Improve the Forecasting Accuracy using GJR-GARCH and MODWT (C6)

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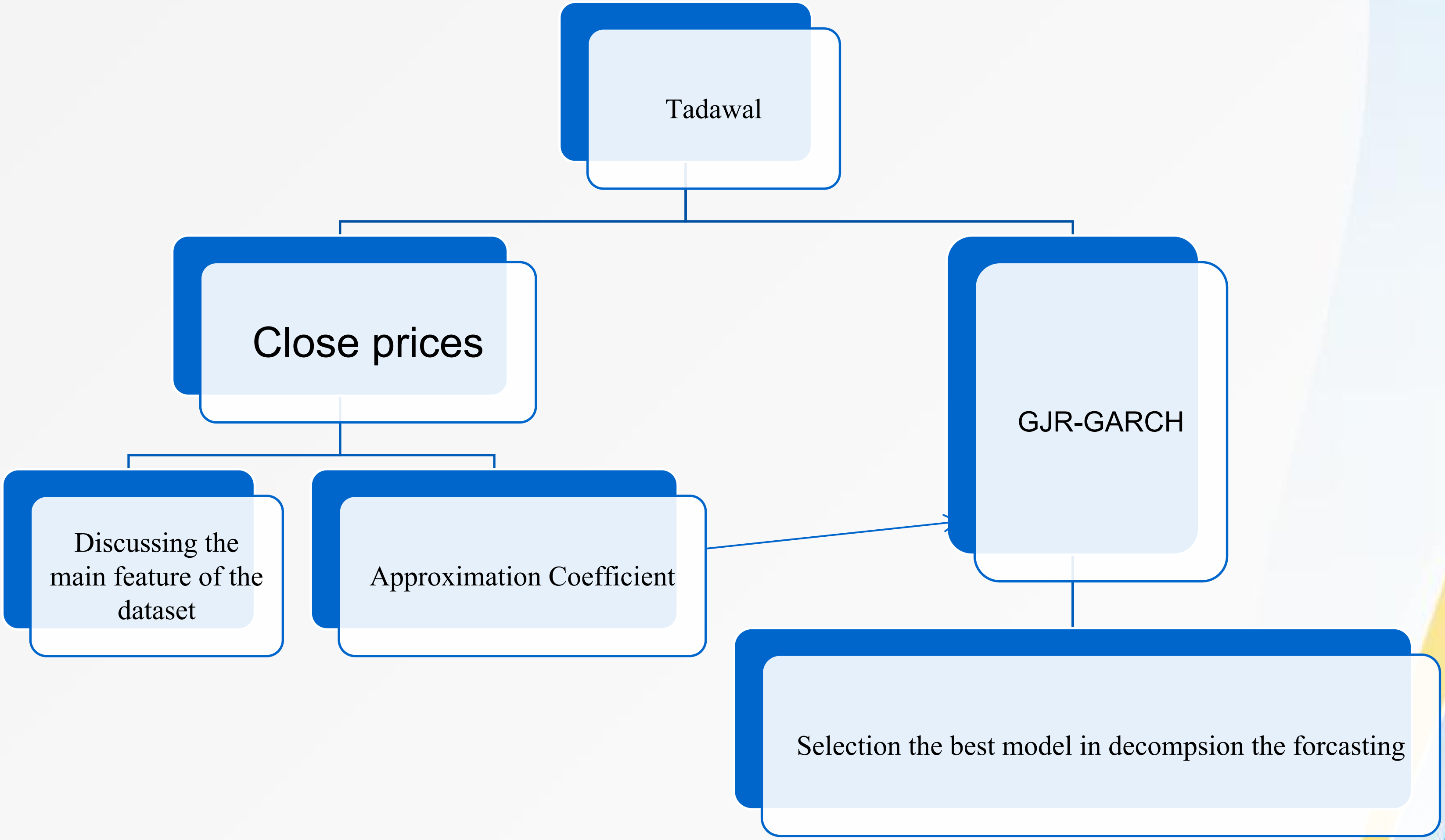
Abstract

This empirical research aims to model and improve the volatility pattern's forecasting accuracy by employing the Saudi Arabia stock market (Tadawul). This study uses daily closed price index data from October 2011 to December 2019 with the number of observations is 2048. In order to achieve significant results, this study employs many mathematical functions which are non-linear spectral model, Maximum overlapping Discrete Wavelet Transform (MODWT) coiflet(c6), autoregressive integrated moving average (ARIMA) model and the Glosten-Jagannathan-Runkle Generalized Autoregressive Conditional Heteroskedasticity (GJR-GARCH) models. The present study's significant findings are that all the previous event during the mentioned period of time will be explained while a new forecasting model will be suggested by combining the best MODWT function (C6) and the fitted GJR-GARCH model. Moreover, the present study also shows that the ability of MODWT in decomposition the stock market data, highlighting the significant events which have the most highly volatile data and improving the forecasting accuracy. The performance of the forecasting will be evaluated based on some mathematical criteria such as Mean absolute percentage error (MAPE), Mean absolute scaled error (MASE) and Root means squared error (RMS).

Methodology



In order to make a fair comparison then we do the following; applying 90% of the dataset (original data and the transformed data) for the suggested model then selecting the best model. Then applying the best model with the other suggested models for the rest data (10%).

GJR-GARCH

The GJR-GARCH model of Glosten et al (1993) models positive and negative shocks on the conditional variance asymmetrically via the use of the indicator function I.

$$\sigma_t^2 = \left(\omega + \sum_{j=1}^{m} \zeta_j v_{jt} \right) + \sum_{j=1}^{q} (\alpha_j \varepsilon_{t-j} + \gamma_j (I_{t-j}) \, ({\varepsilon^2}_{t-j}) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

where γ_j now represents the 'leverage' term. The indicator function I takes on value of 1 for $\varepsilon < 0$ and 0 otherwise. Because of the presence of the indicator function, the persistence of the model now crucially depends on the asymmetry of the conditional distribution used. The persistence of the model $\widehat{P}$ is,

$$\widehat{P} = \sum_{j=1}^{q} \alpha_j + \sum_{j=1}^{P} B_j + \sum_{j=1}^{q} \gamma_j k,$$

Where k is the expected value of the standardized residuals z_t below zero (effectively the probability of being below zero).

$$k = E\left(I_{t-j} {z^2}_{t-j}\right) = \int_{-\infty}^{0} f(z, 0, 1, \ldots) dz$$

where f is the standardized conditional density with any additional skew and shape parameters. In the case of symmetric distributions the value of k is simply equal to 0.5.

Results

Table 1 Descriptive statistic of returns and closing prices in Saudi stock market

		Return	Closed Price
N		2026	2027
Minimum		-0.0755	5416.4700
Maximum		0.0855	11149.3600
Mean		0.0002	7735.5495
Std. Deviation		0.0107	1156.9609
Skewness	Statistic	-0.5497	0.5519
	Std. Error	0.0544	0.0544
Kurtosis	Statistic	10.7936	-0.1951
	Std. Error	0.1087	0.1087

Result

Table 4. GARCH- MODWT models for 90% and 10% of observations

Sample %	GARCH-MODWT models	ARIMA(p, d ,q)	RMSE	MAE	MAPE	MASE
90% of observations	c6	(2,1,2)	0.000496	0.000205	1.8895	0.402738
	ARIMA-direct	(0,1,0)	0.001456	0.0006	4.833779	0.997392
	ARMA&GARCH	(1,1)	0.009654	0.008364	83.65335	-
10% of observations	c6	(5,1,2)	0.003986	0.003097	45.20488	0.946989
	ARIMA-direct	(0,1,1)	0.004379	0.003437	54.42026	0.947027
	ARMA&GARCH	(1,1)	0.009856	0.009438	4455.461	-

Conclusion

- In this study, the volatility pattern of Saudi Arabia stock market (Tadawul) is modeled, studied and improve its forecasting accuracy using all closed price index from October 2011 to December 2019 using non-linear spectral model which is Maximum overlapping Discrete Wavelet Transform (MODWT) coiflet(c6) and GJR-GARCH model. Therefore, some of fluctuations and events were discussed. Moreover, all the previous event during the mentioned period of time will be explained. Furthermore, a new model is modified which is GJR-GARCH-MODWT using (c6 function) , this model is the best model compared with other suggested models which are ARIMA direct with GJR-GARCH model based on statistical criteria such as MSE, RMSE, MAE and MAPE. As a result, the ability of MODWT in decomposition, highlighting the significant events and forecasting were showed.

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Thank You