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Modeling the volatility of stock prices for the Saudi stock market general index (TASI)

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ABSTRACT:

This paper aims to model the daily closing prices of the General Index (TASI), which expresses the Saudi stock market by studying three time period. The first period is short, which extends from (October 1, 2018 to May 21, 2020) and the intermediate extends from (January 1, 2017 to May 21, 2020), a total period extends from (April 26, 2015 to May 21, 2020). GARCH family models were used through identification, estimation, selecting the best model, diagnosis checking of the model and forecasting. The results concluded that the best model for representing the time series data for the intermediate and total period is the model is EGARCH (1,1). As for the short period, the best model is TGARCH (1,1).

Keywords: GARCH Models, Stock Prices, The Financial Market, volatility

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1. Introduction

Financial markets are considered an essential pillar of the economy of any country in the world, because the efficiency of financial markets depends on the behavior of stock prices and the development of trading systems in them, and also reach to the fair value of stock price. Financial markets often come across price movements known as the state of (Volatility) which is one of the main variables in financial decision-making. Most of the practical studies applied to the time series of the returns of stock traded in financial markets. These series have a set of characteristics and attributes of them, such as leptokurtosis, volatility clustering, leverage effects and Heteroscedasticty. Modeling of Conditional Heteroscedasticty has become one of the most important recent developments in time series and thus ARCH(p) and GARCH(p,q) models have emerged. The researchers toward an interest in risk and an insufficient forecasting of expected returns from stocks and bonds Traded in financial markets, despite the importance of the ARCH(p) and GARCH(p,q) models, they are directed at criticisms of some economists such as (Nelson, 1991) and (Cao & Tsay, 1992), especially with regard to determining the relationship of. The squared of error term with conditional variance which leads to the emergence of other models among them (EGARCH (Exponential GARCH), TGARCH (Threshold GARCH) and PGARCH (Power GARCH) as well as (GARCH Mean) GARCH–M even taking into consideration the various positive and negative effects of shocks. Studies have been conducted Scientific proof of the efficiency of the family of GARCH models through practical application in a large number of financial markets in the world. The Saudi financial market is considered one of the most important Arab and Gulf markets, where the beginning of trading in stock at the end of the seventies of the last century and is one of the markets that were affected. The global financial crisis [2] where this market witnessed the attention of researchers, including Hassan Ghadban, Hassan Al-Haghuj in (2012) who tried to determine the impact of volatility analysis in the Saudi stock market by examining structural transformations using GARCH-M models from 2001-2010 and reached. The researchers reported that negative shocks via leverage increase in volatility compared to positive shocks [3]. Abdalla [4] has examined the effect of inflation rates on the returns and volatility of the Saudi general index for the period 1990-2011 by using GARCH models with a set of applied methods that have found that the effect of inflation rates has no significant in the return equation. There has been an significant effect Positive inflation, when included in the equation for conditional variance. The importance of GARCH models in modeling and forecasting volatility as a mechanism for crisis management and early warning through his study of nine Arab stock exchanges, including Saudi Arabia, for the period 2007-2012 is highlighted in ref [1] . Lokofi and Al-Sheikhi discussed the modeling of stocks price volatility for Saudi Telecom Union for the period 2010-2015 using a number of symmetrical and asymmetric ARCH models and it was found that the best model represents the time series ARIMA (1,1,3) -TGARCH (1,1) [3]. It turns out that positive shocks with good news give less volatility than negative shocks with negative news.

In this paper, we aim to study the market, to find the best model that expresses the Saudi stock market through the overall trading index (TASI) for three periods after the daily closing prices. Period studied in this research are (April 26, 2015 to May 21, 2020), short series (from October 1, 2018 to May 21 2020), which includes (418) observation and the intermediate series (from January 1, 2017 to May 21, 2020), which included (851) observation as well as (1271) observation included in the full series from (April 26,2015to May 21,2020). The models used in study are (ARCH, ARCH-M, GARCH, GARCH-M, TGARCH, TGARCH-M, PGARCH and PGARCH-M).

2. Materials and methods

2.1. Autoregressive conditional heteroscedasticty (ARCH (M))

Engle proposed an ARCH (m) model in 1982 to address the volatility in time series [8] and based on the Autoregressive of conditional variance, i.e. the variance of the current error limit is dependent on the square error limits of previous periods and their formula:

$$\text{Mean equation} \qquad \varepsilon_t = z_t \sigma_t \tag{1}$$

$$\text{Variance equation} \qquad \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_m \varepsilon_{t-m}^2 \tag{2}$$

where $z_t \sim N(0,1)$ iid, α_0>0 and α_i ≥0 for i >0

2.2. Generalized autoregressive conditional heteroscedasticty (GARCH Model (1, 1))

The researcher (Bollerslov, 1986) [6] presented the generalized autoregressive conditional Heteroscedasticty GARCH. This model allows conditional variation to be dependent on its previous form and its form

$$\text{Mean equation} \qquad \mathrm{X_t} = \mu + \varepsilon_t \tag{3}$$

$$\varepsilon_t = z_t \sigma_t$$

$$\text{Variance equation} \qquad \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{4}$$

Where $\boldsymbol{X_t}$ represents the return time series $\boldsymbol{\mu}$ represents the average return, $\boldsymbol{\varepsilon_t}$ represents the remaining return, σ_t is the conditional standard deviation, and α_0 , $\alpha_1 and$ β_1 are non-negative parameters

2.3. The exponential generalized autoregressive heteroscedasticty (EGARCH (1, 1))

Nelson 1991introduced this model [10], which is characterized by entering the logarithm of the conditional variance and the form of Variance equation:

$$ln\sigma_t^2 = \alpha_0 + \alpha_1 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_1 ln\sigma_{t-1}^2 \tag{5}$$

Whereas γ measures the asymmetric effect, if its value is equal to zero, this means that positive and the negative shocks will have the same effect on the instability of the stock returns. If it is negative, this means that negative shocks have a greater contribution to oscillations than positive shocks.

2.4. The threshold generalized autoregressive conditional heteroscedasticty (TGARCH (1,1))

This model was proposed by the researchers (Rabemananjara & Zakoian) in 1991 [14] and the Variance equation:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} \tag{6}$$

Since γ is the asymmetric effect and I_{t-1} is the variable used to distinguish between good and bad news when $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ this indicates the bad news and when $I_{t-1} = 0$ if $\varepsilon_{t-1} \geq 0$ the good news. The specification of the TGARCH model assumes that unexpected changes in market returns will have a different impact on stock return fluctuation σ_t^2

2.5. The power generalized autoregressive conditional heteroscedasticity (PGARCH (1,1))

This model was introduced by researchers Ding and Granger in 1993 [7] to deal with asymmetry and the Variance equation is:

$$\sigma_t^{\delta} = \alpha_0 + \beta_1 \sigma_{t-1}^{\delta} + \alpha_1 (|\varepsilon_{t-1}| - \gamma \varepsilon_{t-1})^{\delta} \quad (7)$$

Since α_0 is constant, $\alpha_1$and β_1 are the parameters of ARCH and GARCH ,the γ is leverage parameter and δ is the power parameter δ> 0, γ≤1 when $\delta = 2$ the equation above becomes the classic GARCH model that allows leverage effects and when δ = 1 the conditional standard deviation will be estimated.

2.6. The GARCH-in-Mean GARCH-M (1,1)

These models are considered to be the most important models used in assessing risk in financial markets, by measuring the relationship between return and risk and studying the market reaction, risk premium when the market is exposed to a negative shock, such as economic crises, and in it, the variance of the conditional is an explanatory variable for the conditional average where the Variance equation is:

$$\text{Mean equation} \qquad X_t = \mu + \lambda X_{t-1} + \boldsymbol{\varepsilon_t} \quad (8)$$

Where $\boldsymbol{X_t}$ represents the time series of returns $\boldsymbol{\mu}$ represents the average return, $\boldsymbol{\varepsilon_t}$ represents the residual return and $\boldsymbol{\lambda}$ is the risk factor, if its value is positive, this indicates that the return is positively correlated with its instability, in other words, the higher average return is the result of an increase in conditional variance [9].

3. Experimental procedures

The data represents the daily closing prices of the TASI index, which expresses the Saudi stock market through studying three time periods. The first (short time series) extending from (October 1, 2018 until May 21, 2020) includes (418) observation and the second period (intermediate time series) extended from (January 1, 2017 to May 21, 2020) which included (851) observation and the third period (full time series) that Includes (1271) observation that run from (April 26, 2015 to May 21, 2020), Where the time series were converted to the daily return series through the formula: $X_t = \log(\frac{P_t}{P_{t-1}})$

Where as X_t is the returns series and P_t is the prices index for the current day and P_{t-1} the prices index for the previous day. Figures (1) and (2) show the full series of closing prices and daily return series for period from April 26, 2015 to May 21, 2020.

Figure 1. Daily closing prices of TASI-Index

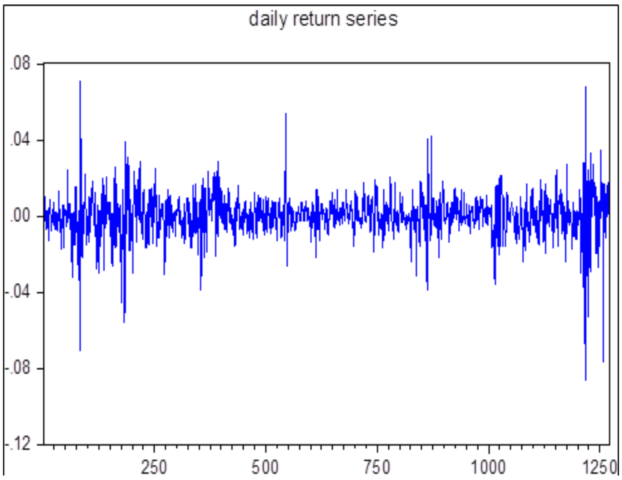


Figure 2. Daily Return Series

3.2. Summary statistics and testing

Table 1 illustrates descriptive statistical indicators that describe each of the return series (short, intermediate and full series). We find that the value of the Skewness coefficient for the three return series is negative, that is the distribution is Skewness to the left, which means that stock prices are affected by the negative shock more than positive shocks, and we find that the value of the kurtosis factor is greater than 3 indicating the presence of outlier values in the time series Especially in the intermediate series extending from (January 1, 2017 to May 21, 2020) where the value of kurtosis (17.26). For the Jarque-Bera test, the value of (Prob = 0) for the three time series is indicative that they do not follow the normal distribution they do not follow the normal distribution. This is what characterizes the financial time series

Table 1. Descriptive statistics for return series

	Mean	Median	Max	Min	Skewness	Kurtosis	Jarqua-Bera	Prob.	N.
Full series	-0.00025	0.000335	0.071208	-0.08685	-0.95742	12.37575	4845.649	0	1271
Intermediate series	-3.1E-05	0.000458	0.068315	-0.08685	-1.24942	17.25686	7419.866	0	851
Short series	-0.00031	0.000912	0.068315	-0.08685	-1.40429	13.83773	2177.86	0	418

Table 2 presents the results of the ARCH -LM test, through which it is possible to verify the presence of the ARCH effect to the residuals . Here we note that the value of (Prob = 0) for (Obs R-Squared and F-statistic), which means that there is a (Heteroscedasticty) effect.

Table 2. The results of the ARCH -LM test

Full series	F statistic	330.6819	Prob. F(1,1267)	0.000*
	$n * R^2$	262.6526	Prob. Chi square	0.000*
Intermediate series	F statistic	225.5833	Prob. F(1,847)	0.000*
	$n * R^2$	178.5598	Prob. Chi square	0.000*
Short series	F statistic	120.0536	Prob. F(1,414)	0.000*
	$n * R^2$	93.51554	Prob. Chi square	0.000*

*Indicates significance at 5% level

Table (3) present the ADF test (Augmented Dickey Fuller Test Statistic) for both the closing price series and the return series, where the test we reject of the hypothesis of unit root for the return series for (short, intermediate and full series) studied, i.e. the return series dose not contain a unit root therefore it is stationary. Thus, no need to difference the return series. while the three daily closing price series is no stationary because it has a unit root.

Table 3. The ADF test for both the closing price series and the return series

Time period	return series				closing prices series			
	ADF test	Test Critical values			ADF test	Test Critical values		
		1%	5%	10%		1%	5%	10%
Full series	-13.552*	-3.435	-2.864	-2.568	-2.530	-3.435	-2.864	-2.568
Intermediate series	-26.214*	-3.438	-2.865	-2.569	-1.893	-3.438	-2.865	-2.569
Short series	-18.758*	-3.446	-2.868	-2.570	-1.084	-3.446	-2.868	-2.570

*Indicates significance at 5% level

3.3. Estimation

The model estimated using the maximum likelihood method, and the results of the estimate were presented in Table 4, which represents the estimate of the Mean Equation while The Variance Equation was presented in Tables 5 and 6.

Table 4. Parameter estimation for mean equation to the models for each series

Time period	model	Mean Equation Constant	model	Mean Equation Constant	λ (risk)
Full series	ARCH	2.45E-04	ARCH-M	-0.00084	0.122636
	GARCH	0.000119	GARCH-M	-0.00107	0.134937
	TGARCH	-0.00012	TGARCH-M	5.01E-05	-0.0206
	EGARCH	-0.00015	EGARCH-M	-0.00017	0.002293
	PGARCH	-0.00015	PGARCH-M	-5.44E-05	-0.011153
Intermediate series	ARCH	0.000342	ARCH-M	-0.0029*	0.399989*
	GARCH	0.000182	GARCH-M	-0.00132	0.181286
	TGARCH	-5.95E-06	TGARCH-M	-0.00013	0.016063
	EGARCH	-5.62E-05	EGARCH-M	-0.00032	0.035638
	PGARCH	-5.08E-05	PCARCH-M	-0.00051	0.059587
Short series	ARCH	0.000578	ARCH-M	-0.00275*	0.35289*
	GARCH	0.000306	GARCH-M	9.27E-05	0.021954
	TGARCH	-0.00013	TGARCH-M	0.001139	-0.149452
	EGARCH	-7.25E-05	EGARCH-M	-0.00275*	0.35289*
	PGARCH	-3.60E-05	PGARCH-M	0.000781	-0.091259

*Indicates significance at 5% level

Table 5. parameter estimation for variance equation to the models for each series

Time period		Full series		Intermediate series		Short series	
model	**Variance Equation**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**
ARCH	α_0	3.19E-05	0*	2.78E-05	0*	3.88E-05	0*
	α_1	0.213233	0*	0.179024	0*	0.138489	0.0086*
	α_2	0.197631	0*	0.206698	0*	0.179189	0.0046*
	α_3	0.063899	0.0114*	0.057003	0.0497*	0.057825	0.2378
	α_4	0.191917	0*	0.197368	0*	0.233964	0.0001*
	α_5	0.18583	0*	0.193207	0*	0.260941	0*
GARCH	α_0	4.90E-06	0*	4.86E-06	0*	5.04E-06	0.0119*
	α_1	0.193933	0*	0.203976	0*	0.208887	0*
	β_1	0.785892	0*	0.770538	0*	0.787312	0*
TGARCH	α_0	4.07E-06	0*	3.89E-06	0*	3.26E-06	0*
	α_1	0.080167	0*	0.09241	0*	-0.09473	0*
	γ	0.167573	0*	0.171702	0*	0.19437	0*
	β_1	0.816364	0*	0.80286	0*	0.963183	0*
EGARCH	α_0	-0.60394	0*	-0.625334	0*	-0.51022	0.0001*
	α_1	0.28987	0*	0.321116	0*	0.280933	0*
	γ	-0.11226	0*	-0.102799	0*	-0.10874	0*
	β_1	0.958134	0*	0.958825	0*	0.966803	0*
PGARCH	α_0	8.19E-05	0.2687	9.89E-05	0.3487	0.000197	0.4694
	α_1	0.161765	0*	0.182936	0*	0.156567	0*
	γ	0.367152	0*	0.334263	0*	0.438174	0.0001*
	β_1	0.835973	0*	0.822478	0*	0.856731	0*
	δ	1.344249	0*	1.293967	0*	1.110394	0.0002*

*Indicates significance at 5% level

From Tables 4 and 5, all parameters of the models were significant in periods of the specified series except for the constant parameter in PGARCH model in addition to the α_3 parameter of ARCH model in the short series. Also, we note that in Table 6, all parameters of the models were significant except for The constant parameter for the PGARCH-M model was also not significant for all the specified time series specified as well as the parameter α_3, α_2 for the ARCH-M model in the short series.

Table 6. parameter estimation for variance equation to the models for each series

Time period		Full series		Intermediate series		Short series	
model	**Variance Equation**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**
ARCH-M	α_0	3.17E-05	0*	2.56E-05	0*	3.55E-05	0*
	α_1	0.213047	0*	0.191963	0*	0.124099	0.0084*
	α_2	0.196798	0*	0.148123	0*	0.100899	0.1278
	α_3	0.060138	0.0155*	0.059103	0.0252*	0.055506	0.1868
	α_4	0.200124	0*	0.241957	0*	0.301534	0*
	α_5	0.187975	0*	0.222179	0*	0.323871	0*
GARCH-M	α_0	5.12E-06	0*	5.20E-06	0*	5.04E-06	0.015*
	α_1	0.199882	0*	0.215119	0*	0.20906	0*
	β_1	0.779158	0*	0.758496	0*	0.7873	0*
TGARCH-M	α_0	3.97E-06	0*	3.96E-06	0*	1.93E-06	0.0118*
	α_1	0.078339	0*	0.094008	0*	-0.08523	0*
	γ	0.169151	0*	0.170331	0*	0.18327	0*
	β_1	0.818472	0*	0.801098	0*	0.976614	0*
EGARCH-M	α_0	-0.60509	0*	-0.646012	0*	-0.47616	0.0002*
	α_1	0.290028	0*	0.325592	0*	0.271518	0*
	γ	-0.11217	0*	-0.10022	0*	-0.11238	0*
	β_1	0.958024	0*	0.957015	0*	0.96972	0*
PGARCH-M	α_0	7.96E-05	0.2681	0.000124	0.367	0.000118	0.4997
	α_1	0.160999	0*	0.188992	0*	0.136948	0.0004*
	γ	0.369979	0*	0.315893	0*	0.500761	0.0003*
	β_1	0.83711	0*	0.815107	0*	0.875312	0*
	δ	1.347096	0*	1.262433	0*	1.176503	0.0001*

3.4 Selecting the best model

The criteria for selecting the best model was (the Akaike information criteria, Schwarz and Hannan-Quinn criteria) are compered for all the specified models, where it was indicates that EGARCH (1,1) is the best model for the full and intermediate series while the best model in the short series was TGARCH(1,1) model.

Table 7. Model Comparison between Akaike,Schwarz and Hannan-Q criteria

Time period	criterion	ARCH	GARCH	TGARCH	EGARCH	PGARCH
Full series	Akaike info	-6.372	-6.37915	-6.39844	-6.40404	-6.400017
	Schwarz	-6.34363	-6.36294	-6.37818	-6.38378	-6.375702
	Hannan-Quinn	-6.36134	-6.37306	-6.39083	-6.39643	-6.390883
Intermediate series	Akaike info	-6.58073	-6.584	-6.5979	-6.6006	-6.598792
	Schwarz	-6.54166	-6.56167	-6.56999	-6.57269	-6.565296
	Hannan-Quinn	-6.56577	-6.57545	-6.58721	-6.58991	-6.585961
Short series	Akaike info	-6.1641	-6.16569	-6.21873	-6.18898	-6.181273
	Schwarz	-6.0964	-6.127	-6.17037	-6.14062	-6.123243
	Hannan-Quinn	-6.13733	-6.1504	-6.19961	-6.16986	-6.158331

Time period	criterion	ARCH-M	GARCH-M	TGARCH-M	EGARCH-M	PGARCH-M

Full series	Akaike info	-6.37169	-6.37948	-6.39691	-6.40247	-6.398455
	Schwarz	-6.33927	-6.35922	-6.37259	-6.37815	-6.370087
	Hannan-Quinn	-6.35951	-6.37187	-6.38778	-6.39333	-6.387799
Intermediate series	Akaike info	-6.58716	-6.58425	-6.59557	-6.59836	-6.596535
	Schwarz	-6.54249	-6.55634	-6.56208	-6.56487	-6.557457
	Hannan-Quinn	-6.57005	-6.57356	-6.58274	-6.58553	-6.581566
Short series	Akaike info	-6.16383	-6.16095	-6.21916	-6.18467	-6.177518
	Schwarz	-6.08646	-6.11259	-6.16113	-6.12664	-6.109816
	Hannan-Quinn	-6.13324	-6.14183	-6.19622	-6.16173	-6.150751

3.5. Diagnosis chickening

After selecting the best models for each of the specified periods, the suitability and efficiency of the models are used ARCH-LM test, present in Table 8 the value of Prop> 0.05. Then, we accepted the null hypothesis meaning that no ARCH effect in the residuals. The Ljung-Box test is also used to determine the Autocorrelation of the square residual were the value of Prop <0.05 for all displacements from lag1 to lag36 for the specified models present in Table 9, which means no serial correlation in the residuals therefore the models selected representing data volatility.

Table 8. ARCH-LM test for ARCH effects

Time period	ARCH-LM test		**model**
Full series	F statistic	0.267349	EGARCH(1,1)
	$n * R^2$	0.267714	
	Prob.F(1,1267)	0.6052	
	Prob. Square	0.6049	
Intermediate series	F-statistic	0.121508	EGARCH(1,1)
	$n * R^2$	0.121777	
	Prob.F(1,847)	0.7275	
	Prob. square	0.7271	
Short series	F-statistic	2.943941	TGARCH(1,1)
	$n * R^2$	2.937276	
	Prob.F(1,414)	0.0869	
	Prob. square	0.0866	

Table 9. Ljung-Box test for all time lags

Ljung-Box Test	Full series		Intermediate series		Short series	
lag	EGARCH(1,1)		EGARCH(1,1)		TGARCH(1,1)	
	Q stat	probability	Q stat	probability	Q stat	probability
1	0.2685	0.604	0.1223	0.727	2.9639	0.085
5	2.4191	0.789	2.0432	0.843	5.7339	0.333
10	8.9446	0.537	9.2879	0.505	12.64	0.245
15	14.282	0.504	13.085	0.596	14.233	0.508
20	15.95	0.72	14.504	0.804	16.457	0.688
25	19.092	0.793	18.262	0.831	19.421	0.777
30	20.315	0.908	20.421	0.905	21.394	0.875
35	23.058	0.939	24.148	0.916	24.065	0.918
36	28.632	0.804	29.024	0.789	24.928	0.918

A Jarque-Bera test was performed for each of the best models for each time periods as present in Table 10, where the value of (Prob = 0) for models indicates that the Standardized Residuals series for each models does not follow the normal distribution, which is characterizes Financial time series.

Table 10. Jarque-Bera test statistics

Time period	model	Jarque-Bera	Probability
Full series	EGARCH(1,1)	407.3071	0*
Intermediate series	EGARCH(1,1)	439.7038	0*
Short series	TGARCH(1,1)	262.3229	0*

Consequently, the variance equation of EGARCH (1,1) models for the full series as follows:

The formula for the variance equation of is for the EGARCH model (1,1) for the Intermediate full series as

For the short series the variance equation for the TGARCH (1,1) as follows:

3.6. Forecasting

The forecasting process was conducted for a series of daily closing prices (20) days for specified models in the time period using the dynamic method . Figure below clarify the accuracy of the forecasting through the proximity between the forecast series and the actual series the evaluation of forecasting using static forecast for models in the time periods, where the test values for the best models is the smallest within each time period present in Table 11, which gives us a positive indication of the accuracy of the forecasting.

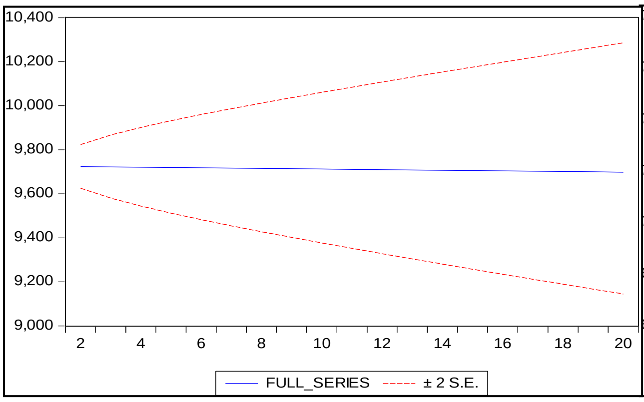


Figure 3. Full series

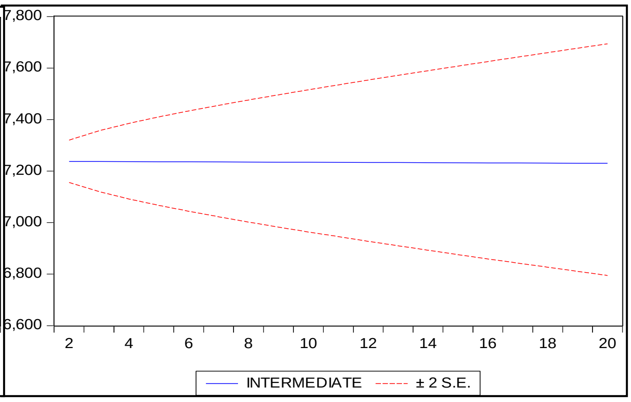
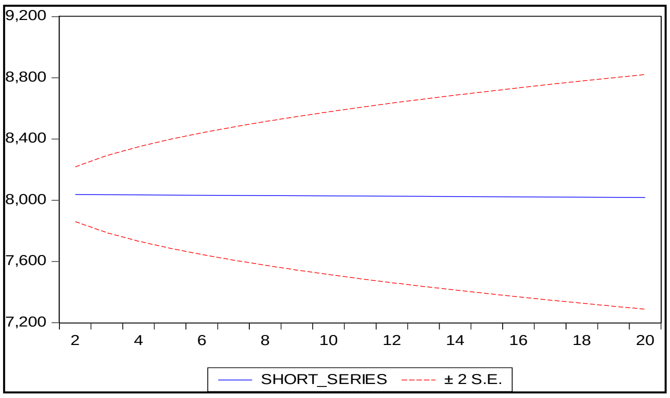


Figure 4. Intermediate serie



EFigure 5. Short series

Table 11. Static forecast for the specified models

Time period	model	Root mean squared error	Mean absolute error	Mean abs. percent error	theil inequality coefficient	Theil U2 Coefficient	Symmetric MAPE
Full series	EGARCH(1,1)	72.74107	60.53329	0.620549	0.003739	1.285368	0.621975
Intermediate series	EGARCH(1,1)	246.9245	206.6522	2.979008	0.01731	4.275551	2.916559
Short series	TGARCH(1,1)	352.8566	295.5141	3.888382	0.022387	2.416995	3.781941

4. Conclusions

This paper focuses to model the daily closing prices of the General Index (TASI), which expresses the Saudi stock market by studying three time periods ,the results showed The stock prices are affected by negative shocks more than positive shocks in all the time periods and the return series content outlier values especially in the intermediate series, the return series in time period is stationary with an effect (heteroscedastisticity) while not following the normal distribution, which is characteristic of financial time series. EGARCH (1,1) model was the best model selecting in intermediate and full series while TGARCH (1,1) model was the has the best in the short series period. that there is continuity in volatility with an asymmetric effect and the leverage effect that negative shocks associated with bad news cause more volatility in relation positive shocks associated with good news. The test of residues of the selected models are no serial correlation and no ARCH effect, and this confirms the accuracy in their selection. Finally The static of the forecasting accuracy tests showed indication of the accuracy of the forecasting meaning that the preference of the models selected within each time period.

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