“Assessing the impact of the coronavirus pandemic and non-pharmaceutical interventions on Bursa Malaysia KLCI Index using GARCH-M (1,1) models”

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ASSEING THE IMPACT OF THE CORONAVIRUS PANDEMIC AND NON-PHARMACEUTICAL INTERVENTIONS ON BURSA MALAYSIA KLCI INDEX USING GARCH-M (1,1) MODELS

Abstract

This study aims to explore the impact of coronavirus pandemic-related variables and non-pharmaceutical interventions on fluctuations in the Malaysian stock market during the period from January 7, 2020, to March 31, 2021. By employing GARCH-M (1,1) family models (GARCH-M, EGARCH-M, and PGARCH-M), the study seeks to understand the intricate dynamics of market volatility amidst the pandemic and associated interventions. The findings suggest that while past market volatility and conditional variance continue to influence current market fluctuations, their effects have diminished over time during the study period. Additionally, the EGARCH-M (1,1) model reveals a leverage effect, indicating increased market volatility following negative news compared to positive news. Interestingly, the EGARCH-M (1,1) model emerges as the optimal choice for accurately capturing data dynamics. Conversely, the PGARCH-M (1,1) model does not exhibit a statistically significant leverage effect. These insights contribute to a better understanding of market behavior during crises, informing future research and risk management strategies.

Keywords COVID-19, non-pharmaceutical measures, Malaysian stock market, market volatility, leverage effect

JEL Classification C58, G01, G18, H12

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INTRODUCTION

The coronavirus pandemic spread unexpectedly around the world at the end of 2019. It emerged from central China and reached 216 countries worldwide. On June 19, 2020, 8.3 million verified instances of the newly identified COVID-19 virus and over 450,000 deaths had been reported around the world (Topcu & Gulal, 2020). On the global stage, the World Health Organization (WHO) made a public proclamation on the coronavirus pandemic rampaging menace in 2020 (Park, 2020). The outbreak of the coronavirus pandemic has led to unprecedented challenges across various sectors, including financial markets. In response to the pandemic, governments around the world have implemented non-pharmaceutical interventions to contain the spread of the virus (González & Gallizo, 2021). These interventions, such as lockdowns, travel restrictions, and social distancing measures, have had significant implications for economic activity and financial markets (Jamison et al., 2021; Al-Alawnh et al., 2024). The devastating effect of the pandemic has caused worldwide economic uncertainty and disruptions, leading to decreased demand for goods and services and reduced international trade (Latif et al., 2021). Therefore, the term "Black Swan

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theory" refers to occurrences that are usually infrequent and hard to foresee but potentially affect the economy or the financial markets significantly. This could be set off by anything from a natural disaster or geopolitical event to a financial crisis or technological breakthrough to a shift in consumer behavior (Limba et al., 2020). Black Swan occurrences are characterized by their inability to be predicted and their appearance when least expected to produce uncertainty and volatility in capital markets (Ahmad et al., 2021). Menace of the disease has caused significant disruption to people's lives through government action, from curfews, panic, fear, and shutting down factories, businesses, including institutions of learning to curb the epidemic (Khan et al., 2020). The shutdown of corporate activity and the uncertainty surrounding the coronavirus pandemic influenced investment and investor choices, causing a significant effect on stock prices and currency values and high volatility in either market (Nwosa, 2021).

The epidemic and non-pharmaceutical interventions caused a severe drop in stock prices worldwide as investors became cautious and sold off stocks due to concerns about the future of the world economy (Youssef et al., 2021; Aharon & Siev, 2021). This coronavirus pandemic resulted in significant losses for stock markets (Al-Awadhi et al., 2020). This study complements previous studies to understand how the coronavirus pandemic and non-pharmaceutical interventions have affected Malaysia's market stock volatility. The study specifically concentrated on the Malaysian stock market, a prominent and influential entity within the realm of major exchanges in Southeast Asia (Yu et al., 2013). Besides, evidence suggests that the coronavirus pandemic possessed harmful consequences on the market stock (Aldhamari et al., 2023; Keh et al., 2021). Moreover, Malaysia, like other countries, enforced lockdowns and various restrictions (Aziz et al., 2020). These measures caused numerous businesses in Malaysia to shutter, leading to significant job losses for many individuals (Kadhim et al., 2021). Additionally, the government's actions in Malaysia to address the deadly virus by implementing the Stringency Index have shown volatility and indirectly resulted in adverse effects on stock market returns (Rowland et al., 2023).

1. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Several studies have used the GARCH models to examine the impact of the coronavirus pandemic and non-pharmaceutical interventions on the volatility of stock markets, which has witnessed a significant increase in recent times across various countries. Some studies that employed the GARCH model found that COVID-19 contributed to increased volatility in the stock market (Endri et al., 2020; Chaudhary et al., 2020; Bora & Basistha, 2021). Endri et al. (2020) applied the GARCH model to test stock price volatility during the COVID-19. During the COVID-19 pandemic, Indonesian stock markets experienced higher volatility. Chaudhary et al. (2020) used the GARCH model to examine the impact of COVID-19 on the return and volatility of the stock market indices of the top 10 GDP countries. Volatility remained greater than usual, indicating a negative trend. Bora and Basistha (2021) examined how COVID-19 affected stock price volatility in India using a generalized autoregressive conditional heteroscedasticity model. The findings indicate that the Indian stock market experienced volatility amidst the outbreak.

Moreover, several studies have employed diverse GARCH models (Emenogu et al., 2020; Jindal & Gupta, 2022; Hawaldar et al., 2020; Yong et al., 2021; Fakhfekh et al., 2023; Harjoto & Rossi, 2023; Onuorah et al., 2022; Szczygielski et al., 2021). These investigations have concluded that the effects of the coronavirus pandemic have negatively affected the fluctuations in stock markets. Emenogu et al. (2020) showed that during the COVID-19 period in Nigeria, stock returns were lower, and volatility was higher than under the non-COVID-19 era. Jindal and Gupta (2022) utilized standard GARCH models, including GARCH, EGARCH, TGARCH, and PARCH models, to evaluate volatility in both the Thailand and India markets. The results indicate that adverse events had a more pronounced impact on these markets during the pandemic compared to favorable events. Hawaldar et al. (2020) evaluated the COVID-19 volatility spillovers in the Japanese stock market using GARCH, GJR, and EGARCH models. The sample returns of the selected stock market showed significant volatility. Yong et al. (2021) examined return volatility on the Malaysian and Singapore stock exchanges using the GARCH, PGARCH, EGARCH, TGARCH, and GARCH-M models. They reported that both stock markets continue to operate despite the pandemic's effect on market stability. Fakhfekh et al. (2023) showed that following the onset of COVID-19, the Tunisian time series for the stock index exhibited increased volatility across EGARCH, FIGARCH, FIEGARCH, and TGARCH models. Harjoto and Rossi (2023), utilizing Carhart and GARCH (1,1) models, found that the COVID-19 pandemic exerted a notably more pronounced adverse effect on emerging market stock markets compared to developed ones. Onuorah et al. (2022) utilized GARCH (1,1) and EGARCH models to analyze market volatility amidst the COVID-19 crisis in Nigeria, showing that volatility persisted moderately during this period. Szczygielski et al. (2021) used ARCH/GARCH models to study when and how COVID-19 uncertainty affects returns and volatility in regional markets. Asian markets showed more resilience, whereas Latin American markets were hit hardest in terms of returns and volatility.

Other scholars used EGARCH, TGARCH, and DCC-GARCH and found that the COVID-19 pandemic led to heightened fluctuations in the stock markets (Liu, 2021; Aliani et al., 2022; Kusumahadi & Permana, 2021; Zhang et al., 2022). Liu (2021), utilizing the EGARCH model, reveals a substantial correlation between increased uncertainty induced by the COVID-19 pandemic and the decline observed in China's composite index. Aliani et al. (2022) utilized the wavelet coherency approach and the DCC-GARCH (1,1) model to assess the impact of COVID-19 on the stock indexes of both Islamic and conventional banks. The findings indicate that the fluctuations in returns of Islamic banks are relatively less volatile than those of conventional banks. Kusumahadi and Permana (2021) investigated how COVID-19 has influenced stock return volatility across 15 countries globally, employing both fundamental equation analysis and the TGARCH model. COVID-19's emergence has influenced stock return volatility in all examined nations, with the exception of the United Kingdom. Zhang et al. (2022), using the TGARCH model, examined the impact of China on the volatility of the most advanced countries, including Switzerland, Sweden, the Netherlands, and the UK, excluding the USA. The findings suggest that China plays a significant role in explaining volatility in these nations.

However, other researchers contend that stock market volatility responds unfavorably to government lockdown policies, employing models from the GARCH family (Engle, 2020; Bakry et al., 2022; Ibrahim & Sundarasen, 2020; Yu & Xiao, 2023; Ncube et al., 2024). Engle (2020) analyzed global stock markets using both realized volatility and the GJR-GARCH model. The study suggests that countries with stricter policy responses, as indicated by higher levels of the OxCGRT Stringency Index, tend to exhibit lower stock market volatilities. Bakry et al. (2022) investigated COVID-19 announcements, government interventions, and stock market volatility, finding significant differences between emerging and developed markets using an asymmetric GJR-GARCH model over a year. Ibrahim and Sundarasen (2020) utilized the continuous wavelet transformation (CWT) and GJR-GARCH models to analyze the volatility of Asia-Pacific equity markets amid the COVID-19 crisis. The findings underscore the substantial influence of government interventions on market volatilities. Yu and Xiao (2023), employing the COVID-19 stringency index, examined the interplay between government restrictions and stock market volatilities using the GARCH (1,1) model. Adverse outcomes from COVID-19 policies amplify stock market fluctuations more than positive outcomes. Ncube et al. (2024) employed GARCH models to evaluate volatility and SHAP for Explainable Artificial Intelligence, identifying stock volatility drivers during the pandemic. The findings reveal notable volatility spikes initially, with government measures boosting volatility in major exchanges, but vaccination programs help mitigate it.

Additionally, previous studies have followed event study analysis to explore the impact of non-pharmaceutical interventions and lockdowns (S. Shrimali & D. Shrimali, 2021; Sinaga et al., 2022; Bouri et al., 2022; Xie et al., 2022; Alam et al., 2020). S. Shrimali and D. Shrimali (2021) suggested that the epidemic and associated lockdown announcements negatively affected stock prices within the Indian banking sector. Sinaga et al. (2022) evidenced that stock returns in Jakarta exhibited negative trends during the lockdowns, albeit to a lesser extent compared to other countries. Bouri et al. (2022) found that the

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closure had a positive impact but varied among New Zealand's equity market indices. According to Xie et al. (2022), an announcement of lockdown implementation by governments had a significant depressing effect on the majority of stock markets across 44 countries. Alam et al. (2020) suggested that the lockdown positively influenced the stock market performance in India.

Other studies investigated how government actions affected equity markets using a panel data analysis methodology (Zhuo & Kumamoto, 2020; Ashraf, 2020; Raifu et al., 2021; Guven et al., 2022; Saif-Alyousfi & Saha, 2021; Bakry et al., 2022). According to Zhuo and Kumamoto (2020), government measures to restrict costs significantly reduce stock returns across G7, BRICS, and four other countries. Ashraf (2020) found that government announcements regarding social distancing measures lead to direct negative effects on stock market returns in 77 countries. Raifu et al. (2021) discovered that impulse response functions demonstrated that COVID-19 confirmed cases, deaths, and lockdown policy shocks initially affect Nigerian stock market returns negatively and positively, respectively, before reaching long-term equilibrium. Following Guven et al. (2022), the rise in daily COVID-19 cases and fatalities adversely affects stock market returns in 21 developing nations, while government response strategies appear to have an indirect positive impact. Saif-Alyousfi and Saha (2021), spanning 88 countries across the Americas, Europe, Asia-Pacific, Middle East, and Africa, revealed that the regions most affected by confirmed COVID-19 cases are the Americas and the Middle East, with Europe following closely behind. Europe experiences the most severe negative impact due to COVID-19 fatalities compared to other regions, particularly the Middle East. According to Bakry et al. (2022), investor responses to factors such as new confirmed cases, mortality rates, recovery rates, and defensive government initiatives differ markedly across the 24 emerging and 15 developed countries studied.

Previous studies have indicated a negative impact of COVID-19 and governmental measures (positive or negative) on stock market fluctuations.

This study seeks to investigate the combined effect of COVID-19 and non-pharmaceutical measures, which has not been thoroughly explored and may have either a positive or negative impact on the Malaysian stock market.

Therefore, this study elaborated on the following hypotheses based on the literature review:

H1: *The coronavirus pandemic and non-pharmaceutical interventions significantly affect Malaysia's stock market volatility.*

H1a: *The coronavirus pandemic and non-pharmaceutical interventions significantly affect the total volatility in Malaysia's stock market.*

H1b: *The coronavirus pandemic and non-pharmaceutical interventions significantly affect the negative volatility of Malaysia's stock market.*

H1c: *The coronavirus pandemic and non-pharmaceutical interventions policy significantly affect the positive volatility of Malaysia's stock market.*

2. METHODOLOGY

2.1. Data sources

Daily secondary data concerning new cases and new deaths, as well as non-pharmaceutical interventions such as lockdown measures, were sourced from the COVID-19 Government Response Tracker (OxCGRT) database. Daily data on the FTSE Bursa Malaysia KLCI Index were gathered from the Eikon Refinitiv database. Additionally, control variables were obtained from the Eikon Refinitiv database. This study utilizes the logarithmic transformation formula proposed by Busse and Hefeker (2007), expressed as

$$\log y_t = \left[\log\left(y_t + \sqrt{y_t^2 + 1} \right) \right]. \quad (1)$$

Logarithmic transformation proves to be a beneficial preprocessing method in financial econometrics, providing practical advantages in enhancing the appropriateness of data for GARCH modeling (Emenogu et al., 2020; Özdemir, 2022). This paper chose a data collection period for the analysis that spans from January 7, 2020, to March 31, 2021.

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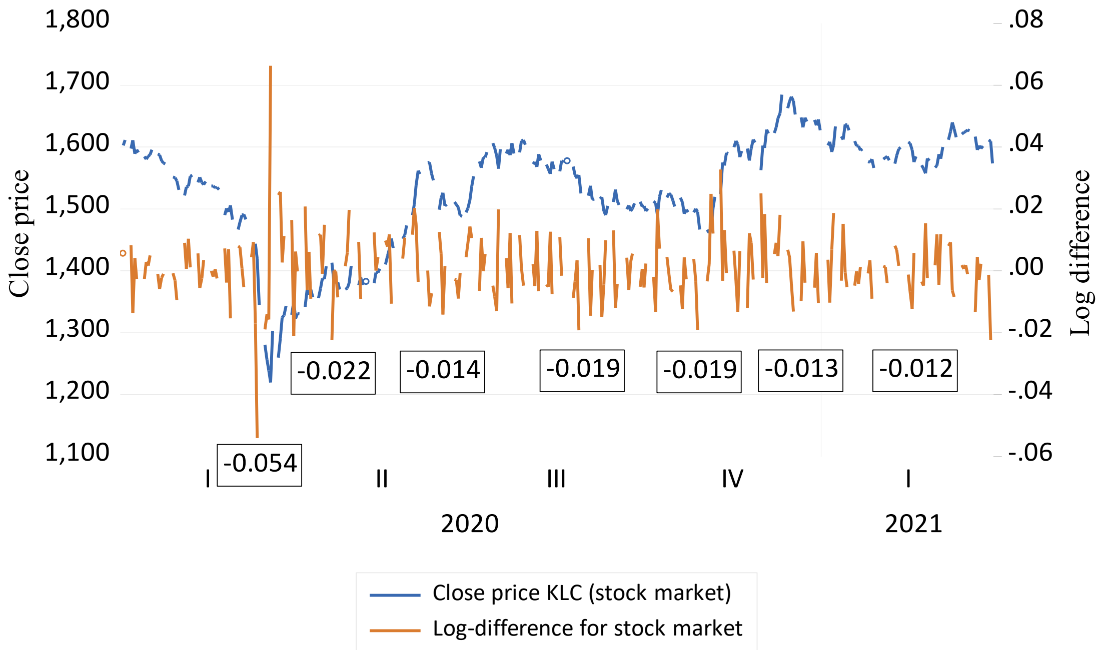
Table 1. Descriptions of the variables

Source: Eikon Refinitiv database provides the daily closing prices for the stock index (dependent variable), as well as the computation and application of logarithmic returns.

No.	Variables	Abbreviation	Measures	Data Source
1	FTSE Bursa Malaysia	KLCI	Close price	Eikon Refinitiv database
2	New cases	NC	Daily basis	(OxCGRT)
3	New deaths	ND	Daily basis	(OxCGRT)
4	School closures	C1	Indicator 0–3	(OxCGRT)
5	Workplace closures	C2	Indicator 0–3	(OxCGRT)
6	Canceled public events	C3	Indicator 0–2	(OxCGRT)
7	Restrictions on gathering size	C4	Indicator 0–3	(OxCGRT)
8	Closed public transport	C5	Indicator 0–2	(OxCGRT)
9	Stay-at-home requirements	C6	Indicator 0–3	(OxCGRT)
10	Restrictions on internal movement	C7	Indicator 0–2	(OxCGRT)
11	Brent crude oil	BCO	Close price	Eikon Refinitiv database

The study uses the FTSE Bursa Malaysia KLCI (FTSE), which represents the close price of the Malaysian stock index, as one of the variables in Table 1. Additionally, the OxCGRT database provides daily data on new COVID-19 cases (NC) and new deaths (ND). Various non-pharmaceutical interventions are also considered, with indicators ranging from 0 to 3 or 0 to 2, including school closures (C1), workplace closures (C2), cancellation of public events (C3), restrictions on gathering size (C4), closure of public transport (C5), stay-at-home requirements (C6), and restrictions on internal movement (C7), all sourced from OxCGRT. Finally, data for Brent crude oil prices were collected from the Eikon Refinitiv database, which represents the closing price of Brent crude oil. These variables collectively provide comprehensive insights into the relationship between stock market performance, COVID-19 dynamics, and governmental interventions during the specified period.

Figure 1 reveals the substantial influence of the coronavirus pandemic on stock market prices. Notably, there was a pronounced negative downturn in both stock indexes at the pandemic's outset. Throughout the study period, this downward trend persisted along with ongoing fluctuations, indicating a protracted and unsettling state of the market.



Note: The KLC stock index and log difference index for the study period are represented on the left and right vertical axes, respectively.

Figure 1. Trends in coronavirus and the stock market in Malaysia

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2.2. GARCH family models

The GARCH model, an extension of Engle's ARCH model by Bollerslev, is renowned for forecasting market volatility, particularly through its subcategory, the GARCH (1,1) model, which is adept at capturing volatility clustering (Bollerslev, 1986; Engle, 2004).

The GARCH (1,1)-M model incorporates stock market volatility ($\log\sigma_t^2$) in its mean equation (Habibullah et al., 2022, 2024):

$$\Delta sm_t = \lambda_0 + \sum_{i=1}^{q} \lambda_i \Delta newcases_{t-i} + \sum_{i=1}^{q} \lambda_i \Delta newdeaths_{t-i} + \sum_{i=1}^{q} \lambda_i \Delta NPI_{t-i} + \lambda \log\sigma_t^2 + \varepsilon_t, \quad (2)$$

$$\varepsilon_t \sim \left(0, \sigma_t^2\right),$$

$$\sigma_t^2 = c + a\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2. \quad (3)$$

where sm_t is the FTSE Bursa Malaysia KLCI Index; NPI_{t-i} encompasses non-pharmaceutical interventions like school closures, gathering restrictions, stay-at-home orders, workplace closures, cancellation of public events, and movement restrictions; and Z_{t-i} is control variables such as Brent crude oil. The variance equation (2) in the GARCH (1,1) models explains conditional variance incorporating lagged squared errors (ε_{t-1}^2) and conditional variances (σ_{t-1}^2). Constants like "c" represent long-term average volatility, while α and β govern the impact of current news and past volatility, ensuring non-negativity to maintain positivity. The decay speed of the volatility shock is dictated by the sum of α and β, with a slower decay as the sum approaches 1.

Nelson (1991) proposed the Exponential GARCH (EGARCH) model, an extension of the GARCH model allowing for asymmetry in conditional variance.

The EGARCH (1,1) model is as follows

$$\log\left(\sigma_t^2\right) = c + a\left|\frac{\varepsilon_{t-1}}{\sqrt{\sigma^2}}\right| + \Upsilon \cdot \frac{\varepsilon_{t-1}}{\sqrt{\sigma^2}} + \beta \log\left(\sigma_t^2\right). \quad (4)$$

In the EGARCH model, the logarithm of conditional variance replaces the dependent variable, implying an exponential leverage effect rather than a quadratic one. Parameters c, α, γ, and β are unconstrained by non-negativity. The model exhibits a leverage effect denoted by "γ," indicating differing responses to positive and negative shocks; $\gamma < 0$ suggests a greater impact of negative shocks on volatility, while $\gamma = 0$ denotes symmetry, devoid a leverage effect.

Ding et al. (1993) introduced the Power GARCH (PGARCH) model to address asymmetry concerns. The conditional variance equation for a PGARCH (1,1) model is provided as follows:

$$\sigma_t^d = c + \alpha\left(\varepsilon_{t-1} + \Upsilon\varepsilon_{t-1}\right)^d + \beta\sigma_{t-1}^d. \quad (5)$$

The GARCH model with a Power GARCH (PGARCH) specification incorporates heteroscedasticity. In this model, the power term "d" is utilized to determine the form of the function employed for modeling the conditional variance of the time series data. The model estimates the conditional standard deviation when the value of "d" is equal to 1. The PGARCH (1,1) model can be simplified to a GARCH (1,1) model when the value of "d" is equal to 2 and the leverage effect "γ" is equal to 0. The leverage effect, denoted as "γ," quantifies the imbalance in the association between the conditional variance and the previous innovation, namely the residuals derived from the mean model. A substantial value of "γ" that is not equal to 0 suggests the existence of a leverage effect within the dataset.

Time series data often deviate from normality, displaying traits like volatility clustering and fat tails. Financial returns frequently show skewness and excess kurtosis, prompting the use of distributions like the normal distribution, Student's *t*, and the generalized error distribution (G.E.D) for error term modeling (Bollerslev, 1987; Nelson, 1991). This study estimates all GARCH, EGARCH, and PGARCH models, assuming ε_t conformed to a normal distribution.

2.3. Model selection criteria

Diagnostic checking with the ARCH LM test for GARCH-type models is a common method for choosing the best-fitting model for a time series.

It evaluates residuals for homoskedasticity versus heteroskedasticity (Engle, 1982). Furthermore, forecast performance is frequently assessed using the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Theil Inequality Coefficient (TIC); a smaller forecast error indicates a higher level of model accuracy (Okakwu et al., 2019).

Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Theil Inequality Coefficient (TIC) are calculated as follows:

$$RMSE=\sqrt{\frac{\Sigma_{l-1}^{T}\left(\sigma^2-\hat{\sigma}^2\right)^2}{T}},$$

$$MAE=\sum_{t=1}^{T}\left|\frac{\sigma^2-\hat{\sigma}^2}{T}\right|,\quad \text{and} \tag{6}$$

$$Theil=\frac{\sqrt{\frac{\Sigma_{l-1}^{T}\left(\sigma^2-\hat{\sigma}^2\right)^2}{T}}}{\sqrt{\frac{\Sigma_{t-1\sigma^2}^{T}}{T}}+\sqrt{\frac{\Sigma_{t-1\hat{\sigma}^2}^{T}}{T}}}.$$

In statistical evaluation, σ2 and σ^2 represent actual and anticipated volatility, respectively, with T as the observation count. RMSE is sensitive to outliers, whereas MAE, less so, assigns equal weight to all errors, which is beneficial when significant errors are limited. The Theil inequality coefficient measures relative entropy, ranging from 0 to 1.

3. RESULTS AND DISCUSSION

3.1. Descriptive statistics

Table 2 presents descriptive statistics for a range of variables. It includes data on stock market indexes such as FTSE Bursa Malaysia, as well as COVID-19. Furthermore, it covers a variety of non-pharmaceutical interventions and control variables for Brent crude oil. The study describes each variable in terms of its mean, observed maximum and minimum values, standard deviation, skewness, kurtosis, and the Jarque-Bera statistic to test for normality. Notably, except for new deaths and closed public transport, all variables have negative skewness values, while their kurtosis values exceed 3 for FTSE Bursa Malaysia, school closures, workplace closures, canceled public events, and restrictions on gathering size. This indicates that the series has a leptokurtic distribution. Furthermore, the statistically significant at 1% Jarque-Bera statistic highlights the data's deviations from normality. This comprehensive overview aids in understanding the distributional characteristics and variability of the variables under examination.

3.2. Unit root test

Stationarity is an important assumption in time-series analysis because it implies that the series' statistical features remain constant over time. In Table 3, stationarity tests all study variables to ensure that the data are stationary, a requirement for

Table 2. Descriptive statistics

Variables	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
FTSE Bursa Malaysia	8.0253	8.1224	7.7995	0.0609	–1.2374	4.2634	91.3630***
New cases	5.1438	9.1206	0.0000	2.8465	–0.3733	1.8911	21.1489***
New deaths	1.1172	3.9124	0.0000	1.1933	0.5011	1.8323	28.0189***
School closures	1.3942	1.8184	0.0000	0.6485	–1.4211	3.4603	98.0994***
Workplace closures	1.3946	1.8184	0.0000	0.6371	–1.5620	3.8433	123.9076***
Canceled public events	1.1789	1.4436	0.0000	0.5088	–1.6771	4.1565	148.9667***
Restrictions on gathering size	1.4754	2.0947	0.0000	0.6899	–1.2186	3.4314	72.4928***
Closed public transport	0.2793	0.8814	0.0000	0.4108	0.7871	1.6195	51.8743***
Stay-at-home requirements	0.9341	1.8184	0.0000	0.6897	–0.4717	1.4698	38.2398***
Restrictions on movement	0.9875	1.4436	0.0000	0.6390	–0.8152	1.7834	48.9713***
Brent crude oil	8.7132	9.2565	8.0372	0.2550	–0.0210	2.6671	1.3323

Note: All variables are in logarithms. This study employs the logarithmic transformation approach by Busse and Hefeker (2007).

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Table 3. Results of unit root test

At Level	(ADF) Intercept		(ADF) Intercept & Trend	
	t–Statistic	Prob.	t–Statistic	Prob.
FTSE Bursa Malaysia	–1.7776 (0)	0.3912	–2.5341 (0)	0.3115
New cases	–1.6803 (3)	0.4402	–1.9679 (3)	0.6158
New deaths	–1.5242 (4)	0.52	–2.3630 (4)	0.3982
School closures	–2.5328 (0)	0.1088	–2.4162 (0)	0.3703
Workplace closures	–2.3594 (0)	0.1544	–2.4646 (0)	0.3456
Canceled public events	–2.2953 (0)	0.1742	–1.9411 (0)	0.6302
Restrictions on gathering size	–2.076 (0)	0.2547	–2.5543 (0)	0.3019
Closed public transport	–1.5192 (0)	0.5226	–1.3736 (0)	0.8667
Stay-at-home requirements	–2.5947 (0)	0.0952	–3.4576 (10)	0.0462
Restrictions on movement	–2.2971 (0)	0.1737	–2.5171 (0)	0.3197
Brent crude oil	–1.9592 (0)	0.305	–2.3924 (0)	0.3827
At first difference	**(ADF) Intercept**		**(ADF) Intercept & Trend**	
	t–Statistic	**Prob.**	**t–Statistic**	**Prob.**
Δ FTSE Bursa Malaysia	–16.9088 (0)	0.0000	–16.9061 (0)	0.0000
Δ New cases	–14.2731 (3)	0.0000	–14.2828 (2)	0.0000
Δ New deaths	–13.0259 (3)	0.0000	–13.0014 (3)	0.0000
Δ School closures	–16.7535 (0)	0.0000	–16.7776 (0)	0.0000
Δ Workplace closures	–17.2842 (0)	0.0000	–17.2925 (0)	0.0000
Δ Canceled public events	–16.8053 (0)	0.0000	–16.8654 (0)	0.0000
Δ Restrictions on gathering size	–16.8053 (0)	0.0000	–16.8128 (0)	0.0000
Δ Close public transport	–16.7332 (0)	0.0000	–16.7396 (0)	0.0000
Δ Stay at home requirements	–	–	–	–
Δ Restrictions on movement	–16.7512 (0)	0.0000	–16.7288 (0)	0.0000
Δ Brent crude oil	–15.6364 (0)	0.0000	–15.8526 (0)	0.0000

Note: The Augmented Dickey-Fuller (ADF) test employed in this study includes both intercept and intercept and trend. Study variables were statistically significant at the 1% level after the first difference, excluding stay-at-home that was significant at the level.

correct analysis using GARCH models. All study variables demonstrated stability in their initial differences. However, the requirement to stay at home exhibited stability at a level with a probability of 0.0462. This implies taking the first difference of variables (FTSE Bursa Malaysia, new cases, new deaths, school closures, workplace closures, canceled public events, restrictions on gathering size, closed public transport, restrictions on movement, Brent crude oil) when estimating GARCH models.

3.3. GARCH (1,1)-M models for Malaysia

After incorporating coronavirus pandemic-related variables and non-pharmaceutical measures, noticeable changes have been observed in the fluctuations of the Malaysian market. Table 4 presents the analysis of the GARCH-M (1,1) model, indicating that public event cancellation, public transport cancellation, and stay-at-home requirements are not statistically significant. Meanwhile, at the 1% level, both workplace closures, restrictions on gatherings, and the Brent crude oil index show statistical significance. Additionally, variables such as new cases, deaths, school closures, and movement restrictions also exhibit statistical significance at the 5% level. This indicates that both the alpha and beta coefficients are below one. This implies that while past market volatility (alpha) and past conditional variance (beta) continue to affect the current volatility of the Malaysian stock market, their influence diminishes gradually over time. In simpler terms, the effects of previous market volatility and conditional variance on present market fluctuations are present but declining as time elapses. In the GARCH-M (1,1) model, the ARCH test is higher than the 5% significance level. Therefore, the study concludes that there is no significant heteroscedasticity in the residuals, meaning the model has effectively captured the volatility patterns in the data.

Table 5 highlights the statistical significance of several factors in the main equation. Workplace closures, restrictions on gatherings, internal movement restrictions, and the Brent index are

Table 4. Findings from the GARCH-M (1,1) model estimations

Independent variable–mean equation				
Variable	**Coefficient**	**Std. Error**	**z–statistic**	**Prob.**
LOG(GARCH)	0.00147	0.00123	1.19703	0.23130
Δ (NC)	0.00147	0.00062	2.37445	0.01760
Δ (ND)	–0.00175	0.00079	–2.21450	0.02680
Δ (C1)	–0.00946	0.00476	–1.98701	0.04690
Δ (C2)	0.02121	0.00599	3.54172	0.00040
Δ (C3)	–0.00656	0.00578	–1.13560	0.25610
Δ (C4)	0.01088	0.00310	3.50591	0.00050
Δ (C5)	0.00061	0.01762	0.03454	0.97240
(C6)	0.00040	0.00082	0.48916	0.62470
Δ (C7)	–0.01148	0.00488	–2.35167	0.01870
Δ (BCO)	0.08898	0.01729	5.14497	0.00000
C	0.01317	0.01167	1.12850	0.25910
σ_t^2				
C (constant)	0.00002	0.00001	2.27583	0.02290
RESID (–1)^2	0.32297	0.08581	3.76388	0.00020
GARCH (–1)	0.50797	0.13329	3.81089	0.00010
R^2	0.08568			
Adj R^2	0.04857			
S.E.R	0.012245			
ARCH LM TEST	0.9388			

Note: The study employed a GARCH-M (1,1) model with a normal distribution assumption (Gaussian), which aligns with the study variables for the coronavirus pandemic and non-pharmaceutical interventions on the Malaysian stock market. R^2 and SER denote *R*-squared and standard error of regression, respectively, while the ARCH test is conducted to assess heteroscedasticity in the model.

highly significant at the 1% level, indicating a very strong and reliable impact on the dependent variable. This strong significance suggests that these factors play a crucial role in influencing the outcome. In contrast, new cases, new deaths, and school closures are significant at the 5% level. This indicates that these factors also have a meaningful impact on the dependent variable, but the confidence in these results is slightly lower than those significant at the 1% level. It implies that while their influence is still important and statistically significant, there is a slightly higher probability, up to 5%. On the other hand, the cancellation of public events, public transport closures, and stay-at-home requirements do not show statistical significance. This means that these factors do not have a discernible impact on the dependent variable, as their effects are not statistically different from random noise. As a result, these variables do not significantly contribute to the model's explanation of the variations in the dependent variable.

The results of the analysis in the variance equation indicate that both the ARCH and GARCH components are statistically significant at the 1% level. This finding carries important implications for understanding the volatility dynamics in the examined time series data. The leverage effect in the EGARCH-M (1,1) model indicates that negative news has a greater impact on the Malaysian stock market than positive news. The release of bad news triggers increased market volatility, reduced trading activity, and larger price fluctuations. Essentially, the market exhibits a stronger reaction to negative news, with more pronounced volatility and significant price movements compared to positive news. This heightened response is likely due to market participants' rapid and decisive actions when faced with negative information, which amplifies market reactions and leads to greater price instability, meaning asset prices experience more significant and rapid fluctuations. Investors, fearing potential losses, often become more risk-averse and reduce their trading activities. This decrease in trading volume can further heighten volatility because, with fewer participants in the market, any transactions that do occur can cause larger price shifts. The lack of liquidity during these periods magnifies the impact of each trade, contributing to even more dramatic price movements.

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Table 5. Findings from the EGARCH-M (1,1) model estimations

Independent variable–mean equation				
Variable	**Coefficient**	**Std. Error**	**z–statistic**	**Prob.**
LOG(GARCH)	0.00283	0.00122	2.32660	0.02000
Δ (NC)	0.00105	0.00062	1.70401	0.08840
Δ (ND)	–0.00155	0.00077	–2.01388	0.04400
Δ (C1)	–0.00863	0.00495	–1.74161	0.08160
Δ (C2)	0.02264	0.00547	4.14154	0.00000
Δ (C3)	–0.00912	0.00580	–1.57155	0.11610
Δ (C4)	0.00990	0.00314	3.15074	0.00160
Δ (C5)	0.00094	0.01699	0.05552	0.95570
(C6)	–0.00004	0.00070	–0.06448	0.94860
Δ (C7)	–0.01151	0.00416	–2.76599	0.00570
Δ (BCO)	0.09129	0.01529	5.97107	0.00000
C	0.02597	0.01170	2.21956	0.02640
$\log\left(\sigma_t^2\right)$				
C	–2.51873	0.83103	–3.03086	0.00240
RESID (–1)^2	0.54578	0.10109	5.39885	0.00000
ϒ(leverage effect)	–0.14803	0.06939	–2.13331	0.03290
GARCH (–1)	0.77222	0.08630	8.94777	0.00000
R^2	0.08016			
Adj R^2	0.04283			
S.E.R	0.012282			
ARCH LM TEST	0.3908			

Note: The study employed an EGARCH-M (1,1) model with a normal distribution (Gaussian), which aligns with the study variables for the coronavirus pandemic and non-pharmaceutical interventions in the Malaysian stock market. R^2 and SER denote R-squared and standard error of regression, respectively, while the ARCH test is conducted to assess heteroscedasticity in the model.

The ARCH test results for the EGARCH-M (1,1) model indicate that the p-value is higher than the 5% significance level. Consequently, the outcome suggests that the EGARCH-M (1,1) model not only captures the volatility patterns in the data effectively but also addresses the asymmetries in the volatility responses to positive and negative shocks, ensuring a more robust representation of the underlying data dynamics.

Table 6 shows that the variables in the main equation exhibit statistically significant effects at the 1% level for workplace closures, internal movement restrictions, restrictions on gatherings, and the Brent index. New cases and school closures have statistically significant effects at the 5% level, whereas new deaths have a statistically significant effect at the 10% level. On the other hand, the cancellation of public events, public transport closures, and stay-at-home requirements have no statistical significance. The analysis results in the variance equation indicate that both the ARCH and GARCH components are statistically significant at 1%, whereas the leverage effect is not statistically significant in the PGARCH-M (1,1) model. In the standard PGARCH-M (1,1) model, the power term “d” is equal to 2. When “d” is less than 2 in a PGARCH-M (1,1) model, it deviates from this standard specification. This distinction suggests a unique modeling approach that adjusts the persistence of past volatility effects to be slower than the conventional assumption in the GARCH framework. The study can conclude that the model deviates from a standard GARCH model. The ARCH test results for the PGARCH-M (1,1) model show a p-value higher than the 5% significance level.

After estimating the GARCH-M (1,1) models, the study found that both the COVID-19 pandemic and non-pharmaceutical interventions significantly impacted the Malaysian stock market. This finding aligns with the first sub-hypothesis (H1a), which posits that the pandemic and associated interventions have a significant effect on the total volatility of the Malaysian stock market. Moreover, the analysis revealed that COVID-19 had a negative effect on the Malaysian stock market, supporting the second sub-hypothesis (H1b). This sub-hypothesis

Table 6. Findings from the PGARCH-M (1,1) model estimations

Independent variable–mean equation				
Variable	**Coefficient**	**Std. Error**	**z–statistic**	**Prob.**
LOG(GARCH)	0.00296	0.00143	2.06366	0.03910
Δ (NC)	0.00126	0.00062	2.03966	0.04140
Δ (ND)	–0.00156	0.00081	–1.92924	0.05370
Δ (C1)	–0.00986	0.00482	–2.04537	0.04080
Δ (C2)	0.02377	0.00576	4.12488	0.00000
Δ (C3)	–0.00880	0.00569	–1.54758	0.12170
Δ (C4)	0.00914	0.00322	2.84280	0.00450
Δ (C5)	0.00100	0.01793	0.05550	0.95570
(C6)	0.00047	0.00082	0.57544	0.56500
Δ (C7)	–0.01093	0.00417	–2.62120	0.00880
Δ (BCO)	0.08601	0.01681	5.11655	0.00000
C	0.02686	0.01355	1.98292	0.04740
σ_t^d				
C	0.00007	0.00028	0.24107	0.80950
RESID (–1)^2	0.32685	0.08060	4.05519	0.00010
Υ(leverage effect)	0.17592	0.14771	1.19099	0.23370
GARCH (–1)	0.42678	0.15981	2.67049	0.00760
d	1.82478	0.88853	2.05371	0.04000
R^2	0.07940			
Adj R^2	0.04203			
S.E.R	0.012287			
ARCH LM TEST	0.5705			

Note: The study employed an EGARCH-M (1,1) model with a normal distribution (Gaussian), which aligns with the study variables for the coronavirus pandemic and non-pharmaceutical interventions in the Malaysian stock market. R^2 and SER denote R-squared and standard error of regression, respectively, while the ARCH test is conducted to assess heteroscedasticity in the model.

suggests that the pandemic and non-pharmaceutical interventions significantly affect the negative volatility of the market, indicating increased market fluctuations in response to adverse news related to COVID-19. However, the study contradicts the third sub-hypothesis (H1c). This sub-hypothesis proposed that the pandemic and non-pharmaceutical interventions would significantly affect the positive volatility of the Malaysian stock market. The lack of evidence for a positive effect suggests that any positive news or interventions related to COVID-19 did not have a measurable stabilizing impact on the market volatility.

3.4. Result model selection criteria

The study evaluated multiple models using various performance metrics to determine the most suitable one for capturing the underlying data dynamics. Table 7 summarizes the outcomes of this comprehensive evaluation process. After careful examination of the metrics, it became apparent that the EGARCH-M (1,1) model stood out as the top performer among the models considered. This finding underscores the EGARCH-M (1,1) model's superior ability to effectively capture the complexities of the data compared to other models. Specifically, it exhibited the lowest root mean square error (RMSE) and mean absolute error (MAE) values, indicating a better fit to the observed data. Theil U2 statistic, which shows how accurate the forecasts were compared to the model, was also much lower for the EGARCH-M (1,1) model than for the others, which showed that it was even better at making predictions. This suggests it can correctly account for the uneven responses of volatility to positive and negative shocks, giving a more complete picture of how the data change over time. Therefore, the evaluation results concluded that the EGARCH-M (1,1) model is the best option for analysis.

Table 7. Forecast evaluations

Models	RMSE	MAE	Theil U2
GARCH-M (1,1)	0.0661	0.0661	5.2732
EGARCH-M (1,1)	0.0433	0.0298	3.4743
PGARCH-M (1,1)	0.0903	0.0771	7.1724

Note: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Theil, respectively.

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CONCLUSION

The aim of this study is to assess the impact of the coronavirus pandemic and non-pharmaceutical interventions on the volatility and performance of the Bursa Malaysia KLCI Index, utilizing GARCH-M (1,1) models. The analysis using the GARCH-M (1,1) model indicated that while past market volatility and conditional variance continued to influence current volatility, their impact gradually diminished over time. Moreover, the EGARCH- M (1,1) model has a leverage effect, suggesting that negative news had a more pronounced impact on the financial market compared to positive news. This heightened volatility, triggered by unfavorable economic data, led to reduced trading activity and larger price swings. Essentially, the market displayed stronger reactions to adverse news, resulting in amplified market responses and greater price fluctuations, potentially driven by swift and decisive reactions from market participants.

Additionally, the EGARCH-M (1,1) model revealed the impact of both coronavirus pandemic-related shocks and non-pharmaceutical interventions on market dynamics. However, the leverage effect was not statistically significant in the PGARCH-M (1,1) model. The study assessed the performance of various models using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Theil's U2 statistic. These metrics were crucial in evaluating how well each model captured the data dynamics. Among the models tested, the EGARCH-M (1,1) model stood out as the most suitable choice. Its superior performance across all the evaluated metrics highlighted its effectiveness in accurately reflecting the intricacies of the data. The EGARCH-M (1,1) model's ability to address both volatility patterns and asymmetries in responses to positive and negative shocks made it the optimal selection for the study.

Future studies can compare countries or regions with markets similar to Malaysian one to understand the impact of the coronavirus pandemic on financial market fluctuations. By examining these comparisons, researchers can identify common trends and unique responses, providing valuable insights for governments and investors to prepare for and mitigate the effects of similar crises. This comparative analysis can help in developing strategies to enhance market resilience and inform policy decisions during periods of uncertainty.

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