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Hadj Khelifa,
Faculty of Economics and Business, University of Mostaganem, Algeria
https://orcid.org/0000-0002-3303-1220

Djamal Dekkiche,
High School of Economics, Oran, Algeria
https://orcid.org/0000-0002-1463-4413

Farid Belgoum,
Faculty of Economics and Business, University of Oran 2, Algeria,
https://orcid.org/0000-0002-8918-2255

THE IMPACT OF SHOCKS ON THE VOLATILITY OF THE DUBAI GENERAL MARKET INDEX (DFMGI), USING ASYMMETRIC GARCH MODELS

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Abstract. *This research paper aims to study the effects of good and bad news on the volatility of the Dubai General Market Index (DFMGI) return series for 5,5 years during the period spanning from January 1, 2018, to June 30, 2023, using the asymmetric GARCH models: EGARCH(1,1), TGARCH(1,1) and PARCH(1,1). The study concluded that positive and negative shocks asymmetric impact fluctuations in price returns in the Dubai financial market. This means that negative shocks significantly impact volatility more than positive shocks. The study also concluded that the best asymmetric GARCH model among the three used is the PARCH(1,1) model.*

Keywords: *volatility, asymmetric GARCH model, positive and negative shocks, Dubai financial market.*

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Introduction

Financial time series exhibit heterogeneity of volatility or clustered volatility, which vary over time due to a variety of factors, such as unexpected events, news releases, and changes in investor sentiment. This is the reason why many investors and financial analysts are concerned about speculative price fluctuations in the market that result in uncertainty regarding the return on invested assets. In order to predict and anticipate future fluctuations in financial markets, researchers and stakeholders have been able to design and develop quantitative statistical models that account for these fluctuations and oscillations. Among these models are the symmetric GARCH model (with symmetric effects) (Bollerslev, Chou, & Kroner, 1992)، (Engle & Bollerslev, 1986)، (Engle & Patton, 2001), which are represented by generalized autoregressive models subject to heterogeneity of variance, symbolized by the abbreviation (GARCH), and are suitable for measuring the variation affecting the value of Balance in the estimated value of financial assets It is considered to be a suitable method and tool to measure the variability and deviation affecting the value of the Balance in the estimated value of financial assets. The second type of GARCH model is called a Modified Model and takes into account nonlinear or asymmetric effects in financial valuations or the impact of unexpected events. Examples of these derived models include the EGARCH (Daniel B, 1991) (Theodossiou, 1994) (Koutmos & Theodossiou, 1994), TGARCH

(Jean-Michel, 1994), PGARCH (Ding, Granger, & Engle, 1993), and IGARCH models, which take into account asymmetries and asymmetric phenomena in the value distribution. These models have contributed to estimating the volatility of financial assets and forecasting future fluctuations through these models.

One of the most significant financial markets in Arab nations is thought to be the Dubai Financial Market. This market, like other financial markets, is characterized by financial volatility in the returns of its indicators. These fluctuations must be researched and analyzed by modeling the fluctuations that take place across the study periods. We choose to employ asymmetric GARCH models as a result. It is derived from the generalized autoregressive conditional heteroscedasticity (GARCH) model, represented by EGARCH(1,1), TGARCH(1,1), and PARCH(1,1), which is regarded as the key to handling cluster in time series fluctuations as well as the analysis of the impact of positive and negative shocks on these fluctuations. Therefore, the following topic is the subject of our research: What effects do positive (good news) and negative news have?

Research Hypothèses

H1: Volatility shocks will be highly persistent in Dubai financial market returns.

H2: Dubai Financial Market Index DFMGI returns are equally sensitive to good and bad news.

Research Methodology

This study uses the GARCH model and its derivatives to model the volatility of stock returns in the financial market (Dubai); the ARMA model is generally more useful for modeling time series data, but conditions must be met for the remaining models:

- The mean error is zero:

$$E\left(\varepsilon_t\right) = 0$$

- The variance of the errors is uniform (variance is constant with respect to time):

$$V(\varepsilon_t) = \sigma^2$$

- There is no autocorrelation between errors:

$$Cov(\varepsilon_t, \varepsilon_{t-1}) = 0$$

Series can be smoothed on average, but it is difficult to smooth variance (constancy of variance), especially when analyzing financial time series. The instability of variance indicates the existence of fluctuations in time series, and to address the problem of fluctuations, (Engle, 1982) proposed an autoregressive model (ARCH model) subject to heterogeneity in the variance of the residuals (errors) to solve the problem that the ARMA model suffers especially in time series. After determining the existence of the ARCH effect, an autoregressive model conditional on heterogeneity in the variance of generalized residuals (GARCH model) was developed.

Literature Review

1.1. ARMA Model

Alexander (2001) suggested that the conditional mean equation should be in one of the following states

- Random walk model:

$$r_t = c + \varepsilon_t$$

- First order autoregressive model:

$$r_t = c + \lambda r_{t-1} + \varepsilon_t$$

- Any of the model ARMA

r_t : Is the series of returns in financial series, c : average returns.

In this study, we will rely on the ARMA(p,q) model to represent the conditional average equation. The ARMA model, which was proposed by Box and Jenkins (1976), is an autoregressive moving average model that is denoted by the symbol ARMA (p,q).

$$y_t = \mu + \sum_{t=1}^{p} \varphi_t y_{t-1} - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{1}$$

$$\varphi_p(\beta) y_t = \theta_q(\beta) \varepsilon_t \tag{2}$$

If the series is averaged, the model is called an autoregressive integral moving average model (ARIMA), called ARIMA (p, d, q), with the following Equation 3:

$$\varphi_p(\beta)(1-\beta)^d y_t = \theta_q(\beta) \varepsilon_t \tag{3}$$

1.2. The ARCH conditional autoregressive model of heteroscedasticity

The ARCH model introduced by Robert Engle in 1982, is a statistical model that is used to describe the volatility of a time series.

: denotes the rank of the ARCH model and the number of model parameters. The equation for the ARCH model is of order : $(p \geq 1)$ and is given by: (Engle R. F., 1982)

$$r_t = \mu + y_t \tag{4}$$

$$y_t = h^2 \varepsilon_t \quad \varepsilon_t \rightarrow iidN(0,1) \tag{5}$$

$$y_t = \alpha_0 + \alpha_1 y_{t-1}^2 + \dots\dots + \alpha_p y_{t-p}^2 \tag{6}$$

r_t : A chain with no links is called a bounce chain.

μ: Mean bounce series

ε_t : Series of independent identically distributed variables following a standard normal distribution with mean (0) and variance (1);

$\alpha_0 > 1$

$\alpha_i > 0$ For all $i > 0$

α_0, α_1 : Model parameters

h_t : Conditional variance, which is a linear function of the square of the error (residual) and the past observations. Positive constraints on the model parameters guarantee a positive conditional variance. Equation (7) represents the instability equation and can be formulated as follows:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-1}^2 \tag{7}$$

The unconditional variance of y_t is defined by the following relation:

When P = 1, the model is first order ARCH(1), and the conditional variance formula is as in Equation (8):

$$h_t = \alpha_0 + \alpha_1 y_{t-1}^2 \tag{8}$$

1.3. The Generalized ARCH (GARCH Model)

The GARCH (p,q) model is an extension of the ARCH model, as it requires more parameters to accurately describe the inhomogeneity in the series. (Özkan, 2004, p. 28). It is given in the following mathematical formula: (Emmanuel Alphonsus Akpan, 2017, p. 113)

$$x_t = \sigma_t + \varepsilon_t \tag{9}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 x_{t-1}^2 + \cdots + \alpha_p x_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_q \sigma_{t-p}^2 \tag{10}$$

Where:

$$\alpha_i \geq 0, i = 1, \ldots, p, \beta_j \geq 0, j = 1, \ldots, q, \alpha_0 > 0$$

The following is the GARCH(1,1) model's mathematical formula (Marie-Eliette Dury, 2018):

$$x_t = \sigma_t + \varepsilon_t \tag{11}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 x_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{12}$$

If $(\alpha + \beta) \geq 1$: The effect of the oscillation resulting from the shock will continue into the future, as the value of the variation increases with the passage of time, which is called explosive oscillation.

However, one of the conditions of this model is that $(\alpha + \beta) < 1$, which, when it approaches 1, means that past shocks and fluctuations are continuous with respect to future fluctuations but gradually decrease over time, and this process is called the shift-to-the-mean property (Rousan & Alkhouri, 2005, p. 106).

1.4. Asymmetric GARCH Family Model

Securities tend to fluctuate less when returns increase and more when returns decrease, a phenomenon known as the leverage effect. Asymmetric GARCH models, such as the Generalized Exponential Conditional Variance Heterogeneity (EGARCH) model, can be used to model this effect (EGARCH) (By & Nelson, 1991), Thresholded ARCH (TGARCH) (Lawrecne, Ravi, & David, 1993), and PGARCH (Zhuanxin, Clive, & Robert F, 1993).

1.4.1. The Exponential GARCH Model

This model emerged as a complement to the ARCH and GARCH models to address the limitation of negative variation in the GARCH model. By avoiding the positive constraints on coefficients α_i and β_j , it is known as the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) (p.q) model, and the conditional variance equation is as follows:

$$\log(h_t^2) = \alpha_0 + \sum_{i=1}^{p} \alpha_i \left[\left| \frac{\varepsilon_t - 1}{h_t - 1} \right| - \sqrt{\frac{2}{\pi}} \right] + \sum_{j=1}^{q} \beta_j \log(h_{t-1}^2) - \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_t - 1}{h_t - 1} \tag{13}$$

$\log(h_t^2)$: The logarithm of conditional variance and previous values of errors are represented by the parameters of « the log-volatility model ».

$\alpha_0, \alpha_1, \beta, \gamma$: The parameters of the log-volatility model.

γ: The scale of the model is asymmetric and represents the leverage effect.

$\gamma = 0$: The model is symmetrical.

$\gamma<0$: Leverage effect is the phenomenon where negative shocks have a larger impact on volatility than positive shocks

$\gamma>0$: Positive shocks have a larger impact on volatility than negative shocks.

1.4.2. Threshold GARCH Model

Known as the threshold ARCH model, proposed by (Engle & Bollersleve, 1986) and developed by researchers (Rabemananjara & Zakoian, 1991) and called TGARCH the general equation of the TGARCH model is given as follows (Robert F & Victor K, 1993) :

$$r_t = \mu + \varphi r_{t-1} + r_t \tag{14}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{15}$$

d_{t-1} : Dummy variable.

$$\begin{cases} d_{t-1} = 0; if\ \varepsilon_{t-1} \prec 0 : badnews \\ d_{t-1} = 1; if\ \varepsilon_{t-1} \geq 0 : goodnews \end{cases} \tag{16}$$

The leverage effect parameter or asymmetry parameter is denoted by the symbol gamma (γ). Good news has an impact on (α_1), whereas bad news has an impact on ($\alpha_1+\beta_1$), if $\gamma=0$, the model reverts to the conventional GARCH formula. Therefore, negative shocks have a bigger impact on than positive shocks if (ε_{t-1}^2) and significant. (Suliman & Peter, 2012, p. 165).

1.4.3. Power GARCH (PARCH) model

This model was developed by Granger and Engel (1993) to investigate the asymmetric property of volatility (Zhuanxin, Clive, & Robert F, 1993). Unlike the GARCH models, the leverage coefficient was used in the modeling (Qamruzzaman, 2015) (Siourounis, 2002).

$$\sigma_t^\delta = \alpha_0 + \sum_{i=1}^{p} \alpha_i \left(\left| \mu_{t-1} \right| - \gamma_i \mu_{t-1} \right)^\delta + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^\delta \tag{17}$$

This form requires the following:

$$\begin{cases} \alpha_0 > 0 \\ \delta \geq 0 \\ \alpha_i \geq 0 \\ -1 < \gamma_i < 1 \\ \beta_j \geq 0 \end{cases} \tag{18}$$

Where: δ is the force coefficient in the model, and the coefficients: $\alpha_i, \beta_j, \gamma_i$ are the same as the coefficients presented in the previous models. However, the power δ to which the squared standard deviation σ_t will be raised is estimated rather than pre-imposed and determined as in other GARCH models.

Methods

The study data, represented by 2007 daily observations of the closing prices of the DFMGI general index, covering the period extending from 01/01/2018 to 06/30/2023, was obtained from the Dubai Financial Market. As for the returns of the DFMGI general index, which we symbolize (r_t).

At time t it is obtained by the logarithm of the DFMGI index (*P*), which is given by the following formula:

$$r_t = \log\left(\frac{P_t}{p_{t-1}}\right)$$

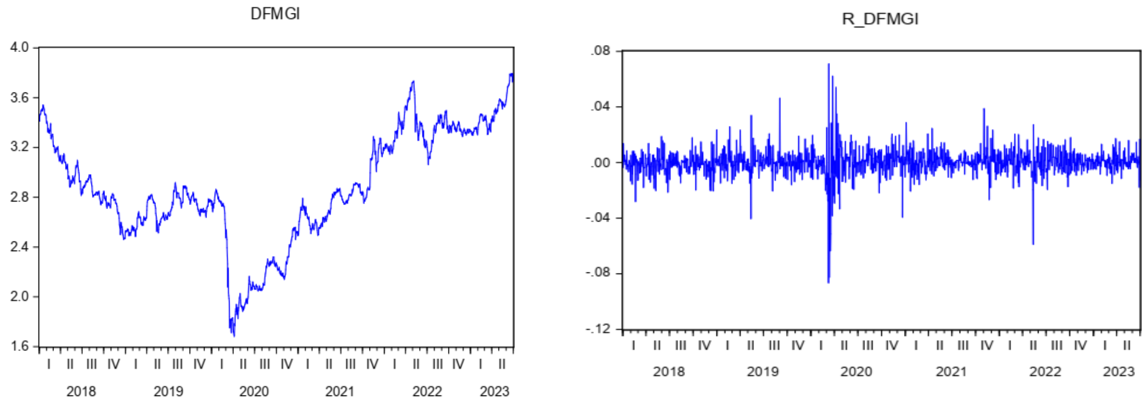

Figure 1. The trend Price and Return of the DFMGI Index during the sample period

Results and Discussion

3.1. Descriptive Statistics for Price Index (DFMGI) and the Return Index (DFMGI):

We present some descriptive statistics in the table to show the distributional characteristics of the daily returns of the DFMGI general index over the analyzed period.

Table 1
Statistics for Price Index (DFMGI) and the Return Index (DFMGI)

	Price index (DFMGI)	Return index (DFMGI)
Mean	2,873136	4,42 x 10^{-5}
Median	2,820855	0,000115
Std. Dev.	0,445245	0,008312
Skewness	-0,263644	-0,826927
Kurtosis	2,585580	24,04872
Jaque-Bera	37,59387	37260,11
Probability	0,000000	0,000000
Observations	2007	2007

Source: The outputs of Eviews.12

Following the results presented in the table above. We observe that the asymmetric swap (Skewness = - 0,826927) is negative for the general index return series, indicating that the return series is asymmetric (left tilt), and also indicates that the returns are powered by negative shocks (bad news) more than saturated opposition (useful news), while its total flatness (Kurtosis = 24,04872) is greater than 3, it expresses how thick the distribution is, and thus confirms the saying that the daily returns series of the general index does not follow the distribution, and this is confirmed by the value of (Jaque-Bera) which is equal to 37260,11 a potential value (Probability = 0,000000 < 0,05).

3.2. Stability test

We use the Augmented Dickey-Fuller (ADF) test to determine whether the daily price index and returns are stationary or contain a unit root (Dickey & Fuller, 1981). After determining the automatically predetermined lag length (maxlag = 25), and based on the Schwarz criterion, we arrive at the results shown in the table below (Table 2).

It is clear from the results of the stability test (ADF) that the daily price index series (DFMGI) is not stable at the level, and therefore it contains the unit root. Unit.

Table 2
Stationarity test for index and Index return (DFMGI)

ADF test for Index					
			Critical values		
		Test statistic	**1%**	**5%**	**10%**
DFMGI index	Intercept	-0,766039 (0,8278)	-3,433412	-2,862779	-2,567476
	Trend and intercept	-1,944126 (0,6307)	-3,962625	-3,412051	-3,127937
	None	0,175951 (0,7372)	-2,566116	-1,940982	-1,616593
ADF test for Return					
			Critical values		
		Test statistic	**1%**	**5%**	**10%**
DFMGI index return	Intercept	-39,98924 (0,0000)	-3,433412	-2,862779	-2,567476
	Trend and intercept	-40,06144 (0,0000)	-3,962625	-3,412051	-3,127937
	None	-39,99815 (0,0000)	-2,566116	-1,940982	-1,616593

Source: The outputs of Eviews.12

3.3. Quantile-Quantile (Q-Q) Plots

In addition to a descriptive analysis of the data, a graphical representation (Q-Q) is needed to know if a series of daily returns of a general index follows a normal distribution. This indicates that the normal distribution does not apply to this data, which is a general characteristic of financial time series.

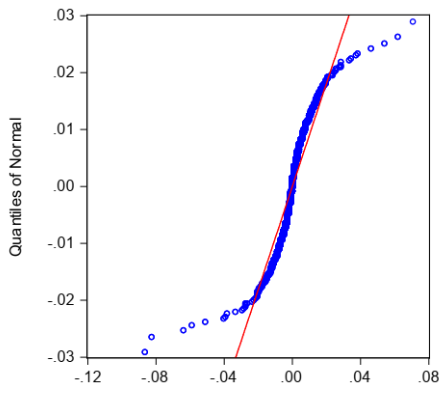

Figure 2. Quantiles of DFMGI Returns

3.4. ARCH effect Test

We test the effect of ARCH on the remainder of the return serie related to the returns of the DFMGI general index (Table 3).

Table 3
ARCH-LM Test results

Heteroskedasticity Test : ARCH			
F-statistic	247.6484	Prob. F(1,2002)	0.0000
Obs*R-squared	220.6067	Prob. Chi-Square(1)	0.0000

Source: The outputs of Eviews.12

Based on the ARCH-LM test, we can check the presence of a trace of ARCH in the residue. According to the results presented in Table 3.

The probability value for both (Obs*R-Squared = 220,6067{0,0000} and F-Statistic = 247,6448{0,0000}) is less than 0.05, and we chose a lag period of 1 to incorporate the ARCH effect. According to the results, the null hypothesis on No ARCH effect is rejected. This means that the residuals are characterized by the presence of ARCH effect. In other words, heteroscedasticity exists.

3.5. Selection of the Optimal asymmetric GARCH Model

To determine the optimal model among the asymmetric GARCH models, we rely on three criteria : the Akaike information criterion (AIC) (Akaike, 1974), the Schwartz information criterion (SIC) (Schwartz, 1978), and the log likelihoods criterion (LogL). The optimal model is the one that has the lowest AIC and SIC values and the highest LogL value.

Table 4
Selecting the optimal model for the distiribution

	Model	Distribution	LogL	AIC	SIC
1	TGARCH (1,1)	Normal (Gaussian)	7131,022	-7,107254	-7,090486
2	TGARCH (1,1)	t	7397,302	-7,371872	-7,352309
3	**TGARCH (1,1)**	**GED**	**7446,137**	**-7,420585**	**-7,401022**
4	TGARCH (1,1)	t with fixed df	7289,874	-7,265709	-7,248941
5	TGARCH (1,1)	GED withe fixed P	7290,150	-7,265985	-7,249216
6	EGARCH (1,1)	Normal (Gaussian)	7115,437	-7,091708	-7,074940
7	EGARCH (1,1	t	7412,826	-7,387358	-7,367795
8	**EGARCH (1,1**	**GED**	**7433,136**	**-7,407617**	**-7,388054**
9	EGARCH (1,1	t with fixed df	7267,578	-7,243469	-7,226701
10	EGARCH (1,1	GED withe fixed P	7245,531	-7,221477	-7,204709
11	PARCH (1,1)	Normal (Gaussian)	7130,949	-7,106183	-7,086620
12	PARCH (1,1)	t	7398,987	-7,372556	-7,350198
13	**PARCH (1,1)**	**GED**	**7448,612**	**-7,422057**	**-7,399699**
14	PARCH (1,1)	t with fixed df	7291,418	-7,266252	-7,246689
15	PARCH (1,1)	GED withe fixed P	7290,530	-7,265366	-7,245803

Source: The Outputs of Eviews.12

We will continue our analysis by estimating the parameters of the conditional mean and variance equations. We used the asymmetric GARCH models EGARCH(1,1), TGARCH(1,1), and PARCH(1,1) for this. We used the Broyden-Fletcher-Goldfarb-Shanno (BFGS) method to estimate the parameters, which helps to solve non-linear problems without constraints. The following table shows the results.

Table 5
Results of asymmetric GARCH model estimation for the return Index DFMGI

Coefficients	EGARCH (1,1)	TGARCH (1,1)	PARCH (1,1)
Mean Equation			
μ (Mean return)	$7{,}94 \times 10^{-5}$	$7{,}97 \times 10^{-5}$	$8{,}04 \times 10^{-5}$
Variance Equation			
(α_0) constant	-7,443799***	$2{,}52 \times 10^{-5}$ ***	0,008161
(α_1)	0,813313***	0,8499976***	0,596337***
(β_1)	0,300645***	0,047875	0,013711
(γ)	-0,033130	0,073568	0,027758
$(\alpha_1+\beta_1)$ (persistence coefficient)	1,113958	0,8978726	0,610048
Log likelihood	7433,155	7446,196	7448,612
Akaike Info. Criterion (AIC)	-7,407636	-7,420645	-7,422057
Schwarz Info. Criterion (SIC)	-7,388073	-7,401082	-7,399699
Heteroscedasticity LM			
F-statistic	1,411891{0,2349}	2,961916{0,0854}	1,596432{0,2066}

Source: The Outputs of Eviews.12

From the results shown in Table 5, and considering the AIC and SIC criteria (their lowest value) and the most significant value of the Log Likelihood criterion, it is clear that the best suitable model for modeling the fluctuations of returns of the Dubai Financial Market Index is the PARCH(1,) model.

The sum of the two parameters α and β in the TGARCH(1,1) model is 0.8978726, which is close to 1. This implies that the conditional variance (volatility) is explosive. The leverage coefficient γ is positive (0.073568), which indicates that negative shocks (bad news) have a more significant effect in increasing volatility than the effect of positive shocks (good news). This provides evidence of the effect of financial leverage. This means that the Dubai Financial Market shows continuous volatility returns with leverage effects (asymmetric news effects).

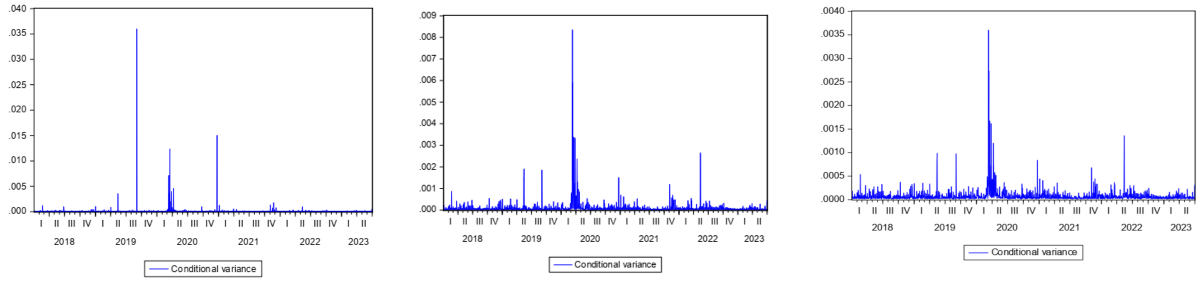

Figure 3. Conditional variance of EGARCH(1,1), TGARCH(1,1), PARCH(1,1)

The negative value of the EGARCH(1,1) model parameter γ (-0.033130) indicates the existence of an effect of leverage, meaning that bad news (negative shocks) generates more volatility than good news (positive shocks).

The positive value of the TGARCH(1,1) model parameter γ (0.073568) demonstrates that bad news (negative shocks) raises volatility more than good news (positive shocks).

Conclusion

In this study, we attempted to model the effect of asymmetric news and volatility in the returns of the DFMGI index of the Dubai financial exchange for the period 01/01/2018 to 06/30/2023 by applying three asymmetric models: EGARCH(1,1), TGARCH(1,1), and PARCH(1,1). The PARCH(1,1) model with Generalized Error Distribution (GED) for the residuals was the best model, as it had the lowest AIC and SIC values. This is consistent with other studies' findings that TGARCH and PARCH are the best models for describing asymmetric volatility. (Banumathy & Azhagaiah, 2015), (Goudarzi & Ramanarayanan, 2010), (Mittal, Arora, & Goyal, 2012). The study also found that bad news (bad shocks) have a greater effect on the volatility of DFMGI returns than good news (positive shocks).

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