Identification of Finite-Mixture of ARIMA-GARCH Model for forecasting NIFTY50

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Forecasting of stock prices and indices using different time-series models always poses a challenge for selection of appropriate model based on its predictive efficacy. It is observed in past that people get very high returns on one time line and make loss on the other time line. Thus, it is difficult for any trader, investor or asset manager to create portfolio value for sustainable growth in portfolio value in today's scenario. So, here the purpose of this study is to test and suggest the most fitted time-series model. For that, it is required to confirm the normality and more importantly, whether data is stationary or non-stationary. Data were collected for the NIFTY50 indices of India from NSE India. In this study, various ARIMA (p,d,q) models were tested and best-fit model was selected using Box-Jenkins methodology. This selected model was compared with GARCH (1,1) and ARIMA (p, d, q) - GARCH (1, 1) to yield the best-fit model for forecasting of indices. At last, 10 points forecasting were shown using best model of prediction for NIFTY50. Thus, traders and asset managers can leverage the benefits using the suggested model for accurate prediction of indices for the purpose of trading gains.

Key words: Time Series, ARIMA, Box-Jenkins, Nifty50, GARCH, Sustainable Returns

INTRODUCTION

In financial investments, every stakeholder desires to get higher returns than the average return, and thus use various fundamental or technical tools to satisfy their inner urge. In practicing such tools, they can get either huge profits or huge loss on different time-lines. Therefore, getting consistent returns in portfolio is always poses a challenge to any investor or trader and this demands an identification of model which assures consistent returns and eventually sustainable growth in their portfolios' valuation in longer run.

However, practice of fundamental or technical analysis as a predictive tool for stock price or index is not worthy in case of perfectly efficient market. No one could hope to earn consistently higher returns than a naive investor could do. Many researchers try to find out state of market (whether it is in weak form, semi-strong form or strong form of efficiency). Past research shows that Indian market is not in its weak form of efficiency (Joshipura, 2009). Therefore, there is a possibility of predicting price based on its historical price. However, stock prices and indices have been considered to be time-series and require some time-series model for the prediction. In literature as observed by Hossain and Nasser (2011), many classical models have been developed in predicting financial time series.

Practice of fundamental or technical analysis as a predictive tool for stock price or index is not worthy in case of perfectly efficient market.

This research attempts to identify the right model of time-series for the purpose of forecasting NIFTY50.Thus, this research provides a method of estimation of time-series model by comparing all possible models among themselves which enable investor or trader for maximizing their wealth for sustainable growth in today's scenario.Using autoregressive integrated moving average model(hereafter ARIMA), these relationships become equations in an interlinked system of equations.NIFTY50 stock returns are stationary data which satisfies necessity condition of ARIMA (Dickey and Fuller, 1981; Granger and Newbold, 1974; Tse, 1996, 1997).Moreover, this study utilizes Box-Jenkins methodology to forecast stock prices or indices as it is appropriate when observations are statistically dependent on or related to each other (Tse, 1997).

Current research aims to estimate ARIMA, GARCH and combination of these models for better prediction and value creation for investor.

But, it is important to identify most appropriate ARIMA model for NIFTY50 closing price forecasting, Box-Jenkins Methodology is used to propose a model with careful examination (Box and Jenkins, 1976).On the contrary, for stock prices or indices, mean values do not change with time but variances do change. Therefore, it is believed that generalizedautoregressive conditional heteroskedasticity (hereafter GARCH) is more suitable for forecasting NIFTY50 with variable variances. Considering this basic variability of stock prices or indices, current research aims to estimate ARIMA, GARCH and combination of these models for better prediction and value creation for investor.

In this present work, next section refers to review of literature relating to different economic models for time-series data. Based on this, ARIMA and GARCH model are estimated using NIFTY50 data from 3rd January, 1994 to 31st December, 2012. Next, two models were combined to develop a new model striving higher accuracy level for NIFTY50 closing price prediction. Findings were discussed followed with implications and limitations of the study.

REVIEW OF LITERATURE

Univariate time-series forecasting literature highlights the wide popularity of some traditional linear models and among them ARIMA was common technique. Box and Jenkins (1976) developed the first model combining three basic class of variation models namely AR (Auto regression), I (Integrated series), and MA (moving average). The applications of an ARIMA model were well documented in various studies such as Cleary and Levenbach (1982), Barras (1983), Hanke and Reitsch (1986), Nazem (1988), Herbst (1992), andChow and Choy (1993). The ARIMA technique assumed any particular pattern in the historical data of the series to be forecasted. And that's why even if market was seem to be efficient, one could use ARIMA for the prediction of NIFTY50 closing price.

Recently, ARIMA model was developed using an iterative approach for identification of best-fit model from a general class of models. ARIMA models were excellent for short-term factors which are expected to change slowly (Tse, 1997).Ordinary and partial autocorrelation were incorporated to determine stationary data in ARIMA model. Opposite to this, sometimes presence of non-stationary data in stock prices can be identified through plot of values in correlogram which do not diminish at large lags.When the original series or correlogram exhibited non-stationary, successive differencing was carried out to fit for ARIMA model.In the literature for univariate time-series forecasting, Box and Jenkins (1976) ARMA approach on stationary time series was a most powerful model.

In conventional econometric models, the variance of the disturbance was assumed to be constant. But many economic and financial time series such as exchange rates, stock market indices, market returns, inflation rate, etc. demonstrated large and small disturbances unequally (Tse, 1997). This was a form of heteroskedasticity where in variance of the disturbance depends on the size of preceding disturbance and hence the conditional variance is non-constant over the sample period.

In fact, simpler autoregressive and moving average models were actually special cases of ARIMA class-of-models. In this vein, Box and Jenkins (1976) developed a model using mean series only. Further, Engle (1982) developed a model using mean and variance of a series simultaneously so called autoregressive conditional heteroskedastic (ARCH) and used in Van Dijk*et al.* (1999, 2000) and Ronchetti and Trojani (2001). Later on, this original work was further extended by Bollerslev (1986) who has modeled the conditional variance to be an ARMA process and this extended work was known as the GARCH process. GARCH model was widely applied by Cheong (2009), Wei et al. (2010), Nomikos and Pouliasis (2011), Hou and Suardi

(2012) for energy market volatility forecasting. However, studies such as Ray (1988), Wang and Fawson (2001), Alexander and Lazar (2004, 2006) andDrakos*et al*. (2010)used GARCH for stock forecasting.

For intricacy check specially, many studied were performed in various contexts to show the robustness of these models. First attempt was made by Wong *et al.* (1998). Mixture of AR-GARCH instead of GARCH model for prediction of exchange rates was utilized in a study by Wong *et al.* (1998). In another context, Tang *et al.* (2003) explored the mixture of ARMA-GARCH model for stock price prediction. In fact, several features of financial series such as leptokurticity and volatility clustering were captured in stochastic volatility model (Mikosch, 2001).

Despite the wide use of GARCH models in many applications, forecasting ability was evidenced as mixed. For example, in a study of Anderson and Bollerslev (1998), they showed that the GARCH model provided good volatility forecast. On the contrary, some studies using GARCH resulted into poor forecasting performances (Cumby et al., 1993; Jorion, 1995,1996; Brailsford, 1996; Figlewski, 1997; McMillan, 2000). To improve the forecasting ability of the GARCH model, some alternative approaches have been advocated from the perspective of estimation and forecasting.

This study contributed to test the efficacy of finite mixture of ARIMA-GARCH model over traditional models for NIFTY50 index in India, reevaluating literature by making a fresh look to financial returns forecasting.

RESEARCH METHODOLOGY

Selection of Indices and timeline

Basically, two stock exchanges namely National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) are dominant in Indian stock market. BSE and NSE have popular Indices developed as SENSEX30 and NIFTY50. The S&P CNX Nifty 50 (NIFTY50) is a well diversified 50 stocks index accounting for 22 sectors of the economy. Large cap companies are account for 82 percent of total market cap on NSE (NSE India, 1st January, 2013). NIFTY50 is used for variety of purposes such as benchmarking fund portfolios, index based derivatives and index funds. Data from 1994 (since inception of NIFTY50) to 31st Dec, 2012 is used for analysis. This results into 4710 closing prices which when converted in log and first log difference. Finally, 4708 sample observations are available for model testing and comparison which is higher than the threshold value i.e. 50 for ARIMA (Holden et al., 1990).

The model

Prior empirical works on time-series have been undertaken with an assumption of stationary data. Thus, prediction future values of time series, simple model of moving average is used. However, efforts have been made to increase the predictability of these time-series models, new modeling approaches are developed taking single or combinations many features of data and tested the robustness of models. In same line, some econometric models are developed such as AR, MA, ARMA, ARIMA, GARCH, EGARCH, TGARCH, ANN etc.

As far as prediction of stock market price or indices is concerned, ARIMA is considered as one of the most popular methodology yielding good predictability. Thus, in this study, Box-Jenkins methodology is used for deriving the best model of prediction of indices. However, Indices data considered to be non constant variance traditional GARCH also estimated. At last combination of ARIMA and GARCH is also tried and compared using different criteria for selecting best-fit model.

Methodology used- Box-Jenkins

The univariate version of this methodology is a self- projecting time series forecasting method. The underlying goal is to find an appropriate formula so that the residuals are as small as possible and exhibit no pattern. No residual pattern is considered as White Noise Process and is primary assumption for this methodology. This assumption can be confirmed with the help of unit root test and if series is not stationary it can be made stationary using the n^{th} order difference (i.e. I(n)). The Box-Jenkins model- building process involves three stages, namely: identification, Estimating and diagnostic checking.

Steps used for Box-Jenkins Methodology (Box and Jenkins, 1970):

1. Calculate ACF and PACF of the raw data, and check whether the series is stationary or not. If the series are stationary go to step 3 or follow step 2
2. Take log and the first difference of raw data. Again calculate ACF and PACF for the new data series
3. Examine ACF and PACF for find good starting point and Estimate those models
4. Check AIC/SBC criteria to detect the model which is the parsimonious one

Assumptions check

Time series ARIMA model for NIFTY50 was used and formulated mathematically as following with null hypothesis$H_o: a' = 1$ and c_o is a constant:

$$(1 - L')y = c_o + c_1 * t + (a' - 1) * y'(-1) + \cdots + e \qquad (1)$$

Augmented Dickey-Fuller (ADF) unit roof test was performed first (Dickey and Fuller, 1981) to ensure stationary of time series data. ADF test was performed in Eviews. Output indicated that data is not stationary from Monte-carlo simulations (t =0.001935, p=0.4373). Further, findings revealed from ACF and PACF (table 1), time series plot (figure 1) and normality Q- plot (figure 1) about non-stationary form of data as follow:

Non-stationary data was evidenced also from autocorrelation for 10 lags (table 1) which requires a transformation of data into stationary. First difference of log was taken of daily NIFTY50 closing price data having growing mean with some mean percent growth in value.

Table 1: ACF and PACF for Daily Closing Price of NIFTY50

Autocorrelation	Partial Correlation	Lag	ACF	PACF	Q-Stat	Prob.
|*******	|*******	1	0.999	0.999	4705.1	0.000
|*******	| |	2	0.998	-0.027	9402.8	0.000
|*******	| |	3	0.997	0.002	14093.	0.000
|*******	| |	4	0.997	0.005	18776.	0.000
|*******	| |	5	0.996	0.013	23453.	0.000
|*******	| |	6	0.995	0.021	28122.	0.000
|*******	| |	7	0.994	0.010	32785.	0.000
|*******	| |	8	0.993	-0.014	37442.	0.000
|*******	| |	9	0.992	-0.016	42091.	0.000
|*******	| |	10	0.992	-0.003	46734.	0.000

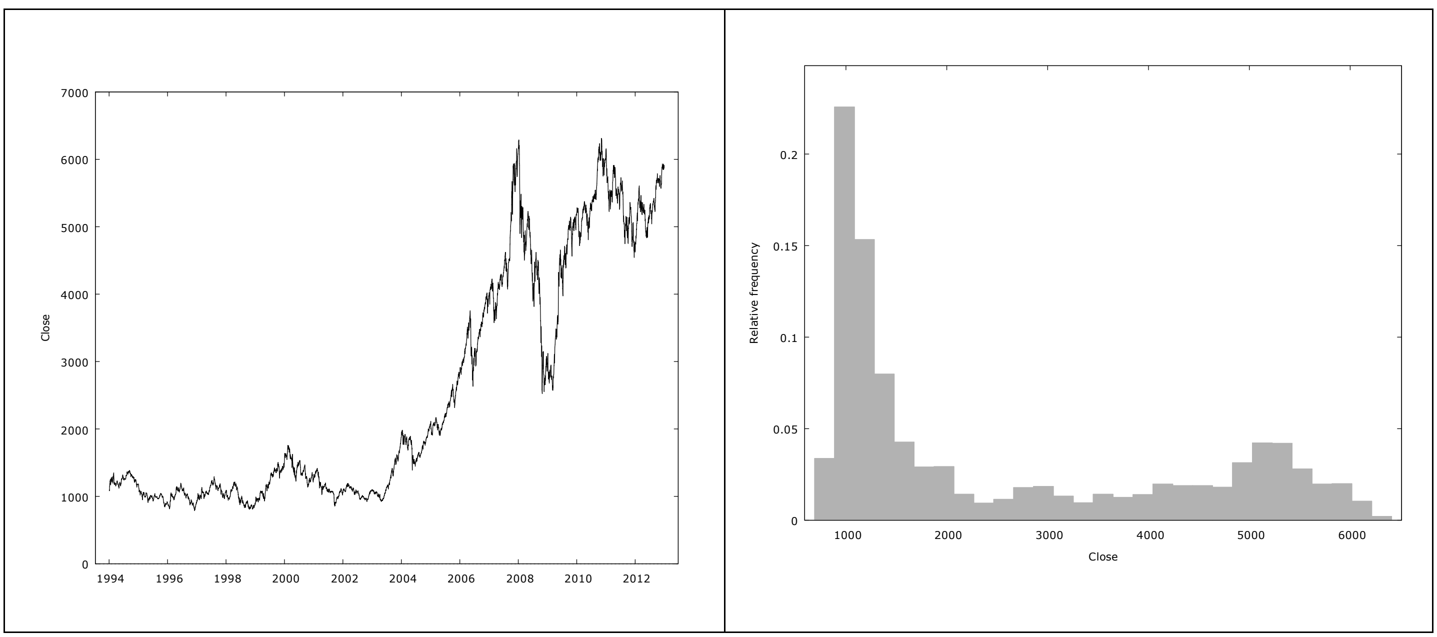

Figure 1: Time Series Plot and frequency distribution for Daily Closing Price of NIFTY50

E-view was used for computing unit test root and normality. One more evidence was recorded from **ADF test statistic concerning stationary of data (t =- 0.9415, p<0.001)** using Monte-

Carlo simulations. Moreover, it was also visible that data is stationary from ACF and (table 2), time series plot (figure 2) and normality Q- plot (figure 3) as follow:

Table 2: ACF and PACF for First Difference Log Daily Closing Price of NIFTY50

Autocorrelation	Partial Correlation	Lag	AC	PAC	Q-Stat	Prob.
|* |	|* |	1	0.076	0.076	26.964	0.000
| |	| |	2	-0.035	-0.041	32.654	0.000
| |	| |	3	0.003	0.009	32.695	0.000
| |	| |	4	0.017	0.015	34.030	0.000
| |	| |	5	-0.008	-0.010	34.325	0.000
| |	| |	6	-0.053	-0.050	47.326	0.000
| |	| |	7	0.006	0.014	47.518	0.000
| |	| |	8	0.027	0.022	50.962	0.000
| |	| |	9	0.025	0.023	53.907	0.000
| |	| |	10	0.036	0.036	60.139	0.000

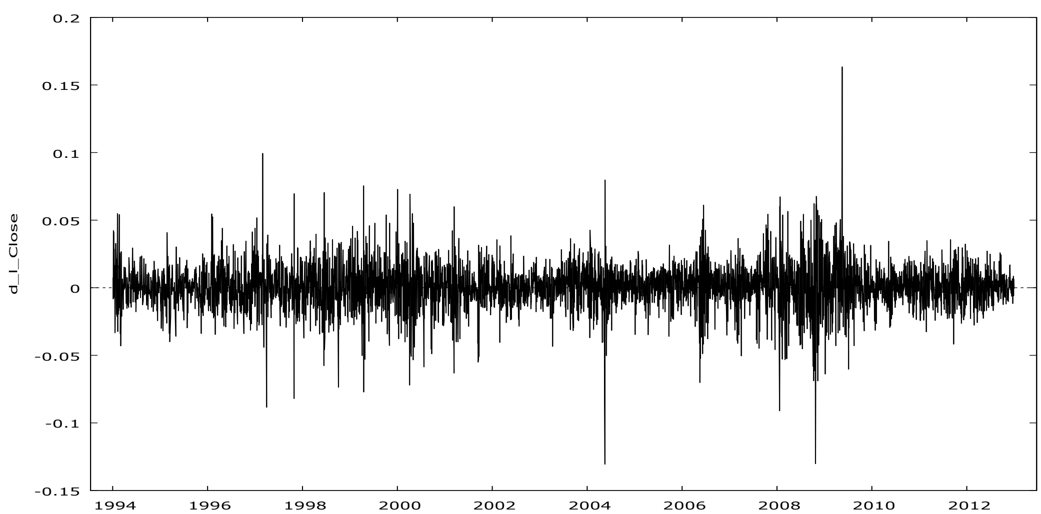

Figure 2: Time Series Plot for First Difference Log Daily Closing Price of NIFTY50

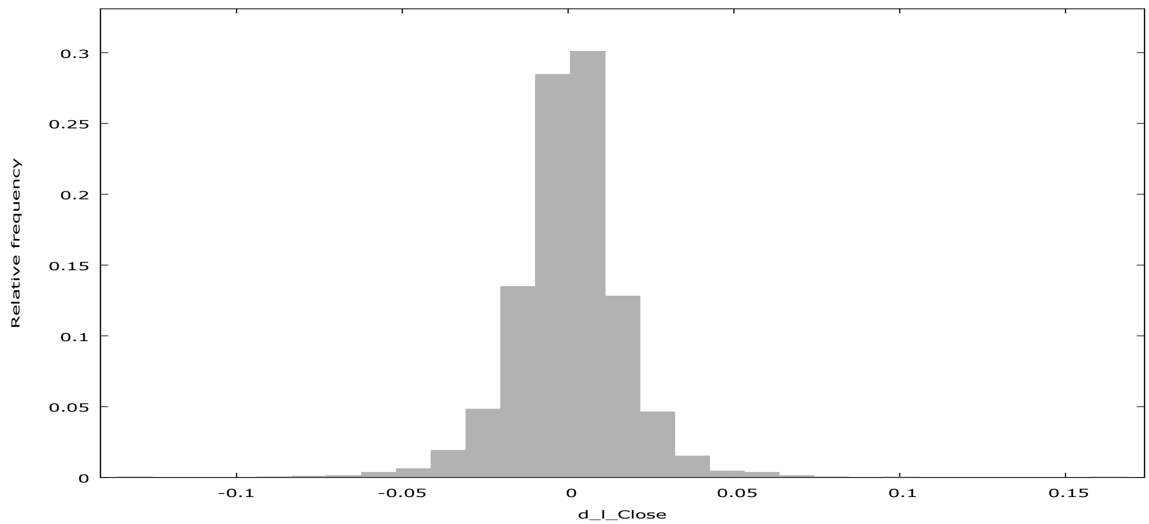

Figure 3: Frequency Distribution for First Difference Log Daily Closing Price of NIFTY50

DATA ANALYSIS

Box-Jenkins methodology (1976) was utilized to compute best-fit model of ARIMA for different p,d,q values. Subsequent analysis was carried out by autocorrelation for 10 lag confirming data is stationary.

Table 3: Comparison between ARIMA (1,1,1); ARIMA(1,1,0) and ARIMA(0,1,1) Models

Variable	ARIMA(1,1,1)		ARIMA(1,1,0)		ARIMA(0,1,1)	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
C	0.000359	0.1543	0.000358	0.1633	0.000360	0.1611
AR(1)	-0.332120	0.0233	0.075647	0.0000		
MA(1)	0.412537	0.0035			0.081874	0.0000
Adjusted R^2	0.006847		0.005511		0.005982	
AIC	-5.3957		-5.3946		-5.3952	
SIC	-5.3962		-5.3919		-5.3925	
HQIC	-5.3943		-5.3936		-5.3943	
F-Statistics	17.2265		27.0861		29.3340	
F (P-Value for Model)	0.0000*		0.0000*		0.0000*	

Note:*p<0.001

ACF and PACF revealed presence of 1 spike confirms ARMA (1,) as most suitable model. Base on this, ARIMA (1,1,1), ARIMA (1,1,0) and ARIMA (0,1,1) were developed. AIC (Akaike Information Criterion, 1974), SIC (Schwarz Information Criterion, 1978) and HQIC (Hannan-Quinn Information Criterion, 1979) values were used for comparison and least AIC value were used to select best model (Akaike, 1977; Geweke and Meese, 1981).

Table 3 evidenced the significance of models ARIMA (1,1,1) (F=17.2265, p=0.000), ARIMA (1,1,0) (F=27.0861, p=0.000) and ARIMA (0,1,1) (F=29.3340, p=0.000). Also, these three models were significant (F=38.44, 140.65 and 81.55 respectively, p<0.001) for White test of heteroskedasticity (1980). It was found that ARIMA(1,1,1) and ARIMA(0,1,1) had negligible difference based on HQC values. Considering AIC/SIC criterion, ARIMA(1,1,1) was most-fitted model for NIFTY50 index as following:

$$y_t = 0.000359 - 0.332120 * y_{t-1} + 0.412537 * u_{t-1} + u_t \qquad (2)$$

Where,y_t is NIFTY closing today, $y_{t-1}$is NIFTY closing yesterday, u_t error term today and u_{t-1} estimated error term yesterday. Having variability in variance of data with time, GARCH was superior than ARIMA as mentioned in literature previously. Ensuring robust results, mixture of GARCH and ARIMA was proposed for estimating stock prices. AIC/SIC/HQC values were used to compare ARIMA(1,1,1), GARCH(1,1) and ARIMA(1,1,1) – GARCH(1,1).

All these models ARIMA(1,1,1), GARCH(1,1) and ARIMA(1,1,1)-GARCH(1,1)were found to be significant (p<0.001) (table IV). This concludes that ARIMA(1,1,1) – GARCH(1,1) was best-fit time series model for the prediction of NIFTY50 index. When plotting predicted and actual NIFTY50 values from 3rd January, 1994 to 31st December, 2012 supports the suitability of combination of ARIMA(1,1,1)-GARCH(1,1)model.

Table 4: Model comparison- ARIMA (1,1,1); GARCH(1,1) and ARIMA(1,1,1) – GARCH(1,1)

Variable	ARIMA(1,1,1)		GARCH(1,1)		ARIMA(1,1,1)–GARCH(1,1)	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
C	0.000359	0.1543	0.000784	0.0000	0.001029	0.2289
y*(-1)			0.109160	0.0000	-0.172853	0.8500
AR(1)	-0.332120	0.0233			0.050506	0.8153
MA(1)	0.412537	0.0035			0.233772	0.7413
For Variance Equation						
C			6.20E-06	0.0000	6.19E-06	0.0000
ARCH(1)			0.123077	0.0000	0.122877	0.0000
GARCH(1)			0.858692	0.0000	0.858855	0.0000
Adjusted R^2	0.006847		0.004578		0.005247	
AIC	-5.3957		-5.6323		-5.6419	
SIC	-5.3962		-5.6254		-5.6323	
HQIC	-5.3943		-5.6299		-5.6385	
P-Value	0.0000*		0.0000*		0.0000*	

Note: *p<0.001

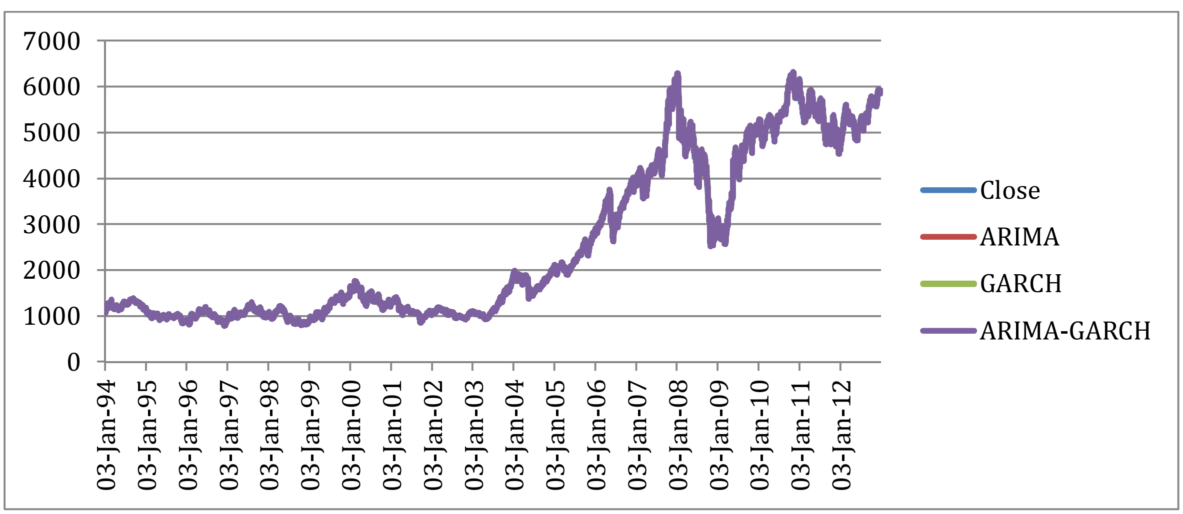

Figure 4: Graphical representation of NIFTY50 Actual vs. Predicted (Since Inception)

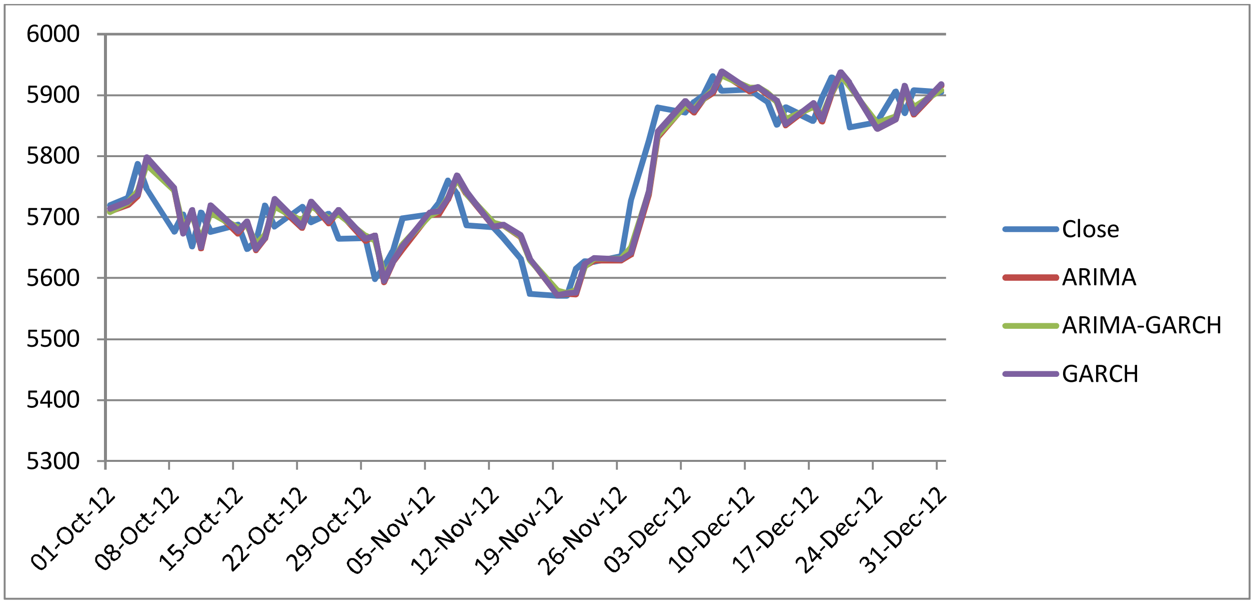

Figure 5: Graphical representation of NIFTY50 Actual vs. Predicted (Last Quarter)

It is obvious that if we try to check model fit graphically with all 4708 sample data, it is difficult (Figure 4). So, using only last quarter data (1st October, 2012 to 31st December, 2012) one can able to observe model fit (Figure 5). It was clearly observed that ARIMA-GARCH (green colored in the diagram) was best fit for prediction. The best-fit ARIMA(1,1,1)-GARCH(1,1) model for NIFTY50 prediction is as follow:

$$y_t = 0.001029 - 0.172853 * y_{t-1}^{*} + 0.050506 * y_{t-1} + 0.233772 * u_{t-1} + u_t \qquad (3)$$

Where, y_t is NIFTY closing today, y_{t-1}^{*} is predicted NIFTY closing yesterday, y_{t-1} is NIFTY closing yesterday, u_t error in estimation today and u_{t-1} estimated error term yesterday. In addition to this, the ARIMA-GARCH equation for variance is as follow:

$$\sigma_t^2 = 0.00000619 + 0.122877 * \sigma_{t-1}^2 + 0.858855 * u_{t-1}^2 \qquad (4)$$

Where, σ_t^2 is predicted variance for today, and σ_{t-1}^2 is variance for yesterday.

IMPLICATIONS AND LIMITATIONS OF STUDY

It is very difficult to predict the direction or price movement of crude oil price and poses a dilemma to stakeholders such as traders, investors, asset managers or government. Here, in current research it is clearly shown that combination of ARIMA and GARCH provides better prediction of NIFTY50. Thus, it is equally applicable to other stocks and indices. Here, using given ARIMA(1,1,1)-GARCH(1,1) model 10day forward points were predicted and compared with actual (Table 5).

Table 5: NIFTY50 10 Point Forward Actual vs. Forecasted

Date	Actual	Prediction
01-Jan-13	5950.85	5902.41
02-Jan-13	5993.25	5925.37
03-Jan-13	6009.5	5955.18
04-Jan-13	6016.15	5976.40
07-Jan-13	5988.4	5991.30
08-Jan-13	6001.7	5990.45
09-Jan-13	5971.5	6001.78
10-Jan-13	5968.65	5998.87
11-Jan-13	5951.3	6003.05
14-Jan-13	6024.05	6003.32

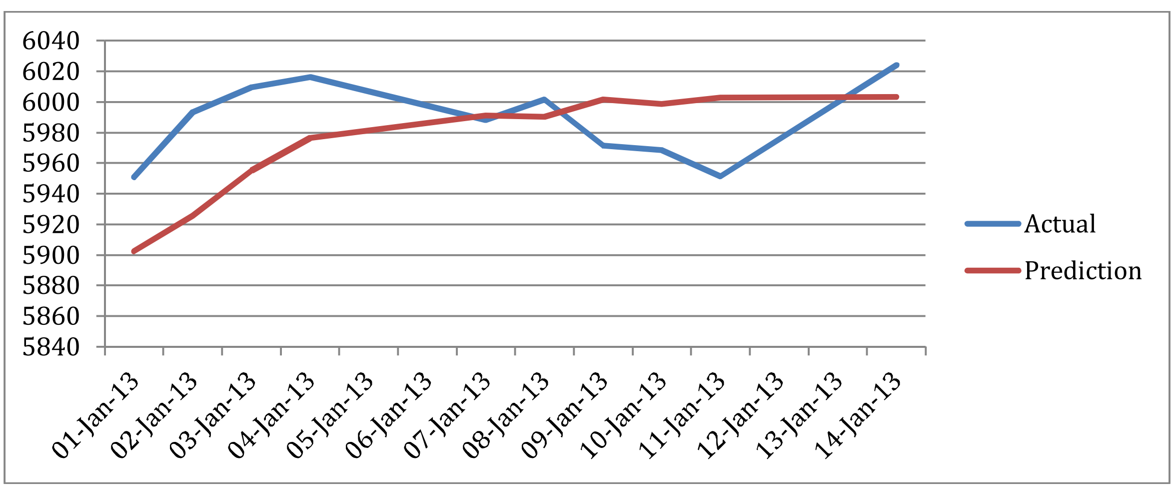

Figure 6: Graphical representation of NIFTY50 Actual vs. Forecasted (10Pt. Forward)

Actual outcome of closing price is fluctuating around the predicted value using mixture ARIMA-GARCH model depicting in table 5 and figure 6. This provides a good estimation of underlying NIFTY 50 closing price forecast. Traders and investors can be benefited by utilizing this model to gain consistent results through ARIMA (1,1,1)-GARCH(1,1) in longer run.

The experimental results reconfirm that the ARIMA-GARCH model is better fitted than other models for NIFTY50 data using any of criterion (AIC,SIC or HQIC).

In current study, closing of NIFTY50 was forecasted using this model. However, for any other stock listed on other exchange in India is required to develop a new ARIMA-GARCH model for respective time-series data of stock taken. Traders and/or investors make caution while using this model for forecasting the closing price for the stocks listed on other indices about the change in parameter estimation.

CONCLUSION

This study presented an ARIMA(1,1,1)-GARCH(1,1) model which has been fitted and provide parameter estimation, diagnostic checking procedures to this model, and predict NIFTY50 index data extracted from NSE India website, and also compare with conventional ARIMA and GARCH model. The experimental results reconfirm that the ARIMA-GARCH model is better fitted than other models for NIFTY50 data using any of criterion (AIC,SIC or HQIC). It is observed that ARIMA(1,1,1)-GARCH(1,1) model fitted the NIFTY50 index data very well and this is confirmed by the graphical representation of actual vs. predicted. A forecasting of data taken illustrates that the model will be helpful to predict the NIFTY50 composite price index. And thus helps investor to get the sustainable returns using forecasting of closing price and sell or buy accordingly. This study adds the theoretical evidence in the literature of stock forecasting and the model ARIMA-GARCH model has board applicability in the financial field for achieving sustainable growth.

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