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Volatility of Technology and Healthcare Sectors Before and During Covid-19 Pandemic

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Abstract— The study investigates the effect of the Covid-19 on the volatility of the technology and healthcare sector stock index in Malaysia. The two sectors pose considerable attention during the pandemic due to the increase in demand for healthcare products and digital services. The volatilities are estimated using the GARCH model for the period before and after the implementation of the nationwide movement order control using daily data from September 2019 to September 2020. The finding shows that the Covid-19 pandemic caused a volatility jump for the technology sector index in March 2020 but subsided afterward with estimated conditional volatility revert to normal in the middle of April 2020. However, during the high uncertainty period, the healthcare sector shows a steady increase in volatility beginning in March 2020 till the end of September 2020. The study confirms that there is a significant difference in the volatility of healthcare and technology sectors before and during the Covid-19 outbreak. The outbreak has a significant impact on increasing the volatilities for both sectors but is impacted in different magnitude.

Keywords— Covid-19; volatility; Technology Sector; Healthcare Sector; GARCH model

I. INTRODUCTION

A. Background

Upon the declaration of COVID-19 as a global pandemic by the World Health Organisation (WHO) on March 11, 2020, the world economies are facing a new level of uncertainty as most countries adopt strict quarantine policies to curb the contagious disease ([1], [2], [3] and [4]). By the end of March 2020, full or partial lockdowns had been implemented by more than 100 countries worldwide affecting billions of people. The movement restrictions cause the businesses to minimise activities or temporary closure of

the operation, while most countries close their borders to foreigners. According to [2] the impact of the pandemic is the worst in history marking the global recession surpassed the value recorded during World War I and the Great Depression. The pandemic has had a massive impact on real economic activity with the global economy is expected to contract by 4.3 per cent in 2020, and rising unemployment for most countries by which the recovery process will take a longer term as reported in reference [2]. A study by [1] examines various forward-looking measures of uncertainty in the UK and the US finds that huge uncertainty jumps in March 2020 in reaction to the pandemic. The heightened uncertainty has made firms and consumers cautious, deter investment, and dampen economic growth.

The value of the firm is the function of the present value of all expected future cashflows adjusting for time and uncertainty. Thus the stock market serves as a unique view of the expectation on the future economic condition as a whole. Past literature such as [5], [6], [7], and [8] examine the impact of SARs, MERS-CoV, and Ebola outbreaks and found contagious diseases affect stock markets. The impact of COVID-19 on the stock market has been examined worldwide and several patterns emerged. Studies by [9], [10] [11], and [12] find a significant negative effect of the pandemic based on the number of cases on the stock market from March to April 2020. Reference [12] finds an increase in reported Covid-19 cases in Vietnam associated with a decline in stock liquidity. By constructing the Global Fear Index (GFI) based on the number of reported cases and death, a study by [13] finds GFI adversely affect stock markets for The Organisation for Economic Co-operation and Development (OECD) and Brazil, Russia, India, China and South Africa (BRICS). The authors of [13] suggest GFI is a better predictor of the stock market fear index than the commonly used the Chicago Board Options Exchange (CBOE) volatility index (VIX) during the pandemic. Using event study, the studies of [14] and [15] on international stock markets indices find a sharp decline in return for most markets during March 2020. The impact is greater for the emerging market and small-cap equity index as shown in [14], and leading Asia stock markets experienced more negative abnormal returns than their western counterparts as found by [15]. According to [16], Covid-19 has caused unprecedented uncertainty to the stock markets. In terms of volatility, the pandemic has caused market jitters during March and April 2020. Reference [16] reported that COVID-19 causes a high frequency of daily price changes in the US stock market greater than reported in the previous economic and financial crises. Increase stock market volatility during Covid-19 is mostly due to the restrictions imposed by the government to control the transmission of the disease ([16], [17], and [12]). Covid 19 news was found to affect stock market volatility with negative news impacted more than positive news [15]. A study using news coverage on the outbreak by [18] finds panic induced by the news is associated with heightened volatility. The impact is greater for industries that are badly hit by the pandemic including transportations, automobiles and components, energy, and travel and leisure.

Though overall stock markets are negatively affected by the emergence of Covid-19 in March 2020, some sectors are reported to perform better during the pandemic. A study by [9] shows information technology and medicine manufacturing sectors performed better than the market in China. In the US, natural gas, food, healthcare, and software stocks earn positive returns while other sectors perform negatively [19]. Reference [20] shows certain industries such as food production industries and beer and liquor industries exhibited low-risk changes between pre and during Covid 19 pandemic. Besides the two earlier mentioned industries, the authors of [20] find healthcare, medical and pharmaceutical industries have low exposure to the pandemic. Healthcare and technology are among the sectors that pose considerable attention from the investors during the pandemic [21, 22]. The demand for healthcare products including rubber gloves

saw a soar in stock prices of related companies in Malaysia such as Supermax, Top Glove, Hartalega, and Kossan [23]. The movement restriction has boosted the technology industry and the demand for digital services. Motivated by the existing findings, the present study aims to examine the technology and healthcare sectors' return volatility using the GARCH model before and during the COVID-19 pandemic in Malaysia. In this study, the volatility of these two sectorial indices is measured at two periods, before the outbreak (from 10th October 2019 until 17th March 2020) and during the COVID-19 pandemic (from 18th March 2020 until 30th September 2020). The study further examined risk-reward investing in both sectors during the two periods.

B. Movement Order Control (MCO) and Malaysian Stock Market

After the first recorded Covid-19 case in Malaysia on January 25, 2020, the number of cases increased suddenly in early March 2020 that force the government to impose the Movement Order Control (MCO) nationwide under the Prevention and Control of Infectious Diseases Act 1988 and the Police Act 1967 to control the spreading of the virus. The first phase of the MCO was implemented on 18 March 2020 for 2 weeks until 31 March 2020. As the number of positive cases stayed extremely high, the MCO has been extended until 28 April 2020. The MCO has forced the private and government agencies to close operations, while important necessary businesses are allowed to operate during a specific time. Until December 2020, the Malaysian government has introduced several types of movement control order including Conditional MCO (CMCO), Recovery MCO (RMCO), Enhanced MCO (EMCO), Targeted Enhanced MCO (TEMCO), and Administrative Enhanced MCO (AEMCO). The decision of the types of enforcement is recently made on a locality basis to minimise the impact of the MCO on the economy.

The pandemic and the announcement of the MCO in March 2020 have caused uncertainty and confusion among the investors because temporary jitters to Bursa Malaysia trading. In Fig. 1, FBM KLCI shows a declining trend since January 2020 and dropped to the lowest point of 1,219.71 on March, 19, the second day of the MCO. Securities Commission and Bursa Malaysia have implemented several measures following heightened volatility and global uncertainties including temporarily suspended of short-selling beginning March 23, 2020, extended until 31 December 2020 [24]. The FBM KLCI bounced afterward and steadily returned to the pre-Covid 19 levels in August. The authors of [25] suggest Bursa Malaysia small capital stocks lose the most during a bad period but yield greater when the market bounced.

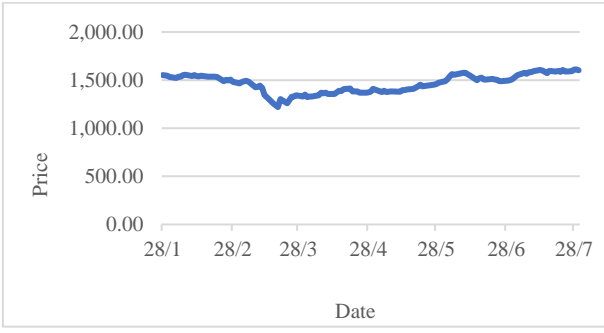


Fig. 1 Time series plot of FTSE Bursa Malaysia Kuala Lumpur Composite Index (KLCI) during January-July 2020

The remainder of this paper is organised as follows. In the next section, the paper explains the data and methodology. Section III presents the results and discussion. The final section concludes.

II. DATA AND METHODOLOGY

A. Data

The study uses the daily closing price of the Healthcare Sector Index and Technology Sector Index retrieved from website investing.com. The period of the study is from 10th September 2019 until 30th September 2020 to compare the volatility differences in both sectors before and during the Covid-19 outbreak. The period during the early Covid-19 pandemic is taken from the first trading day of Movement Control Order (MCO) launched by the Malaysian government until the last trading day of the third quarter of 2020 (18th March 2020 – 30th September 2020), while the period prior to Covid-19 pandemic is from 10th September 2019 to 17th March 2020. Each period accounts for 131 daily observations. For Covid 19 proxies, the study uses the number of new daily cases and the number of new daily death retrieved from <https://ourworldindata.org/coronavirus>. The data for CBOE volatility index (VIX) is used to measure global uncertainty is from website CBOE.com.

B. Returns

The returns are calculated using the following formula:

$$R_t = \ln \frac{S_t}{S_{t-1}} \quad (1)$$

where, R_t is the log return on day t for Healthcare or Technology Sector Index, S_t is the price index at day t , and S_{t-1} is the price index at day $t-1$.

C. Test for ARCH Effects

The ARCH effects for each series are tested before estimating volatility using the GARCH model. The squared residuals are represented by the AR model below:

$$\hat{\mu}_t^2 = b_0 + b_1 \hat{\mu}_{t-1}^2 + b_2 \hat{\mu}_{t-2}^2 + \dots + b_q \hat{\mu}_{t-q}^2 + e_t \quad (2)$$

where, b_0 is the intercept, b_i is the parameters estimated using maximum likelihood, $\hat{\mu}_t^2$ is the squared residual at time t , e_t is the white noise.

Hypothesis testing:

$$H_0: b_1 = 0 \text{ [No ARCH effects present]}$$

$$H_1: b_1 \neq 0 \text{ [ARCH effects present]}$$

The significance of the parameters, b_i means ARCH effects are present. Consequently, failing to reject the null hypothesis means that the model is homoscedastic while rejecting the null indicates the model is heteroskedastic.

D. Returns Volatility

To model index return volatility on healthcare and technology sectors, the study applies the generalised autoregressive conditional heteroskedasticity or GARCH (1, 1) model introduced by [26]. The GARCH (1, 1) is the generalisation of the autoregressive conditional heteroskedasticity (ARCH) model proposed by [27] to capture time-varying volatility. The GARCH model involves modelling the mean return series and also the conditional variance of the residuals. In this study, the mean return series is modelled using a best-fitting Autoregressive (AR) model. Autoregressive simply means having enough statistical knowledge about the past that allows the efficient use of information to predict the future with sufficient accuracy. Then, the GARCH (1, 1) is represented as follows:

$$\sigma_t^2 = \hat{h}_t = \omega + \theta_1 \hat{h}_{t-1} + b_1 \hat{u}_{t-1}^2 \quad (3)$$

where, \hat{h}_{t-1} is the conditional variance, ω is the mean volatility level, \hat{u}_{t-1}^2 is the squared residuals, b_1 is the ARCH parameter and

θ_1 is the GARCH parameter. The stability condition of the GARCH (1, 1) model is such that: $0 < \theta_1 < 1, 0 < b_1 < 1$ and $\theta_1 + b_1 < 1$.

The volatility estimates using GARCH are subjected to a t-test to establish whether there is a statistically significant difference in mean values between a period before the Covid-19 pandemic with the period during the early phase of the Covid-19 outbreak.

E. Regression Analysis

To get further insight on the impact of Covid 19 on healthcare and technology sector index return volatility, the study extends the analysis using OLS regression by including Covid 19 variables. The number of cases and death has been applied in recent studies as the proxies for Covid 19, for example, [10], [11], and [25]. These studies find the stock market decline as the number of cases and death increases. Specifically, the following regression model is estimated:

$$\Delta \hat{h}_t = \alpha + \beta_1 Case_{t-1} + \beta_2 Death_{t-1} + \beta_3 VIX_{t-1} + \varepsilon_t \quad (4)$$

Where $\Delta \hat{h}_t$ is the changes in the healthcare or technology sector index return volatility, $Case_{t-1}$ is the number of new daily Covid-19 cases, $Death_{t-1}$ is the number of new daily death due to Covid 19, VIX_{t-1} is the CBOE volatility index as a measure of global uncertainty, β are the parameters to be estimated and ε_t is the error term.

F. Sharpe Ratio

The study also compares the risk and return premium using Sharpe Ratio. The ratio subtracts the risk-free rate from the index returns and then divides with the index standard

deviation. A higher Sharpe ratio indicates a more efficient portfolio with a higher risk to reward ratio. The annualized Sharpe ratio is calculated for the period during and before the pandemic. The study used two Sharpe ratio measures represented as follow:

$$\text{Sharpe Ratio 1, } SR_1 = \frac{R_t - R_f}{\sigma_t} \quad (5)$$

$$\text{Annualized } SR_1 = \sqrt{252} \times SR_1 \quad (6)$$

where, R_t is the log return on day t for Healthcare or Technology Sector Index, R_f is the risk-free rate proxy by Malaysia 10-Year Bond Yield, σ_t is the standard deviation estimated from GARCH models, and 252 is the number of trading days per year.

$$\text{Sharpe Ratio 2, } SR_2 = \frac{\overline{R_t - R_f}}{\overline{\sigma_t}} \quad (7)$$

$$\text{Annualized } SR_2 = \frac{252 \times (\overline{R_t - R_f})}{\sqrt{252} \times \overline{\sigma_t}} \quad (8)$$

where, $\overline{R_t}$ is the average daily log returns for Healthcare or Technology Sector Index, $\overline{R_f}$ is the average daily risk-free rate, $\overline{\sigma_t}$ is the average daily standard deviation estimated from GARCH models, and 252 is the number of trading days per year.

III. RESULTS AND DISCUSSION

G. Descriptive Statistics

TABLE I
DESCRIPTIVE STATISTICS

	Healthcare Sector before Covid-19	Healthcare Sector during Covid-19	Technology Sector before Covid-19	Technology Sector during Covid-19
Mean (%)	-0.0480	0.8783	-0.1307	0.5219
	1.2096	3.1977	2.0868	2.5272
Std. Dev. (%)				
Skewness	-1.0570	0.0152	-3.1061	-0.1120
Kurtosis	11.9639	0.5010	14.4589	2.5578
Observations	131	131	131	131

Table I presents the descriptive statistics of return for healthcare and technology indices for the period before and during the Covid-19 outbreak. The mean return is an important indicator of whether the sectorial indices are in the position of making profit or loss. From the table, both sectors recorded an average daily loss in the period before the Covid-19 pandemic with -0.0480% for the healthcare sector and -0.1307% for the technology sector. Meanwhile, during the pandemic, both sectors recorded a positive daily return with the healthcare sector's return whopping to 0.8783% and 0.5219% for the technology sector. The finding is similar as reported in [9] and [19]. According to [9], healthcare industries are more resilient during the pandemic. Technology sector also benefit from the process of digital transformation of most aspect in life like working from home, teleconferencing, and online learning as a new norms in curbing the spread of Covid-19.

The standard deviation measures the risk of the investment. The higher the value, the more volatile the index's return.

From Table I, both sectors show a higher standard deviation during Covid-19 compared to the period before the pandemic with the healthcare sector (3.1977%) and technology sector (2.5272%). Based on the standard deviation measure, the healthcare sector is more volatile than the technology sector during the pandemic.

Both sectors exhibit higher kurtosis and more negatively skewed in the period before the Covid-19 pandemic than during the early phase of the pandemic. The information indicates that before the pandemic, both sectors give investors more negative returns with larger risk exposure (high kurtosis). However, during the pandemic, the healthcare sector switches to the position of gaining profit (positive skewness of 0.0152) with medium risk exposure (kurtosis of 0.5010). Meanwhile, the technology sector still recorded an average positive return although negatively skewed (negative skewness of -0.1120) with a lower risk exposure than before the pandemic (kurtosis of 2.5578 vs. 14.4589).

H. Time Series Plot

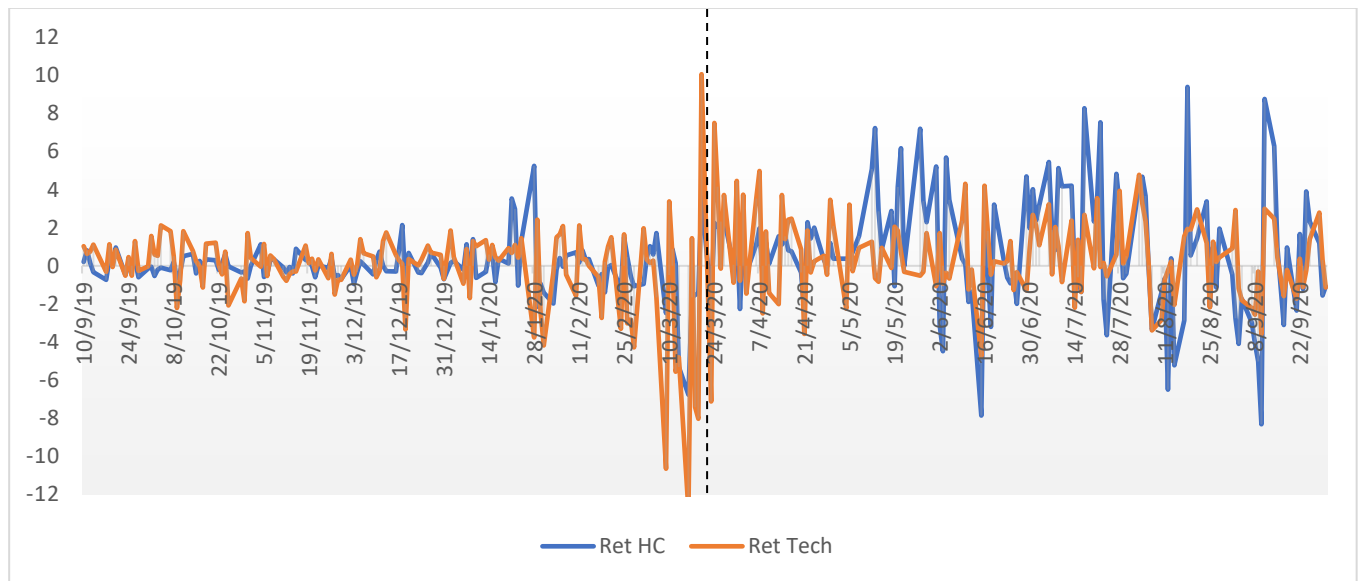


Fig. 2 Time series plot of healthcare and technology indices' returns for the period before and early covid-19 outbreak

Fig. 2 shows the time series plot of healthcare and technology sectors' indices for the whole study period. Both sectors' indices show volatility clustering with more volatile returns in the period during the Covid-19 pandemic. The technology sector exhibits a sudden return volatility spike in March 2020 which subside afterward, but the magnitude is higher than the period before the pandemic. As for the healthcare sector, there is no sudden spike of return volatility

in March 2020, but the magnitude is getting bigger over time. In sum, the pandemic somehow has changed the behaviour of stock returns in both sectors. The observed visual return pattern subject to further analysis using volatility estimates from the GARCH model and a *t*-test to investigate whether the volatility before and during the Covid-19 outbreak are statistically and significantly different.

I. ARCH Effect

TABLE II
ARCH EFFECT TESTS

Sector	Obs	F-statistic	Prob. F (1, n)	Obs*R-squared	Prob. Chi-Square (1)	ARCH Effect
Healthcare	260	16.8183	0.0001	15.91145	0.0001	Reject Ho
Technology	260	25.8191	0.0000	23.65227	0.0000	Reject Ho

J. GARCH (1,1) Model

TABLE III
GARCH (1, 1) ESTIMATION

Sector	C	Prob.	ARCH (-1)	Prob.	GARCH (-1)	Prob.
Healthcare	0.006823	0.9253	0.1191	0.0000	0.9099	0.0000
Technology	0.113505	0.0666	0.1868	0.0033	0.8086	0.0000

Table II shows the result for the ARCH effects test for both time series. The F-test and LM-test statistics show that the time series exhibit the ARCH effect, thus modelling the time series using the GARCH model is appropriate.

Table III shows the estimates of GARCH models for both time series. The ARCH and GARCH parameters are found to be statistically significant at 5% significant level with p-values less than 0.05.

The GARCH (1,1) model for healthcare index can be written in the equation below:

$$\hat{h}_t = 0.006823 + 0.9099\hat{h}_{t-1} + 0.1191\hat{u}_{t-1}^2 \quad (9)$$

The equation of the GARCH (1,1) model for the technology sector is as follow:

$$\hat{h}_t = 0.113505 + 0.8086\hat{h}_{t-1} + 0.1868\hat{u}_{t-1}^2 \quad (10)$$

The estimated volatility for the two-time series is then plotted to understand further the behaviour.

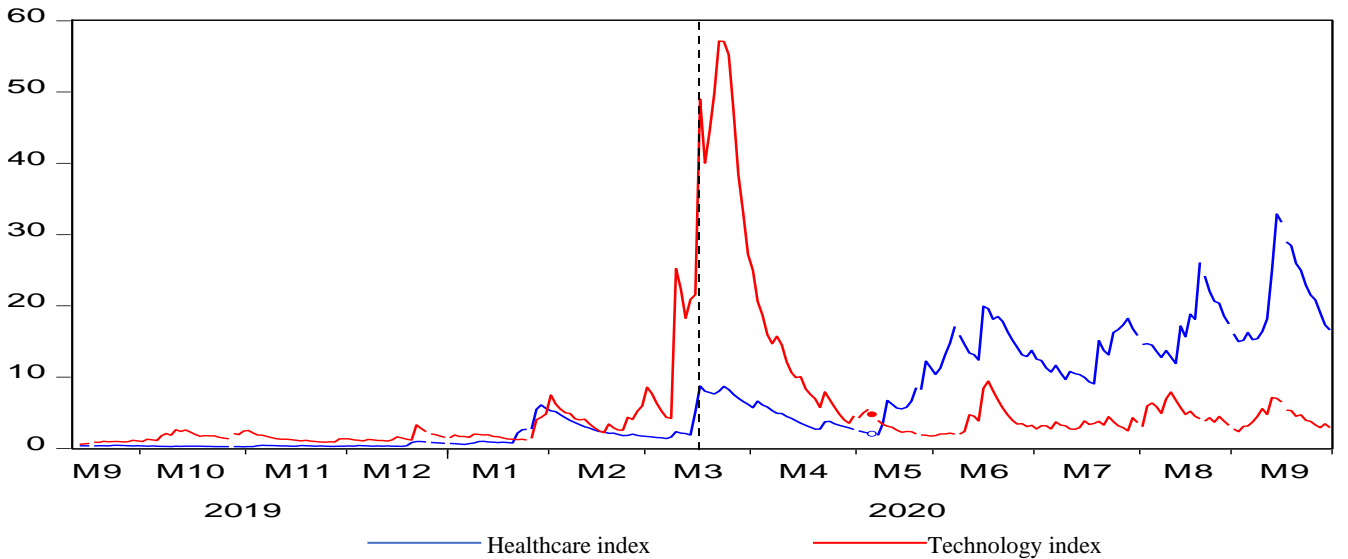


Fig. 3 Conditional variance of healthcare and technology indices

Fig. 3 shows the time series plot of estimated conditional volatility of healthcare and technology indices. The time series plot of volatility for both sectors shows a similar pattern to the time series plot of return discussed earlier. There is a clear distinction of the volatility in the period before and after the outbreak. Technology index exhibit a sudden volatility jump in March 2020, with more than 50%. Volatility jump is also observed in the US [20] [16] and Turkey [28] in March 2020 after WHO declared Covid-19 as a global pandemic. After 1 month, the volatility reverts to the original condition, although slightly higher than the period before the pandemic began. Unlike the technology index, the healthcare index's volatility shows a steady increase over time without a sudden spike.

The estimated volatility from the GARCH models for both sectors is divided into two periods as defined earlier and a t-test is performed to study the pattern. Table IV shows that the healthcare index's volatility is significantly higher during the pandemic with an average of 12.40845. Similarly, the technology index also exhibits a statistically and significantly higher volatility (8.2430) compared to 3.3156 before the outbreak. The results show that investors would be able to gain excessive profit through investment in the technology sector during the early phase of the pandemic. As for the healthcare index, investors could steadily invest in this sector which gains momentum due to the pandemic.

TABLE IV
TWO SAMPLES T-TEST OF VOLATILITY DIFFERENCES BEFORE AND DURING COVID-19 OUTBREAK

<i>t-test: Two-Samples Assuming Unequal Variances</i>				
	Volatility Healthcare Index before pandemic	Volatility Healthcare Index during pandemic	Volatility Technology Index before pandemic	Volatility Technology Index during pandemic
Mean	1.212332	12.40845	3.315616	8.243027
Variance	2.241908	47.46454	33.01266	133.187
Observations	130*	131	130*	131
Hypothesized Mean Difference	0		0	
df	142		191	
t Stat	-18.1728		-4.37127	
P(T<=t) one-tail	0.0000		0.0000	
t Critical one-tail	1.655655		1.652871	
P(T<=t) two-tail	0.0000		0.0000	
t Critical two-tail	1.976811		1.972462	

*Number of observations for estimated volatility before the pandemic reduced by 1 due to GARCH estimation process.

The estimated volatility from the GARCH models for both sectors is divided into two periods as defined earlier and a t-test is performed to study the pattern. Table IV shows that the healthcare index's volatility is significantly higher during the pandemic with an average of 12.40845. Similarly, the technology index also exhibits a statistically and significantly higher volatility (8.2430) compared to 3.3156 before the outbreak. The results show that investors would be able to gain excessive profit through investment in the technology sector during the early phase of the pandemic. As for the healthcare index, investors could steadily invest in this sector which gains momentum due to the pandemic.

K. Covid-19 Effect on the Volatility of the Healthcare and Technology Sector

Table V presents the regression results using lag independent variables for healthcare and technology sector index volatility. The results focus on the coefficient of β_1 , the number of daily cases at $t-1$ and β_2 , the number of daily death at $t-1$. The coefficient for β_1 is positive, but not significant suggesting that the number of new cases does not affect the healthcare and technology sector index return volatility. However, the coefficient of β_2 for both the healthcare and technology sector is significant at 5 percent. The results indicate an increase in the number of new death in the previous day affect the changes in the volatility of the healthcare sector by -1.1681 percent. Meanwhile, the impact is smaller on the technology sector, showing a change of -0.3618 for every new death. The findings suggest the Covid 19 affects the healthcare and technology sector return volatility.

TABLE V
REGRESSION ANALYSIS

Variable	Volatility	
	Healthcare	Technology
Case	0.0035 (0.41)	0.0058 (1.16)
Death	-1.1681** (-2.23)	-0.3618** (-1.97)
VIX	0.0305 (1.06)	0.0024 0.24
constant	-0.5086 (-0.91)	(-0.0486) (-0.26)
Observation	261	261
R-square	0.0924	0.0324

Note: t-statistic is given in parentheses. ***, **, * represent significance at 1%, 5% and 10% level, respectively.

L. Risk-reward of Investing in Healthcare and Technology Sector Before and During Covid-19 Outbreak

The study also analyses the risk-reward of investing in healthcare and technology stocks before and during the Covid-19 outbreak using the Sharpe ratio as depicted in Table VI. There are two methods used to calculate the Sharpe ratio as defined in Eq. 5 and Eq. 7. Despite the higher volatility period, investing in the healthcare and technology sectors during the Covid-19 pandemic provides a more promising risk-reward than the period before with annualized Sharpe ratios of more than 2. Overall, the reward

per unit risk is higher in the healthcare sector compared to the technology sector in both periods. The value of the Sharpe ratio from SR_2 calculated as a linear function of return series, risk-free rate series, and standard deviation series from the GARCH model provides a higher estimated value than SR_1 that calculated using the average of all series. We notice that the technology sector's annualized Sharpe ratio of SR_1 for the period before the pandemic is far lower than SR_2 (0.18 vs 2.35) due to the volatility jump observed in the technology sector that affects the average value of standard deviation, thus affect the Sharpe ratio estimation. In sum, the reward from investing in these two sectors during uncertain periods like the Covid-19 pandemic worth the risk.

TABLE VI
SHARPE RATIO

	Healthcare Sector before Covid-19	Healthcare Sector during Covid-19	Technology Sector before Covid-19	Technology Sector during Covid-19
Mean (%)	-0.0499	0.8783	-0.1396	0.5219
Risk-free rate (%)	-0.1575	-0.1512	-0.1575	-0.1512
Standard deviation	0.9574	3.3708	1.5802	2.5214
Sharpe ratio 1 (SR_1)	0.1123	0.3054	0.0114	0.2670
Annualized SR_1	1.7836	4.8482	0.1800	4.2378
Sharpe ratio 2 (SR_2)	0.1603	0.4200	0.1483	0.3408
Annualized SR_2	2.5452	6.6672	2.3548	5.4099

IV. CONCLUSIONS

This paper investigates the Covid-19 effect on the volatility of the healthcare and technology sector in the Malaysian stock market. The volatilities are estimated using GARCH model from September 2019 to September 2020. The finding of this study finds that the Covid-19 pandemic caused a volatility jump for the technology sector index in March 2020, when the pandemic hits and infected cases increased rapidly. After March 2020, the effect of Covid-19 on the technology sector subsided with estimated conditional volatility revert to normal and the volatility spike disappeared. However, the same trend is not observed for the healthcare sector. During this high uncertainty period, the healthcare sector rather shows a steady increase in volatility beginning in March 2020 till the end of September 2020. The study confirms that there is a significant difference in the volatility of healthcare and technology sectors before and during the Covid-19 outbreak. The results show that the Covid-19 outbreak has a significant impact on increasing the volatilities of both sectors but is impacted in different ways. Further study could investigate the effect of Covid-19 on the various sectors in Malaysia using a longer observed period since the pandemic still happening.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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