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Estimating the Market Volatility: With Special Reference to Sectoral Indices of BSE in India Using by ARIMA Models

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ABSTRACT

The statistical measure of return dispersion for a certain securities or market index is called volatility. Generally speaking, the greater the volatility, the larger the risk attached to the investment. For a number of reasons related to various market participants, volatility estimation is significant Individual and Institutional Investors are focusing more about on returns of their investment at lower risk, even they also equally bother about the risk. In this paper, ARIM (0 1 0) and ARIMA (0 1 1) models have been used for predicting the volatility of various selected sectoral indices of Bombay Stock Exchange (BSE) in India. Monthly closing prices of 10 indices for the last 11 years are considered for the study. The period of 11 years ranging from August 2012 to July 2023 being enveloped for this study. It is analysis descriptive Statistics that found highest-lowest risk returns, were applied ARIMA models for forecasting market volatility of each index, also identified stationarity and non-stationarity of selected sectoral indices of BSE in India.

KEYWORDS: *Descriptive Statistics, stationarity process, non-stationarity process, Forecasting, ARIMA, Time Serie. Market Volatility, BSE*

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1. INTRODUCTION

Recent economic crises and the ensuing financial losses show how urgently markets, financial institutions, and investors needed to enhance their models to gauge and foresee the risks to which they were exposed. When compared to other options, equity investments are a fantastic substitute, especially over extended periods. The brilliant work of Markowitz in demonstrating that a portfolio of n assets has less risk than the weighted sum of the risks of each asset, given a different correlation of 1, laid the groundwork for portfolio selection that focuses on not only profitability but also the correlation between the risk taken and the return on the investment. This study, together with the work of Sharpe and Fama, contributed to the development of modern financial theory, which effectively links assumed risk with anticipated return. Economic time series forecasting may be done using a variety of methods. Univariate forecasting is one method that just incorporates the time series being predicted. A model known as autoregressive integrated moving average (ARIMA)a time series is represented in terms of a certain subset of univariate modelling, the autoregressive component's previous values plus the present and lag values of 'White noise' error term (moving average component). The purpose of this study is to assess the accuracy of the ARIMA model's predictions of the time series of the sectoral indices of the Indian BSE stock market and to compare it to the sectoral indices' stationarity and non-stationarity. We used monthly BSE Market historical data from August 2012 and July 2023

2. Review of literature

Kumar et al. (2004) In order to predict the daily maximum surface ozone concentrations in Brunei Darussalam, he employed the ARIMA model. They discovered that ARIMA (1, 0, 1) was appropriate for the surface O3 data obtained at the Brunei airport.

Darussalam. Tsitsika et al. (2007) They have to predict the production of pelagic fish, they employed the ARIMA model. In the end, ARIMA (1, 0, 1) and ARIMA (0, 1) models were chosen.

Azad et al. (2011) he has projected Bangladeshi exchange rates using the ARIMA model. They sought to identify the most effective forecasting model using the Box Jenkins approach. They discovered that the exchange rate neural network (ERNN) model performs better than ARIMA.

Merh (2011) employed ANN & ARIMA models to forecast the next day's stock market. For predicting the future index value of the sensex (BSE 30), they employed ANN (4-4-1) and ARIMA (1, 1 and 1). Compared to ANN (4-4-1), ARIMA (1,1) has superior predicting accuracy. In order to predict the prevalence of hemorrhagic fever with renal syndrome in China, Liv et al. (2011) employed the ARIMA model. The optimal ARIMA (0, 3, and 1) model's goodness of fit test revealed that the model's residual autocorrelation was not statistically significant.

Datta (2011) he has explained the ARIMA model. In order to anticipate inflation in the Bangladeshi economy He demonstrated how the ARIMA (1, 0, 1) model effectively matches Bangladesh's inflation data. Al-Zeaud (2011) employed the ARIMA model to simulate and predict volatility. The outcome demonstrates that the ARIMA (2, 0 and 2) model is the best ARIMA model for the banking sector with a 95% confidence range.

Uko et al. (2012) he has a compared the relative predictive abilities of ARIMA, VAR, and ECM models. In order to anticipate inflation in Nigeria, the outcome demonstrates that ARIMA is an effective inflation forecasting model and a strong predictor of inflation in Nigeria.

Gómez and Maravall (1998). They have found that The Box-Jenkins process is a semi-formal method that relies on subjective evaluation of plots of auto correlograms and partial auto correlograms of the series for model identification. Some writers have substituted objective metrics of model adequacy for the conventional box-Jenkins method, particularly the penalty function requirements**.**

It is evident from the research stated above that ARIMA may be utilized to predict. Few of them attempted to determine the optimum ARIMA model; instead, the majority of them employed ARIMA to make forecasts. The goal of the current study is to determine which ARIMA model can best predict the average daily/monthly price of sectoral indices on the Indian BSE (Bombay Stock Exchange).

3. ARIMA modeling and forecasting

Time series forecasting techniques using ARIMA are fundamentally neutral. They don't presume understanding of any underlying economic model or structural links, in contrast to other approaches. For forecasting purposes, it is assumed that the series' historical values and prior error terms include relevant information.

The fundamental benefit of using ARIMA forecasting is that it simply needs data from the time series under consideration. First off, if one is predicting a lot of different time series, this capability is helpful. Second, this prevents an issue that might occasionally arise with multivariate models. Take a model with salaries, prices, and money as an example. The length of time over which the model may be estimated may be shortened if a consistent money series is only available for a shorter duration than the other two series. Third, data timeliness might be an issue with multivariate models. The forecasts made using this model are conditional forecasts based on forecasts of the unavailable observations, adding another source of forecast uncertainty. This scenario occurs when one builds a big structural model comprising variables that are only provided with a lengthy lag, such as pay data.

The following are some drawbacks of ARIMA forecasting:

- Some classic model identification procedures are subjective, and the forecaster's skill and experience can influence the model's dependability (although this complaint frequently also applies to other modelling approaches).
- It is not incorporated into any structural or theoretical relationships. Therefore, it is unclear what the selected model means economically. In addition, unlike structural models, ARIMA models cannot be used for policy simulations.
- ARIMA models are 'backward looking' in essence. As a result, unless the turning point signifies a return to a long-run equilibrium, they are typically bad at anticipating turning moments.

Demand forecasting methodologies primarily fall into two categories: qualitative methods and quantitative ones. It is getting close to the best time to generate a reliable prediction of demand using a combination of qualitative and quantitative methodologies. Panel data approach, Delphi technique, scenario planning, informed guess, executive committee consensus, sales force survey, historical analysis, and market research are the key qualitative approaches. Quantitative approaches rely on historical data (time series) and make the assumption that previous outcomes are indicative of the future. Moving Average, Exponential Adjustment, Linear Trend, and Nonlinear Trend are the traditional time series approaches. For these techniques to work, the series must be stationary, which means that the mean and covariance must be constant across time. The most appropriate auto regressive algorithms for stationary series in this situation are AR (Auto Regressive) and ARMA (Auto Regressive Move Average), since they produce more accurate predictions.

Seasonality, or oscillations or disturbances in series that occur at regular intervals of less than one year, has another crucial impact on time series. Additionally, according to Bacci, linear stationary processes and linear homogeneous non-stationary processes may both be described by quantitative ARIMA models.

Three types of stationary linear process are followings:
1. Auto regressive of order p……… (AR(p)),
2. Moving averages of order q ……. (MA(q)),
3. Moving averages process of order P and q …… (ARMA (p, q)).

In this study applied ARIMA (0 1 0) and ARIMA (0 1 1) Models (Auto Regressive Integrated Moving Average) for forecasting market volatility of sectoral indices in BSE.

The equation of ARIMA (0 1 0) model is representing as follows:

$$Y\ t = Y\_(t\text{-}1) + \epsilon\ t \text{ ……………………………. (1)}$$

Where:
Y t represents the time series at time t.
Y_(t-1) represents the time series at the previous time point (lag 1).
ε t represents the white noise or error term.

The ARIMA (0, 1, 0) model predicts the value at each time point as the value at the previous time point plus some random noise, which is a simple random walk. This model assumes that the differences between consecutive observations follow a random walk pattern.

The equation for an ARIMA (0, 1, 1) model can be represented as follows:

$$Y\ t = \mu + \varepsilon\ t + \theta_1 * \varepsilon\_(t\text{-}1) \text{ ………………. (2)}$$

Where:
Y t represents the time series at time t.
μ is the mean or constant term.
ε t represents the white noise or error term at time t.
θ_1 is the coefficient for the lag-1 moving average term.
ε_(t-1) represents the error term at the previous time point (lag 1).

Construction of ARIMA models is using by time series data of sectoral indices where find out market volatility and risk pattern of investors in the existing market situation will be predicted on historical price based of sectoral indices of BSE in India.

4. Material and methods

Required and relevant data is gathered of monthly closing price of 10 sectoral indices for the last 11 years from August 2012 to July 2023. The data was collected and extracted from the official website of Bombay Stock Exchange. Further, SPSS has been employed for the application of statistical software tool. In the study have analyzed descriptive statistical analysis and ARIMA models to estimating market volatility of BSE market in India.

5. Result and Discussion

Table 1 Descriptive Statistics

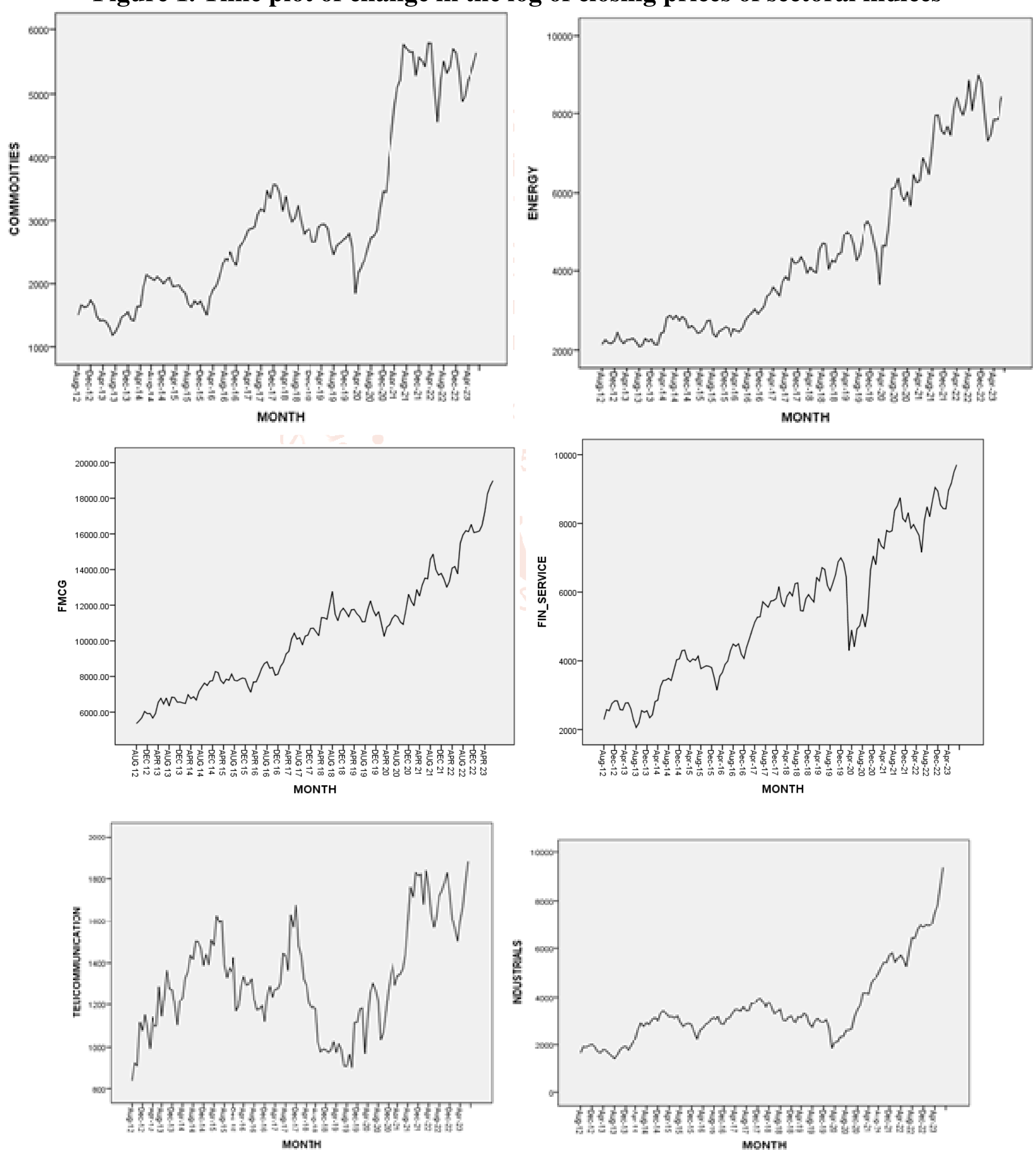
	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Commodities	132	-.2824	.1877	.012326	.0683461	-.243	.211	2.123	.419
Energy	132	-.1796	.2683	.012518	.0654397	.458	.211	1.509	.419
Fmcg	132	-.0994	.1252	.010445	.0407119	.187	.211	-.197	.419
Fin Service	132	-.3318	.2258	.013404	.0684725	-.674	.211	4.536	.419
Industrials	132	-.3041	.1857	.015610	.0702210	-.527	.211	2.520	.419
It	132	-.1708	.2260	.014510	.0612851	.178	.211	1.036	.419
Telicommunication	132	-.1786	.2350	.008691	.0730591	.293	.211	.859	.419
Auto	132	-.3098	.2423	.012577	.0657465	-.704	.211	4.389	.419
Oil_Gas	132	-.2060	.2041	.008461	.0622158	-.013	.211	.629	.419
Bankex	132	-.3401	.2372	.014153	.0734260	-.490	.211	3.827	.419
Valid N (Listwise)	132								

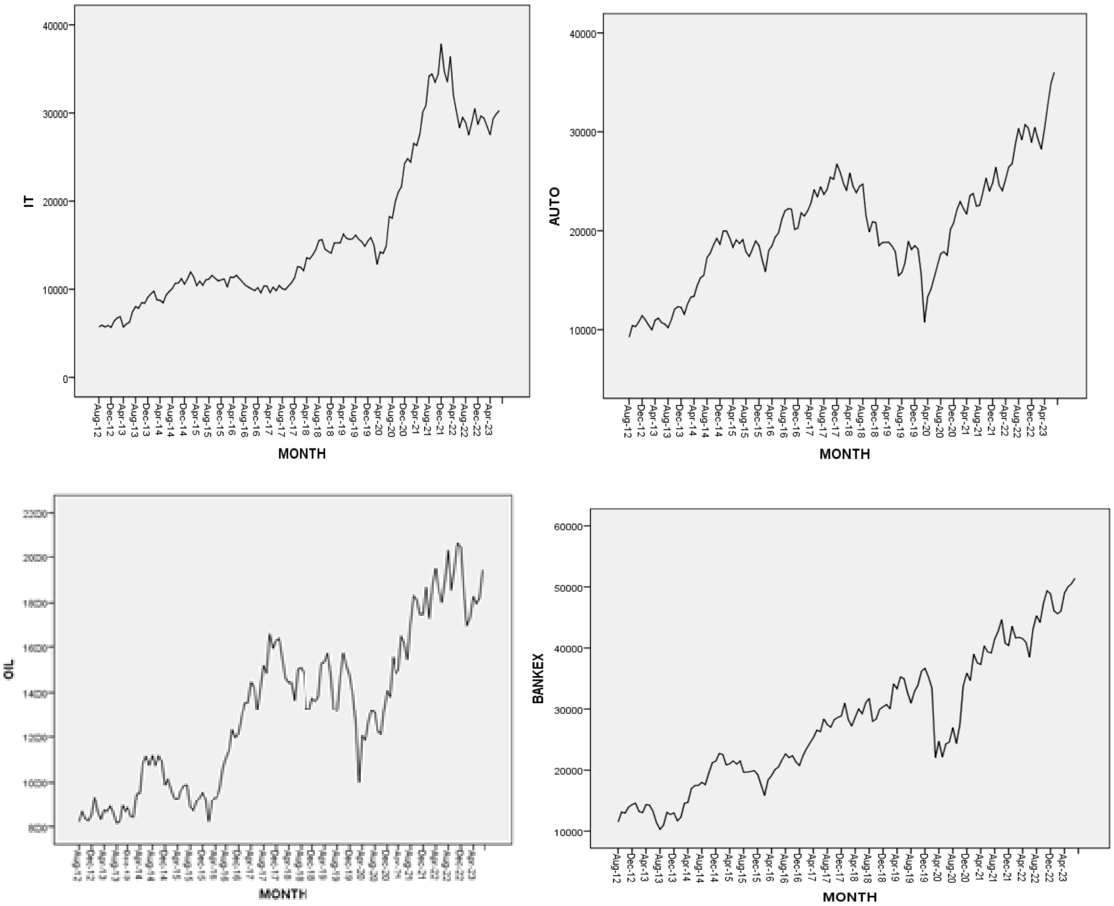
Source: Extracted from SPSS software

All the sectoral indices of BSE are analyzed for the result. Monthly data have collected from last 11 years has a period of august 2012 to July 2023 is taken from the Bombay Stock Exchange website. Table 1 represents the descriptive statistics of the sectoral indices. It is indicating of mean, minimum, maximum, standard deviation, skewness and kurtosis of returns of all sectoral indices. The average returns of INDUSTRIAL is high (0.15610) followed by IT (Information and technology). Industrial sector attractions a more investors than the other sectors and this was a highest portfolio return were expected view of investors. FMCG has lowest standard deviation among the 10 sectoral indices it indicates is the sector have lower market volatility and lower risk return in the market. Whereas, BANKEX has the highest standard deviation followed by IT (information and technology). These sectors had rational market volatility and highest risk return on portfolio in the market compare to other sectoral indices. The table shows the skewness all the sectoral indices had a positive value. Rest of the table kurtosis value shown about distribution data of time series values in the market. Generally, we found that kurtosis value is less than 3 that data was normal distributed. Here some of sectoral indices more than the value of 3. In this case is also data was distributed normally. Hair et al. (2010) and Bryne (2010) argued that data is considered to be normal if skewness is between -2 to +2 and kurtosis is between -7 to +7.

5.1. Volatility clustering

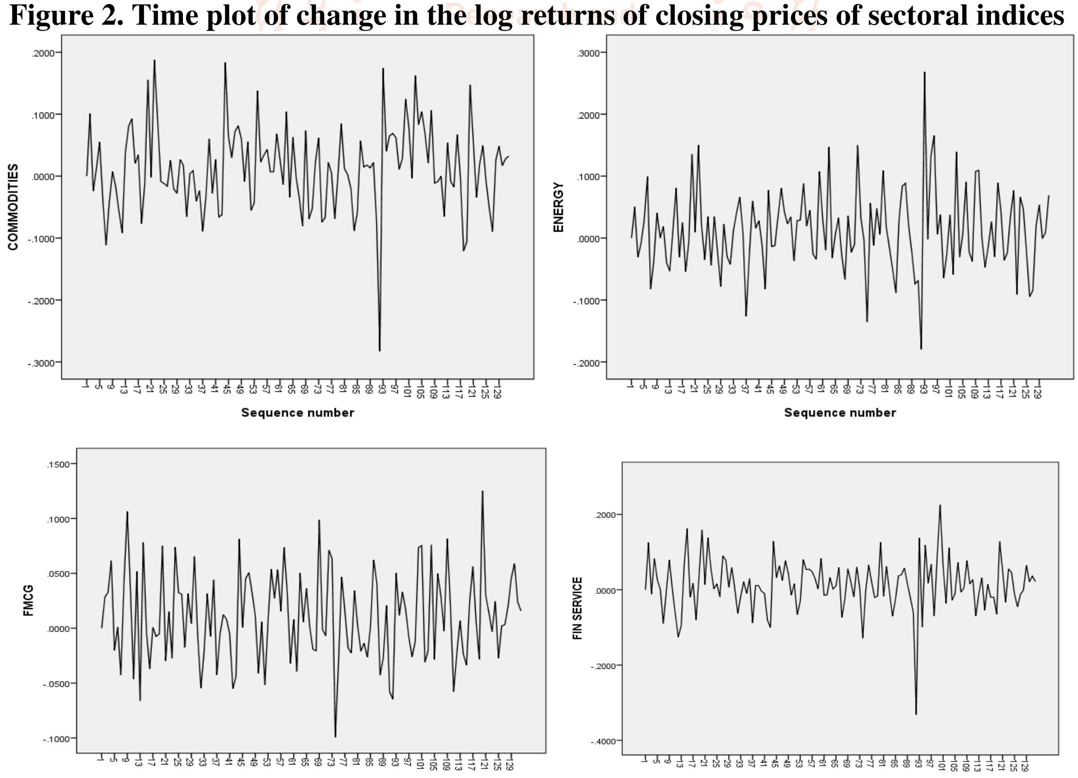
Figure 1. Time plot of change in the log of closing prices of sectoral indices

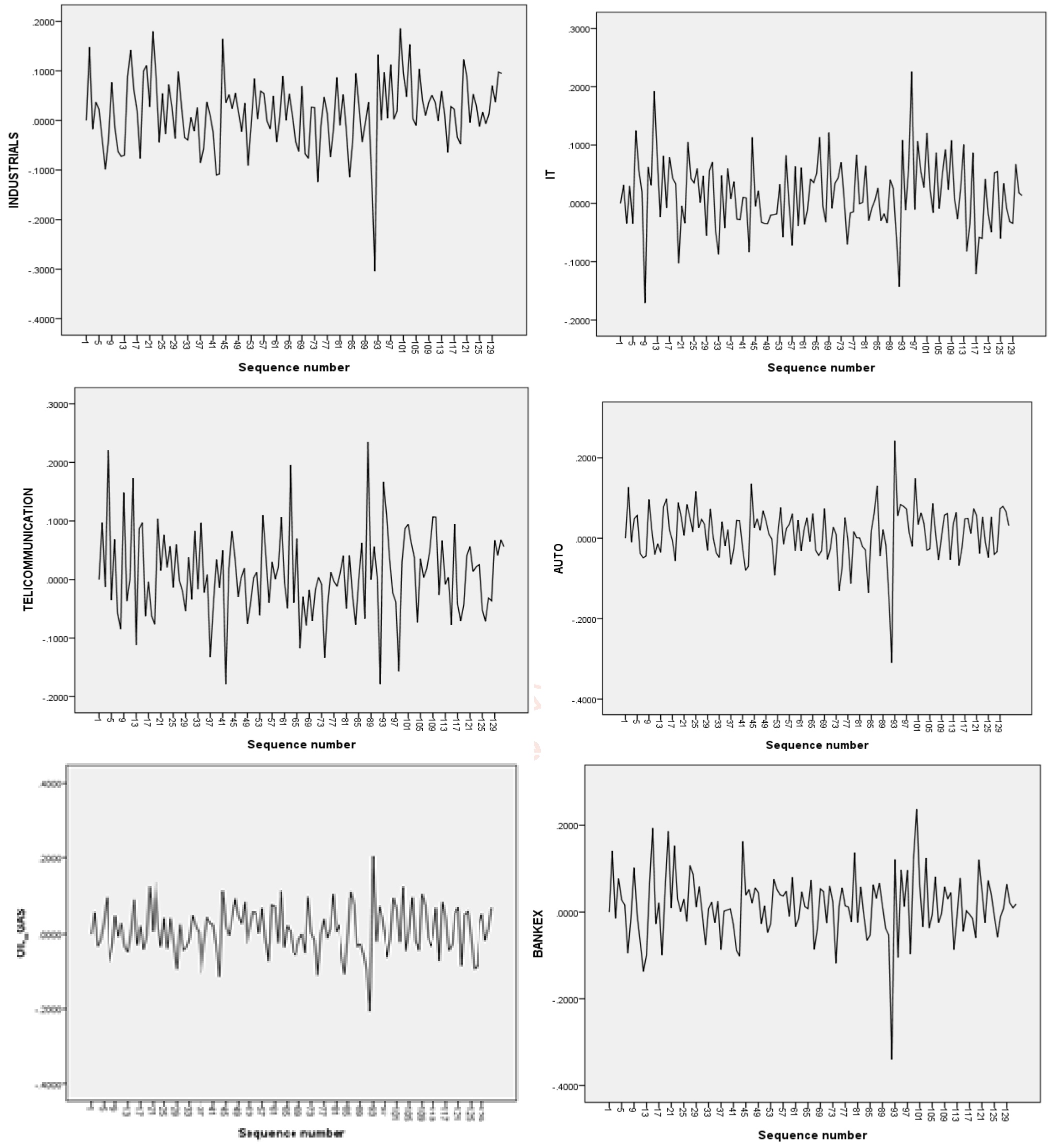




Source: Extracted from SPSS software

Figure 2. Time plot of change in the log returns of closing prices of sectoral indices





Source: Extracted from SPSS software

Figure 1 and figure 2 shows the stationarity and non -stationarity lags of sectoral indices. Above the figure 1 analyze the clustering of closing price of the sectoral indices. Whereas, all the indices performance is more than the significant level of 0.05 that indicates the all-sectoral indices has a non- stationarity process and having more volatile price clustering in the market. Thus, figure 2 shows the stationary process of sectoral indices. All the sectoral indices values are less than the 0.05 at significant level after prices are converting to lag returns. Notably, after converting returns lags of sectoral indices price has become stationarity in the market.

5.2. Application of ARIMA model

Table 2 Model Description

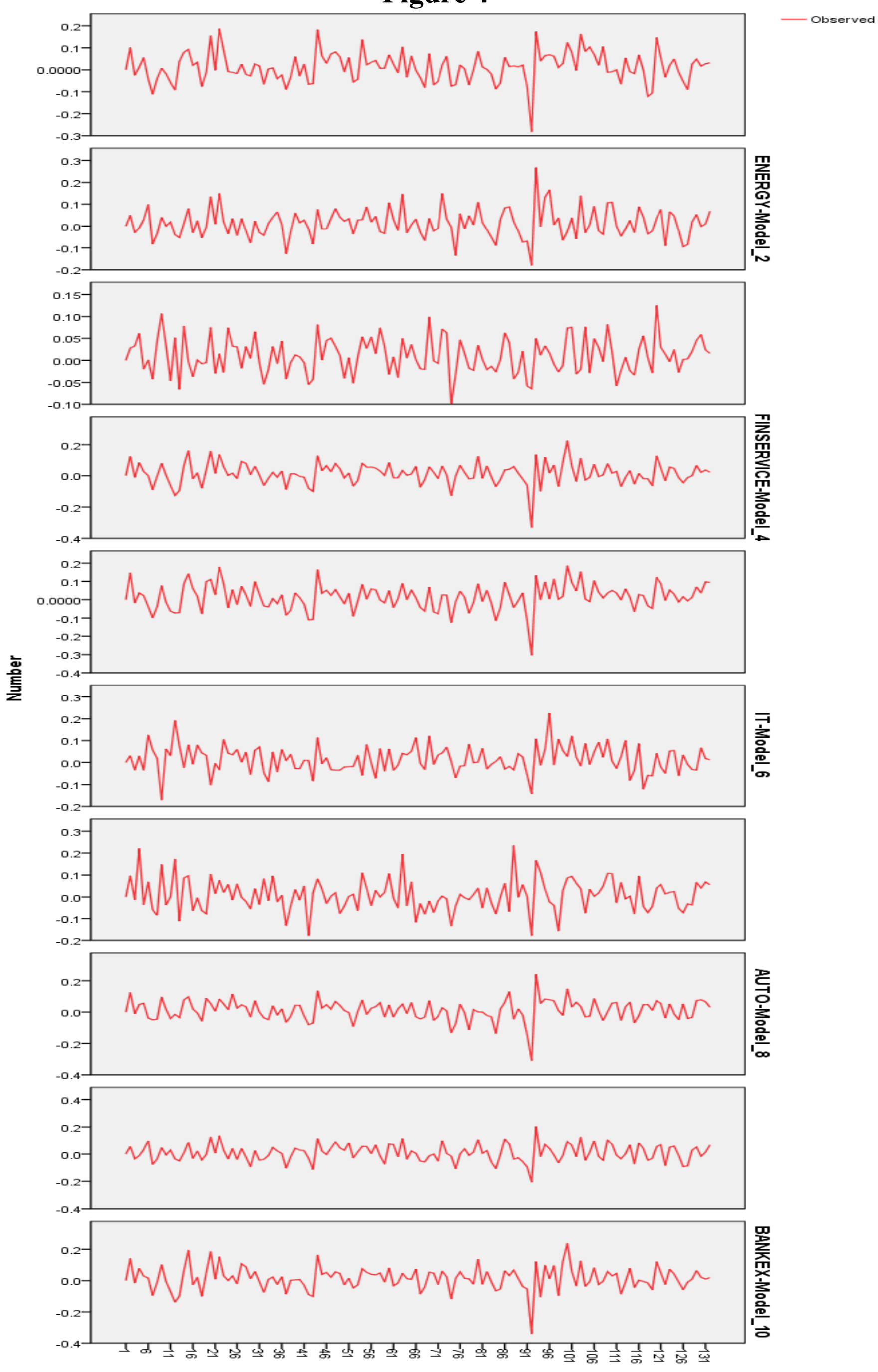
			Model Type
Model ID	COMMODITIES	Model_1	ARIMA (0,1,0)
	ENERGY	Model_2	AIMA (0,1,0)
	FMCG	Model_3	ARIMA (0,1,0)
	FIN SERVICE	Model_4	ARIMA (0,1,0)
	INDUSTRIALS	Model_5	ARIMA (0,1,0)
	IT	Model_6	ARIMA (0,1,0)
	TELICOMMUNICATION	Model_7	ARIMA (0,1,0)
	AUTO	Model_8	ARIMA (0,1,0)
	OIL_GAS	Model_9	ARIMA (0,1,0)
	BANKEX	Model_10	ARIMA (0,1,0)

Source: Extracted from SPSS software

Table 3 Model Statistics

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q (18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
COMMODITIES	1	1.094E-006	44.974	18	.000	0
ENERGY	1	3.729E-005	55.692	18	.000	0
FMCG	1	1.559E-006	70.093	18	.000	0
FIN SERVICE	1	4.788E-007	49.849	18	.000	0
INDUSTRIALS	1	8.176E-005	60.030	18	.000	0
IT	1	5.554E-006	65.810	18	.000	0
TELICOMMUNICATION	1	2.190E-005	69.334	18	.000	0
AUTO	1	7.569E-007	51.752	18	.000	0
OIL_GAS	1	5.237E-005	51.682	18	.000	0
BANKEX	1	1.663E-006	52.473	18	.000	0

Figure 4



Source: Extracted from SPSS software

Table 2 and Table 3 has explained the model ARIMA (0 1 0). The both statistic table suggested all the sectoral indices significant level of p value is less than the 0.01(Table 3). Null hypothesis rejected there is no correlated between the sectoral indices of BSE. Figure 4 has explained the all-sectoral indices data are independent there is no correlation the lags. There is no auto correlation of squared standardized residuals form model I through Q 18 lags.

Table 4 Model Description

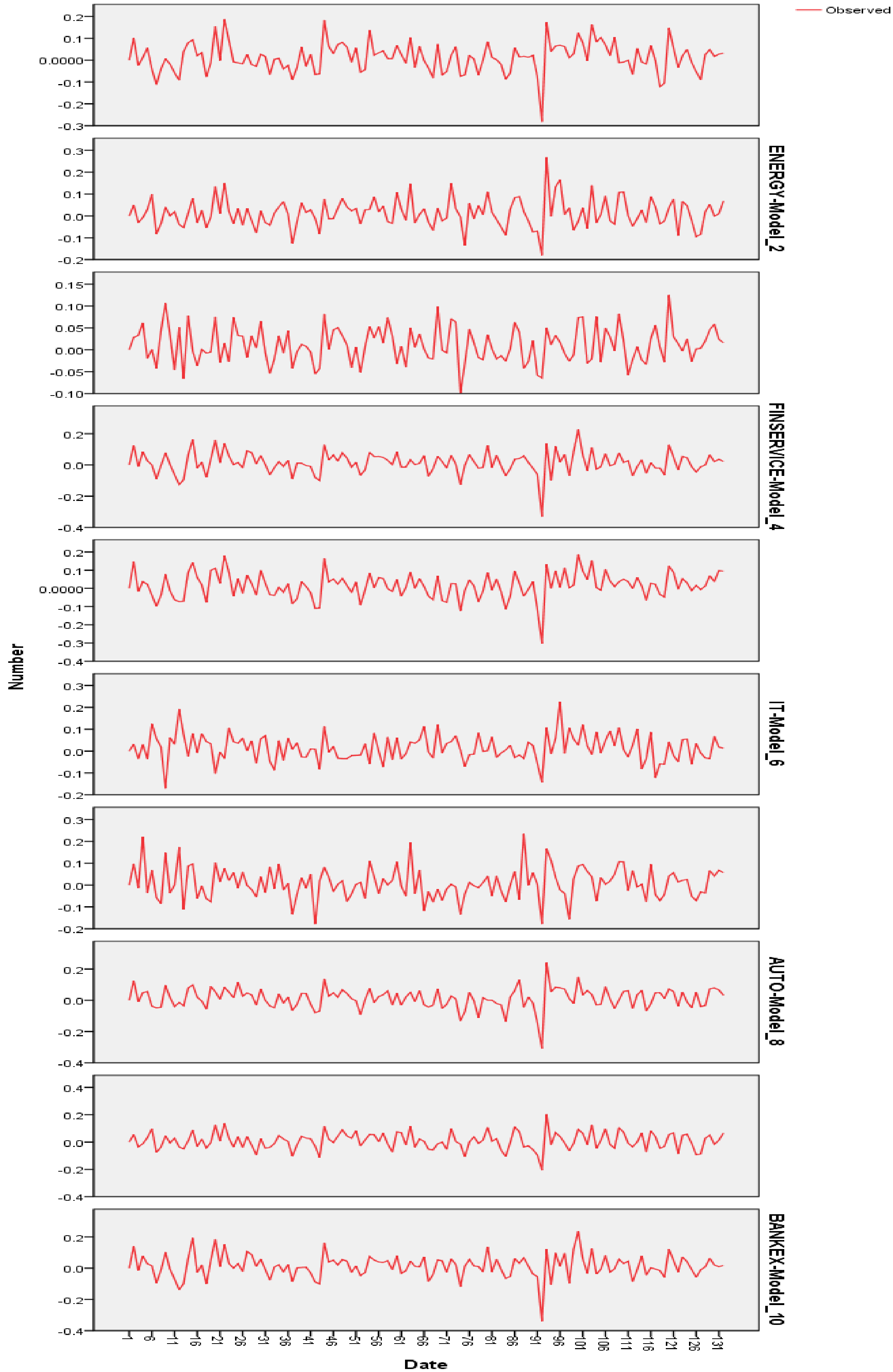
			Model Type
Model ID	COMMODITIES	Model_1	ARIMA (0,1,1)
	ENERGY	Model_2	ARIMA 0,1,1)
	FMCG	Model_3	ARIMA (0,1,1)
	FIN SERVICE	Model_4	ARIMA (0,1,1)
	INDUSTRIALS	Model_5	ARIMA (0,1,1)
	IT	Model_6	ARIMA (0,1,1)
	TELICOMMUNICATION	Model_7	ARIMA (0,1,1)
	AUTO	Model_8	ARIMA (0,1,1)
	OIL_GAS	Model_9	ARIMA (0,1,1)
	BANKEX	Model_10	ARIMA (0,1,1)

Source: Extracted from SPSS software

Table 5 Model Statistics

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q (18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
COMMODITIES	1	.291	27.598	17	.050	0
ENERGY	1	.386	33.531	17	.010	0
FMCG	1	.329	40.130	17	.001	0
FIN SERVICE	1	.383	22.396	17	.170	0
INDUSTRIALS	1	.272	45.242	17	.000	0
IT	1	.487	22.390	17	.170	0
TELICOMMUNICATION	1	.520	21.548	17	.203	0
AUTO	1	.296	36.100	17	.004	0
OIL_GAS	1	.362	36.644	17	.004	0
BANKEX	1	.402	23.899	17	.122	0

Figure 5



Source: Extracted from SPSS software

Operation of ARIMA (0 1 1) model has a variation of P value of sectoral indices than the ARIMA (0 1 0). The Table 5 presents significant level of P values were ENERGY (0.010), FMCG (0.001), INDUSTIREAL (0.000) performances significant level at 0.01 and COMMODITIES (0.05), AUTO (0.004), OIL&GAS (0.004), these are performance at 0.05 significant level of P value and FIN SERVICE (0.170), TELICOMMUNICATION (0.203), IT (0.170) these were has a more than 0.05 significance level of P values. There is still auto correlation of squared standardized residuals all lags. This suggested that the ARIMA (0 1 1) model is no an adequate description of the volatility process and higher capturing the auto correlation. The Figure 5 has shown that ENERGY, FMCG, INDUSTIREAL, COMMODITIES, AUTO and OIL&GAS these lags have stationary process and FIN SERVICE, TELICOMMUNICATION and IT were had the non-stationary process in the ARIMS (0 1 1) model of sectoral indices of BSE.

The auto integrated correlation value has also reduced slightly which suggest that the ARIMA (0 1 0) model is better than the ARIMA (0 1 1) model. Model apparently seems to be on adequate description of volatility process.

6. Result and Conclusion

Through the results obtained, it is observed that the model is effective in its forecasts. The statistics of the AR1MA model coefficients and Chi-square statistics for modified Box-Pierce (Ljung-Box) provide proof to this fact in Descriptive analysis. In the moving average component of ARIMA model has forecasts is the which is best model of ARIMA (0 1 0) and ARIMA (0 1 1). These were explained the stationarity and non-stationarity process before lags return and after lags returns of sectorial indices of BSE in India. This model can be recognized risk and capturing stock market volatility in BSE market also can be used as an aid to decision making mechanism.

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