

This study focuses on normality and student's *t* assumptions on the return series and different types of ARMA-volatility models namely the EGARCH, and GJR models. The findings of this study can be valuable for investors and researchers in the field of volatility analysis or portfolio strategy analysis. Firstly, the inclusion of COVID-19 period in both the markets indicated a positive shift in stock markets. This finding can help investors to take additional precaution to mitigate the potential magnitude of market risk if similar event were to occur in the future. Secondly, the market risk indicators such as Value-at-Risk and expected shortfall suggest that Japanese stock market has higher risk compared to the Singaporean stock market. This information provides useful guidance for investors in term of their risk preferences when making investment decisions. By understanding the behaviour of different stock markets during the COVID-19 period and the risk indicators, investors can make informed decisions and adjust their investment strategies accordingly. Researchers on the other hand can use the findings to further develop their models and theories on volatility and portfolio strategy.

Future research may increase prediction accuracy by extending distributional assumptions and volatility models to model and forecast the price of Singapore and Japan stock prices. Moreover, the data collecting periods should be updated throughout time to reflect changes in results and conclusions and to keep up with changes in the behaviour of the financial stock market. It is also found that the pandemic COVID-19 to certain extent has significant positive impact on both the markets' volatilities. The immediate applications of the estimated volatility models are used in measuring the Value-at-Risk and expected shortfall for Japan and Singapore stock returns. It is found that Japan stock returns showed greater maximum losses than Singapore stock returns, which further indicates that the Japanese stock market is more volatile than the Singaporean stock market. According to the investment strategy analysis, investors could also practice cross-hedging by using Japan and Singapore stocks. A conclusion can be drawn after the discussion as follows: aggressive investors (risk takers) who feel comfortable dealing with an investment strategy favouring higher-than-average volatility may choose to purchase Japan Stock Market. However, cautious investors may prefer to go with Singapore Stock Market. When dealing with the amount of variability in the portfolio, investors should consider their risk tolerance levels and overall investment goals.

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Department of Mathematics
Xiamen University Malaysia
43900 Sepang
Selangor DE, MALAYSIA
E-mail: MAT2004442@xmu.edu.my, wcchin@xmu.edu.my, limmin@xmu.edu.my*

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*Corresponding author