

Received: 01/05/2021

Accepted: 21/05/2021

Modeling the volatility of Banks index returns for the Saudi stock exchange using EGARCH model**MANSOURI hadj moussa ^{*1}, GUENNOUN Abdelhak ²**¹Lecturer class A, University of Tamanghasset (Algeria),Mansouri.hm@cu-tamanrasset.dz²Lecturer class B, University of Tamanghasset(Algeria),guennoun.abdelhak@cu-tamanrasset.dz**Abstract:**

This study aims to model and measures the volatility of the returns of the banking sector in the Saudi stock exchange. The study used the exponential generalized autoregressive conditional heteroskedastic (EGARCH) model. The banking sector index (TBNI), comprises of daily data from the period from 1st April 2019 to 30st April 2020. Asymmetry presence has been detected in the EGARCH model. A using a Generalized Error Distribution was the most appropriate for the model. Besides, we found that “ bad news ” tends to increase volatility in comparison with “ good news ”, because the world is going through a corona epidemic.

Keywords: Volatility, Banking Sector Index, Returns, EGARCH Model.

JEL Classification Codes: G14, C13, C5

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1.INTRODUCTION:

The performance of the stock market affects all economic activities in a concerned country. The directions of the stock volatility determine the facets of the national economy⁽¹⁾. Volatility is used to measure the dispersion of returns in the stock prices. The volatility of stock returns is affected by a large number of risk factors such as political instability, economic fundamentals, government budget deficits, economic policy changes, firm-specific factors⁽²⁾. According to Dammika⁽³⁾, the rise in volatility generally means that information (news) flow into the market has increased. The increase in volatility may be desirable from the viewpoint that the market mechanism is working well in the price-setting process. Lakshmi⁽⁴⁾, who analyzed the volatility occurs due to news coming into the market and traders' consequent trading activity. Dispersing beliefs among the traders would cause volatility to increase. If volatility is strong relative to stock equilibrium values it impacts asset returns. The GARCH model by Engle (1982) and Bollerslev (1986) is the simple approach that can consider two characteristics of the financial asset returns, namely excess kurtosis and time-varying volatility.

Recently, many reliable and precise models have appeared in the financial econometrics that deal with stock market volatility. These models cover various facets of the financial markets⁽⁵⁾.

Many of the previous works suggest that asymmetric models function well in Modelig because there is a clear inverse correlation between volatility and shock, Studies such as Chang⁽⁶⁾ have shown that asymmetric models, Exponential General Autoregressive Conditional Heteroscedasticity (EGARCH) model, perform best for modeling equity indices. And the leverage is correlated with increased volatility for returns from negative shocks and decreases in volatility for returns from positive shock. Hence, it is important to use of the GARCH family models is undoubtedly helpful, but issues related to high data frequency and increased kurtosis pose distribution of the levy on return series⁽⁷⁾.

Furthermore, the majority of researches have been studied in the Saudi stock market, none of the earlier studies concentrated on the banking sector, which is the most actively traded sector on the Saudi Stock Exchange.

The main purpose of this paper is to model and estimate the daily volatility of the banking Stock Index Returns by employing EGARCH model containing base stock return characteristics, such as leverage effect and volatility clustering. and we test the impact of common 'bad' and 'good' news in stock market Saudi.

The rest of the paper is set out as follows: Section 2 shows a summary of the literature. Section 3 represents the data and methods supported in this study. Section 4 gives the estimation results. while section 5 provides the conclusion of the paper.

2- Literature review :

Ashok et al (2017)⁽⁸⁾, capturing the existence of volatility clustering and model the volatility portrait for 10 years of the BankNifty index. BankNifty index constitute the twelve almost liquid and large capitalized stocks from the banking sector, which trades on the National Stock Exchange of India. The results of the study indicated that volatility clusters were there in log-returns of BankNifty and fits ARIMA (0, 0, 1) and GARCH (1, 1). And help subordinate bank-index traders to make rational investment decisions.

Amanjot SINGH (2017)⁽⁹⁾, attempted to capture the conditional variance of the Indian banking sector stock exchange returns during the years 2005 to 2015 by using diverse GARCH depended on symmetric and asymmetric models. The results found the existence of persistence as well as leverage effects in the banking sector return volatility. The global financial crisis reinforced conditional volatility in the Indian banking sector during the years 2007 to 2009; further evidenced by Markov regime switches. The EGARCH model was detected to be the best fit model estimating time-varying variance in the banking sector. They concluded that strong implications for the market participants at the time of devising portfolio management strategies.

Almahadin and Tuna (2016)⁽¹⁰⁾, investigated the inherent nature of volatility in three of the importance indices and the Jordanian classical banks individually that were traded in the Amman stock exchange. Daily stock market returns were used during the period beginning on 3rd January 2010 until 31st December 2015. For this reason, Generalized Autoregressive Heteroscedasticity (GARCH) and its expansion GARCH-M models have been applied. The results showed that the bulk of the return series of the Jordanian commercial banks have negative skewness, relatively huge kurtosis, and contribute indication for removal from a normal distribution. The estimated models found confirmation for the existence of volatility clustering which is well captured within the GARCH framework. The results obtained from the GARCH-M model were heavily consistent with the positive relationship between risk and return. The findings also suggested that stocks of the banking sector give a larger risk premium for investors compared with the whole market and the financial sector, since the evaluated risk premium parameter was the highest one for the banking sector index relatively.

Emenike and Ani (2014)⁽¹¹⁾, checked the nature of the volatility of stock returns in the Nigerian banking sector running GARCH models. Results obtained from GARCH models suggested that stock returns volatility of the Nigerian banking sector move in clusters and that volatility persistence is high for the caseperiod. Finally, They concluded of this study showed that the degree of volatility persistence is higher for the All Share Index than for most of the banks.

Krishna Murari (2013)⁽¹²⁾, pursued to predict the short-term volatility for banking sector stock returns using the best-suited model. In testing whether the financial time series of the bank's sector at 5% level is stationary at the level or not, he had concluded that the stationarity exists for the banking sector at the level. The study was revealed to be the best ARIMA model is chosen using the lowest information criterion (among AIC, SIC, and HQ). The results found the investors in predicting the

short term volatility for bank stocks for supporting their buying or selling decisions.

3. MATERIALS AND METHODS:

This section discusses data, mean equation specification, the EGARCH model, distributions densities and evaluation methodologies.

3.1. Data

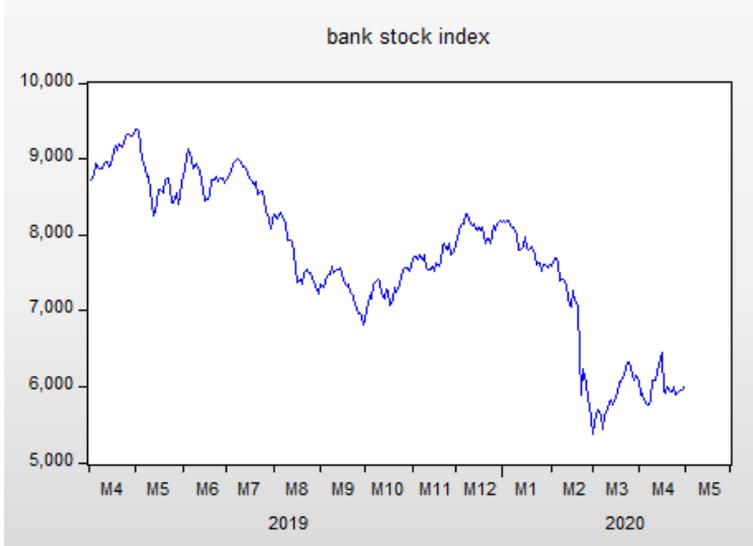
The data used in this study consists of the closing prices of sector banking in the Tadawul exchange (TBNI). We select daily data covering the period from 1st April 2019 to 30st April 2020, with 360 observations to estimate the model. The data extracted from the site <https://sa.investing.com/indices/tbfsi-historical-data>.

Since the closing prices (Figure1) are non-stationary. The following formula was used to obtain log returns:

$$R_t = [\ln(P_t) - \ln(P_{t-1})] * 100$$

where P_t and P_{t-1} are daily closing prices at time t and $t-1$ respectively. Returns are more usually practiced rather than financial asset prices for modeling purposes because financial returns can be assumed to be stationary over periods of time. Asiri and Alzeera⁽¹³⁾, supported this degree by contending that mathematically, the logarithm of the corresponded fee is producing a time collection of constantly commingled returns.

The graph in Figure 1 shows that the Bank stock index (TBNI) was around more than 9000 points in May 2019. It registered a reliable decrease during the year and closed at around 8000 at the year-end. And the index arrived at its minimum value for the first three quarters of 2020.

Figure1. change in price banking stock index (TBNI)

Source: Eviews9

We note through the curve (01) that the banking sector index achieved relatively stable performance during the second quarter of 2019, despite the relative decrease during the fifth month. However, there was a decline in performance during the third quarter of 2019, coinciding with a decline in oil revenues and a rise in the state's public debt. Besides the decrease in the share of institutional investors of total trading, which affected the general index of the Saudi stock exchange. In the fourth quarter of the same year, the performance of the index improved with the overall performance of the Saudi Stock Exchange index, which rose by 6.7% on a monthly basis, by an increase of SAR 9.025 billion in the last 2019.

For the first quarter of 2020, we note a sharp decline in performance, especially in the second month which coincided with the COVID-19 crisis, which reached its peak in February and March, besides economic reasons, the world experienced an economic contraction, followed by uncertainty about its severity and length. What affected the basic interest rates, which reached historically low levels, especially in Saudi banks and the reason was the high cost of risk and weak income from basic banking,

which caused the weak expected return on average shareholder equity.

However, in the third month of the year 2020, it witnessed a relative improvement that witnessed a remarkable fluctuation because of the uncertainty about the health situation in the world and the country in particular, This improvement was for the improvement in the financing situation because of the relative lye increase in deposits with Saudi banks, and the decrease in the cost ratio, and the decrease in operating expenses during the closing period because of the crisis.

Table 1: Descriptive statistics banking stock index, Daily Return

	Mean	Median	Maximum
Return	-0.001304	5.84E-06	0.056188
	Minimum	Std. dev.	Skewness
Return	-0.093592	0.016901	-1.486670
	Kurtosis	Jarque-Bera	Probability
Return	10.23430	721.3652	0.000000

Source: authors estimation

Descriptive statistics on the bank Stock Index return, the return series were examined to understand the behavior of stock return. The descriptive are summarized in Table 1. the bank index return, the skewness statistic is found to be different from zero indicating that the return distribution is skewed to the left. Moreover, the reveals large excess kurtosis suggests that the underlying results are leptokurtic or heavily tailed and clearly peaked about the mean when compared with the normal distribution.

3.2. Volatility Definition and Measurement :

We give a succinct interpretation of the term volatility, at least to clear up the outlook of this paper. Volatility indicates the transmission of all likely outcomes of an uncertain variable. Mostly, we are concerned with the distribution of asset returns in the markets⁽¹⁴⁾. Statistically, volatility may be counted as the standard deviation for the case:

$$\hat{\sigma} = \sqrt{\frac{1}{T-1} \sum_{t=1}^T (r_t - \mu)^2}$$

Over the T-days duration, where r_t is the return on day t and μ is the average return. Usually, the variance σ^2 is used as an indicator of uncertainty. Volatility is correlated with but not necessarily the same as, risk. Risk is related to the adverse outcome, while volatility may be attributed to a favorable outcome as a measure purely for misunderstanding⁽¹⁵⁾.

3.3. EGARCH model :

The following is the general univariate equation regarding this model :

$$r_t = \mu_i \dots \dots \dots (1)$$

The EGARCH model developed by Nelson (1991) gives an alternative designation for the conditional variance. This model relaxes the non-negativity constraint restrictions placed on Alpha and Beta in the GARCH model⁽¹⁶⁾. The model represents the asymmetric effects of good news or bad news on market volatility⁽¹⁷⁾. And the EGARCH[p,q] model is specified as follows:

$$\ln \sigma_{j,t}^2 = \omega_j + \beta_j \ln(\sigma_{j,t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \dots \dots \dots (2)$$

Where ω α β γ are parameters to be estimated. The condition that $|\beta| < 1$ is a sufficient condition for the existence of moments, for consistency, and for asymptotic normality of the EGARCH(1,1) estimators⁽¹⁸⁾. When β is relatively large, then volatility takes a long time to die out following a crisis in the market⁽¹⁹⁾. The coefficient of importance is γk . If the coefficient $\gamma k \neq 0$ in the above equation, the volatility is said to be asymmetric but when $\gamma k < 0$, then the negative news has a greater role in increasing stock returns volatility than positive news of same magnitude. However, if $\gamma k > 0$, in such a situation

the positive news has a stronger impact in increasing stock returns volatility than the negative news of the same magnitude⁽²⁰⁾.

The parameter α in Eq. (2) determines the influence of the past conditional volatility on the current conditional volatility. For the conditional volatility process to be stationary, $\alpha < 1$ is required. It is also possible to measure the persistence of volatility by examining the half-life (HL) identified by :

$$HL = \ln(0.5)/\ln(\beta) \dots \dots \dots (3)$$

which measures the time period required for the innovations to be reduced to one-half of their original size⁽²¹⁾.

According to Joanna Olbryś, the half-life of volatility shows the time taken by the volatility shock to cover half the distance back towards its mean volatility after a divergence from it⁽²²⁾.

3.4. Stationarity:

Unit root analysis is essential in time series modeling and as such, prior unit root tests were examined on the bank Stock Index series. The series revealed a trend just from the basic graphical examination in figure 1. The ADF and PP test of unit root suggesting that the series was not stationary. Following these results, we obtained returns from the bank Stock Index through a log transformation of the first lag in a process explained above. Displayed down in Table 2 are the results of the ADF and PP unit root tests.

Table 2: Unit roots for the Bank Stock Index and returns series

variable	Tests at different levels	ADF test			PP test		
		t-stat.	P-value	lag	t-stat.	P-value	lag
Bank Stock Index (TBNI)	Intercept	-0.554912	0.8768	0	-0.792543	0.8193	0
	Intercept and trend	-2.134761	0.5237	0	-2.218552	0.4770	0
	None	-1.414915	0.1462	0	-1.249791	0.1943	0
Returns	Intercept	-15.03858	0.0000	1	-15.11684	0.0000	1

Intercept and trend	- 15.02718	0.0000	1	- 15.09989	0.0000	1
None	- 14.98367	0.0000	1	- 15.10232	0.0000	1

Source: authors estimation

The variable Bank Stock Index is non-stationary at a level according to the test results, but its first log differences or returns are stationary. The Augmented Dickey-Fuller and PP unit root tests support the rejection of the null hypothesis of a unit root at a significance level of 1%, which suggests that the return series are stationary, and can be modeled directly without any further transformation.

3.5. Test for Heteroscedasticity: ARCH effect

Table 2 : Test for Heteroscedasticity

ARCH-LM	
F-Statistic	P-value
58.7859	0.0000

The heteroscedasticity ARCH LM test for the effect of heteroscedasticity in the model showed that the F-Statistic was significant with probability value of 0.0000 in table 2. These revealed the presence of the ARCH effect in the model. This allows us to use the GARCH model.

4- Estimates of EGARCH (1,1) under GED:

Table 2 presents the results of the EGARCH (1,1) model specified in equation 2 under the assumption that the residuals follow GED.

Table 3 : The EGARCH(1.1) model estimates of Bank stock index returns

	Mean equation	Variance equation			
Coefficient	U_i	ω	α	β	γ
standard errors	-0.000277	-0.850881	0.275613*	0.924204*	-0.082568**

Coefficients refer to the estimates of the mean and variance equations of the following EGARCH(1,1) model: Mean Equation: $R_t = u_i$; Variance Equation in equation (2). *, **, *** indicate the significance level at 1%, 5% and 10% respectively

Table 3 presents the estimation results of the EGARCH model of the bank stock index returns in Equations 1 and 2. The mean equation given in Table 3 suggests that the intercept not significant. And evaluation of the estimates of the variance equations provides a number of important information about the volatility of stock returns. We find the parameters ARCH(α) GARCH(β) are significant at the 1% level, and the leverage estimate (γ) (-0.825) is negative and significant, revealing a leverage effect in the returns series. Moreover, the asymmetric effects exist, implying that the impact of negative news on current volatility is larger than positive news of the same magnitude.

According to Eltahir and all⁽²³⁾, This indicates that banking is the most stable sector in the field of investment in the Saudi stock exchange. Also, this may be due to its low-cost investment, low risk and highly profitable operations. This makes investors feeling comfortable when investing in the banking sector.

An exponential GARCH methodology is also used by Suliman⁽²⁴⁾ to used to investigate the existence of leverage effect in the returns of the TASI. The results show that negative shocks signify a higher next period conditional variance than positive shocks of the same sign, which indicates the existence of leverage effects in the returns of the TASI, Saudi stock exchange during the study period.

Using a different methodology, Naseem and Robert⁽²⁵⁾, investigated the evaluate the forecasting performance of linear and non-linear generalized autoregressive conditional heteroskedasticity (GARCH) for the Tadawul Index (TASI). The results find that traders in the Saudi stock exchange might consider understanding risk in the Saudi stock exchange, which may help them in their approach to risk management strategies for the daily stock market index returns. In their study, Shaik and Syed⁽²⁶⁾, examined the symmetric and asymmetric association between the return and volatility by using different GARCH models. the result of the EGARCH model showed that the estimates were positive and significant, indicating a no-leverage

effect in the return series. The study suggests the volatility was a point of importance to financial professionals. Finally, the study suggests for investors methods of investment management, such as allocations of assets, construction of investment portfolio, managing risk, etc.

Moreover, from the background of the average reversion rate measured by half-life mean); empirical results $HL= 8.79$ are also focused on the fact that the volatility mechanism is average reversion, but it has a speed decline in half.

Thus we might be able to say that investors of the saoudi stock market preferred to hear good news than bad news when they suffer a bad time

5. Conclusion :

In this study, the presence of volatility clustering of the banking Stock Index Returns (TBNI) was tested using EGARCH models. The daily closing prices of the Bank sector index from April 01, 2019, to March 31, 2020. The unit root and ARCH tests were conducted before employing the EGARCH model. The results of the study show that the volatility follows EGARCH (1, 1) model. The results indicate strong asymmetric news impact on conditional the variance of banking Stock Index Returns, which reveals the existence of leverage effects in the returns. Bad news effects were significantly different from good news effects. Data also provide evidence of the persistent effect of volatility shocks.

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