MEASURING AND FORECASTING THE LIQUIDITY BY USING ARIMA MODEL: A CASE STUDY OF NATIONAL STOCK EXCHANGE

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1. Introduction

The stock exchanges are the exclusive centers for trading of securities. Thus, an organized, well- regulated stock market provides liquidity to shares, ensures safety and a fair dealing in selling and buying of securities and help in monitoring of firms in the process of collection and use of funds by them (Aggarwal & Aggarwal, 2000). The stock exchanges contribute to the economic development through providing listing of stocks and their trading. Listed stocks cover about 90 per cent of the corporate sector in which the public companies are at work in India (Singh, 1994). The stock exchanges perform this function by ensuring the marketability of the financial instruments traded in it; this ready marketability enables the investors, without committing their finances to specific securities to change their investment portfolio in light of the developing situation (Gupta, 1972). Economic liberalization and globalization process across the globe has changed the landscape dramatically. This change has brought in a change in the status, structure, profile, activities, liquidity, profitability etc. of the stock exchanges, which is an important indicator of the economic health of the country. The important objective of the stock exchange at world and Indian level is to ensure liquidity primarily, safety and transparency.

Liquidity is one of the driving forces of stock markets, which reflects the state of the financial markets of economies. But the fading away effect of this determinant could be posed as detrimental for the economy like mirror which is no longer able to show the reflection of the things placed before it. Thus, liquidity is considered as one of the important constituent of the stock market which helps the investors to aware themselves about the condition of the markets before making their investment. Recent studies have proposed that the higher the share turnover, the easier it is for investors to buy or sell shares of the stock. Investors are attracted to markets with high share turnover velocity that lead to increase in liquidity (Bureau, 2013). For example, if the total amount of shares traded over the year was 10 billion and the average amount of shares outstanding for the year was 100 million, the share turnover for the year is 100 times. Many studies have also proposed that number of trades (trading volume) as an important proxy for investors' confidence and liquidity. As a result, there is an increasing interest in the literature to improve the understanding of trading volume and investors' trade (Kumar, 2008). Chordia and Subrahmanyam (2001) examined the common determinants of liquidity and find that trading volume is negatively related to spread. Since many investors are using trading volume as a proxy for the liquidity of a given security, differences in trading volume may help investor to compare the level of liquidity among the securities.

The most accepted definition of liquidity is ability to convert stocks into cash and vice versa without affecting the price or with minimal impact on price. Liquidity is the ease of trading a security (Amihud et al., 2005) that just makes it one of the key elements upon which the investor will decide whether or not to invest; very important is quick execution of orders and ability to convert in cash at lowest costs. Liquidity is one of the primary considerations influencing the security investment decisions. Liquidity therefore is necessary to promote and sustain the growth of capital market. There is a clearly perceived need in the capital market for assuring easy and quick liquidity to the securities so as to draw investors in large numbers to the market. Liquidity exists in the stock market if it is possible to execute buy and sell orders of relatively large volumes of securities without much variance from market prices. However, despite the presence of several new institutional players in the market and electronic trading, still there a substantially high number of shares in cash market segment which are hardly traded most of the time. The lack of trading is a major problem causing illiquidity and investors are very often stuck with stocks which cannot be sold (Usha, 1996). A market may be considered deeply liquid if there are ready and willing buyers and sellers of securities in large quantities. The concept of market depth can be measured as the units which are to be sold or bought at a given price. The opposite concept is that of market breadth measured as the price impact per unit of liquidity (Mainelli, 2007).

Liquidity plays a crucial role in financial markets. The improvement and stability of market liquidity is important for market participants and serves as a way to enhance financial market credibility. In case of low liquidity in financial markets, investors are not boosted to invest in. Without this, financial markets would cease to exist. Thus, liquidity is necessary for the very existence of a financial market. Therefore, higher liquidity increases the expected level of satisfaction of market participants. Hence, liquidity directly affects a firm's cost of capital and hence its willingness to undertake real investment. The liquidity of the domestic underlying shares is increasingly gaining the attention of academicians and finance research.

2. Literature review and Hypothesis development

Stock exchange ensures liquidity, transparency and safety. Liquidity is an important aspect to reduce the trading cost of securities (Domowitz, 2001). Therefore, liquidity in a financial market has the ability to absorb smoothly the flow of buying and selling orders (Wyss et al., 2004). Liquidity, measured by trading volume considered as a significant investment style (Chen et al., 2010). Many investors are using trading volume as a proxy for the liquidity of a given security; differences in trading volume may help investors to compare the level of liquidity among the securities (Kumar, 2008). As a result, there is an increasing interest in the literature to improve the understanding of liquidity as follows:

2.1 Literature review relating to developed economies

Massimb and Phelps (1994) presented a comparative analysis of open outcry system and electronic trading system in US on the basis of two measures of market performance, operational efficiency and liquidity. It was revealed that the decision to move from open outcry to electronic matching forces the exchanges, customers and regulators to face a trade-off between efficiency and liquidity. At last, the study suggested that if this technology successfully deployed, then efficiency-liquidity trade-off might vanish. Amihud and Mendelson (1998) examined the benefits of the costs of increasing the liquidity and the method to trade-off the cost and the benefit. They also studied how financial management policies and institutional arrangements could have an impact on enhancing the liquidity. They concluded that increase in liquidity leads to reduce the firm's opportunity cost of capital. In examining the associated trade-offs, they explained a number of observed financial policies and institutional arrangements which might enhance liquidity. At last, they suggested a new perspective for studying the financial management policies. Sioud and Hmaied (1998) made an attempt to study the impact of Tunis stock exchange automation on liquidity and stock price volatility. Furthermore, the study indicated that securities listed on Tunis Stock Exchange shifted to automated trading for consistent liquidity. For the purpose, the study showed 20 securities for the improvement of liquidity in stock market. Hong and Rady (2002) examined a model for the traders with a view to make them aware about the liquidity conditions in the stock market of Germany before they make their investment in the market. A relationship between past prices and trading volume has been found which was said to have its impact on the trading. Sarr and Lybek (2002) analysed the liquidity indicators and developments in financial markets. The study found the different components out of the indicators of liquidity i.e. bid-ask spreads, turnover ratios, price impacts, cost, depth, breadth and resiliency to illustrate the operational efficiency. The study considered the market specific factors and peculiarities for determining the market's degree of liquidity. Soderberg (2008) evaluated the various macroeconomic indicators which facilitate the change in monthly liquidity on Scandinavian order driven stock exchanges in sample and out of sample, modeling is applied. The result focused that out of sample, forecasting of liquidity improve significantly with policy rate on Copenhagen, broad money on Oslo and short term interest rate and net flow from mutual funds on Stockholm stock exchange. Furthermore, the study laid stress on the predicting ability of different variables on three stock exchanges in three different benchmark models. Tetlock, P.C. (2008) examined the liquidity and market efficiency of the securities listed on Trade sports exchange. For the purpose, the study revealed about the limit order that executed during informative time periods having negative returns. Chai et al. (2010) examined two empirical issues regarding stock liquidity: to what degree different liquidity proxies correlated and how different liquidity proxies related to stocks' trading characteristics (turnover). Furthermore, the study had considerable implications for studying stock liquidity, since selecting an appropriate proxy for liquidity is an important issue in empirical research design. Using data from the Australian equity market, the results confirmed prior research that stocks' trading characteristics are important determinants of liquidity. Though the relationships are generally consistent with expectations, some proxies did react differently to certain trading characteristics. Bogdan et al. (2012) investigated the influence of liquidity variables on liquidity ratio and find out the crucial role of decision making process for investing in stocks.Ye et al. (2013) mainly focused on high frequency stock trading which led to increase in order cancellation having lesser value to investors and general public. The study showed an increase in the cancellation-execution ratio of orders as well as a corresponding increase in short-term volatility and a decrease of market depth (volume). The study found that increase in speed of trading increased the liquidity and turnover in the market. The study concluded that while continuing the speed of trading, the cost-benefit analysis would not be justified because it slightly increased volatility. Flood et al. (2014) examined the statistical commonalities in market liquidity across corporate equities and bond markets and in the commodity futures markets, the study focused on the daily data to identify the frequency patterns of individual markets to explain the aggregate and system-wide liquidity conditions. In addition to this, the study has also considered the daily average bid-ask spread and daily turnover as two other measures of the liquidity, to study the liquidity dynamics. The study concluded that there are no significant differences across different markets between; markets before crisis and in the aftermath of the crisis. Panayi and Peters (2015) made an attempt to develop a model for stock market trading activity in the Limit order Book using liquidity motivated agents. Limit Order Book price and volume (securities traded) dynamics have been considered as emergent features of interaction between abstractions of real-world market participants and study has revealed that liquidity motivations is more reflective of current market behaviour. Liu (2015) analysed whether the sentiment of investor is related to time series variation in stock market liquidity. For the purpose, Granger Causality was applied which suggested the investor sentiment granger causes market liquidity. Furthermore, it also analysed that investor sentiment is higher with the increase of trading volume in the market which in turn leads to increase in stock market liquidity in Japan. Dang, T. et al, (2019) examined the effect of stock liquidity on corporate capital structure decision using comprehensive international dataset of 19,939 firms across 41 countries over 2000–2010. The researchers found that, firms with higher stock market liquidity tend to have lower leverage and countries with strong institutional environments are more likely to have a weaker (negative) relationship between stock market liquidity and leverage.

2.2 Literature review relating to developing economies

Biswal and Kamaiah (2001) evaluated the behaviour of stock market development indicators namely market size, liquidity and volatility and examined whether these indicators have exhibited any trend changes after India liberalized its financial policies. The sample data has been collected from the various issues of RBI from 1989 to 1998 by using time series properties. The findings of the study opined that stock market has become larger and more liquid in the post liberlisation period. Prakash (2001) made a comparative analysis of BSE and NSE, leading stock exchanges of a country in the terms of number of companies listed, returns, average daily turnover, market capitalization and the number of share traded during the year 1994-2000. In the study, the author gave a brief account of the functioning of BSE and NSE. The study concluded that NSE registered phenomenonal growth during the period under consideration which comprised the entire span of existence. Singh (2004) examined the liquidity scenario of Indian stock exchanges and raises the issues related to illiquidity. In the paper, the author explained the indicators and present position of liquidity which showed, there were no trades on several companies listed on number of regional stock exchanges. The study indicated that presence of illiquidity in stock exchanges is due to the concentration of trading only on the limited number of stocks. The study suggested that there should be an enquiry into transactions in illiquid scrips and creating investor's interest through spreading of information. It was concluded that inspite of increasing in trading volumes on stock exchange and introduction of various reforms over the past few years, the problem of illiquid scrips has been a matter of major concern. Alnaif (2014) studied the factors that could affect liquidity at Amman Stock Exchange for the period ranging from 2011 to 2013. A panel study has been conducted using regression model. It was concluded that the size of the firm and earnings per share has a positive effect on the liquidity. On the other hand, firm's performance and stock dividends were found to be having no association with liquidity. Zhou and Dionne (2016) examined the impact of the duration of the trade, quotes and other exogeneous variables on the exante liquidity. The modeling of the study involved decomposition of the joint distribution of exante liquidity measures such as activity, size of trade etc.into simpler and interpretable distributions. It was suggested that trade and quote durations in addition to the short run variables such as changes in volume and spreads influence the exante liquidity changes in the market.

2.3 Literature review relating to ARIMA Modeling

Kilian and Ohanian (1998) made an attempt to study the unit root tests against trend break alternatives are based on the premise that the dating of the trend breaks coincides with major economic events with permanent effects on economic activity, such as wars and depressions. Furthermore, the study discussed conventional unit root tests against trend break alternatives based on linear ARIMA models did not capture transitory effects. Shiab (2006) examined the univariate ARIMA forecasting model, of Amman Stock Exchange (ASE) by using its general daily index. The study has applied different diagnostic tests in order to find out the best model describing the data. The study concluded that ASE would continue to grow by 0.195% but the results have been found that ASE followed the Efficient Market Hypothesis (EMH) in its weak form. Izzeldin (2007) highlighted trading volume and the number of trades both used as proxies for market. The paper investigated this issue using high frequency data for Cisco and Intel in 1997. For the purpose, Generalized Autoregressive Conditional Heteroskedasticity Model (GARCH) augmented with lagged trading volume and number of trades, tests based on moment restrictions, regression analysis of volatility on volume and trades has been used. The result of the findings revealed that the number of trades was the better proxy for market activity. Ghosh and Sen (2008) attempted to fit a model to forecast the liquidity positions of the two premier stock exchanges of India, the BSE and the NSE. The data belonged to the study period from Jan 1995 to Dec 2005. The sample taken for the study was 132 monthly observations for both the exchanges by using ARIMA method. It has been observed that an ARIMA could be an appropriate model regarding this when liquidity represented in the terms of turnover ratio. The results for turnover ratio were considered as a proxy to liquidity for both the exchanges. The study suggested that this could provide a better predictive tool to the market analysts and researchers. Jarrett and Kyper (2011) demonstrated the usefulness of ARIMA as a predictive tool for stock returns developed by Pacific Basic Capital Markets. The author explained the spontaneous decline in the price index of Shangai during the world economic debacle. Stuckey and Campbell (2012) examined different methods of ARIMA model to aid in seasonal adjustment. Automatic method of the selection of models has been preferred over manual adjustment. The study found that BPG algorithm be adopted for selecting ARIMA model in order to reduce seasonal adjustments. Corliss (2013) made an attempt to study the statistical concepts of ARIMA Model and application of non-temporal ARIMA Model. The author also reviewed the financial forecasting of data with chaotic fluctuations. Devi et al. (2013) seeks to investigate the best forecasting methods under consideration by taking Nifty Midcap 50 companies data for analysis. The data has been taken for past five years (2006 to 2011) using ARIMA model for forecasting. It infers a new investment decisions or guidelines based on minimum error (%) and Akaike Information Criteria considered a best model for the indices taken. This was done with a view to help attract the investors to stock market which sometimes due to depressed market conditions is not able to attract investors because of risk factor. Thus an approach has been explored that can help the investors to forecast the market behavior based on historic patterns. Satish et al. (2014) made an attempt to study intraday volume and intraday volume percentages and has used ARMA model to forecast the trading volumes used as a proxy for liquidity. Mondal et al. (2014) has made an attempt to explore in to the model that can be used effectively to predict the stock market prices. For this ARIMA model has been tested to see whether it helps in accurate predictability or not and thus it was found that this model was having predictability of stock prices of more than 85%. Moreover the result of this model was found to be accurate particularly for FMCG sectors in comparison to banking or automobile sector. Challa M. et. al (2018) in a study forecasted the beta values of companies listed on Sensex, Bombay Stock Exchange using ARIMA method for 10 years from April 2001 to March 2017. A mixed trend is found in forecasted beta values of the BSE Sensex. The values of actual and forecasted values are showing the almost same results with low error percentage.

2.4 Hypothesis Development

The study develops hypotheses related to existing studies that can be testable and scientifically evident. For the purpose, Abdullah (2012) examined that ARIMA modeling used in financial market forecasting over the period of time (2002-2007). The study asserts that model validation and diagnostic checking involved white noise characteristic for analysing the residuals. The statistic is used to test the following hypotheses:

H_0: Errors are non random (not white noise).

H_1: Errors are random (white noise).

Ghosh and Sen (2008) observed that ARIMA model could be an appropriate model regarding this when liquidity represented in the terms of turnover ratio. The results for turnover ratio were considered as a proxy to liquidity for the stock exchanges (NSE & BSE). The study suggested that this could provide a better predictive tool to the market analysts and researchers. The following hypotheses have been developed on the basis of this study:

H_o: Prediction of turnover is not represented by ARIMA Modeling.

H_1: Prediction of turnover is represented by ARIMA Modeling.

Similarly, for considering the relevant empirical work on liquidity in India and abroad, this paper aims to forecast the liquidity of stock exchange by using ARIMA Model. The hypotheses are as follows:

H_o: Liquidity in terms of number of securities traded at NSE cannot be predicted by ARIMA Model.

H_1: Liquidity in terms of number of securities traded at NSE can be predicted by ARIMA Model.

3. Data set and Research Method

3.1 *Data set*

The study covers the number of securities traded during April 2000 through March 2019 from National Stock Exchange (NSE). The sample for the study was based upon monthly observations taken from Capital Market Segment at NSE before the measurement of liquidity. The securities traded used as a proxy for the liquidity represented the volume in the particular stock exchange.

3.2 *Research method*

ARIMA Method is used for forecasting the liquidity in terms of securities traded. The data for ARIMA model is to be checked whether it is accurate or not by using IF condition in Ms-excel e.g A1 (Actual value)>A2 (Residuals). The accuracy of the data for ARIMA model is more than 60 percent. Hence, it can be said that ARIMA Model is used for analysis. Since ARIMA model is an iterative process and some sort of trial and error is inevitable, rigorous mathematical computation is necessary. Hence, the popular econometrics software Eviews 7 has been used for computation purposes. MS- Excel has been used for calculating the predicted value of ARIMA Model. In ARIMA model, the future value of a variable is assumed to be a linear function of several past observations and random errors (Abdullah, 2012). The procedure for ARIMA model has been developed by Box and Jenkings (1970) popularly known as B-J Procedure. In an ARIMA (p, d, q) modelling the model is constructed based on the identified orders of 'integration' (d); set of autoregressive terms (AR (p)) and set of moving average terms (MA (q)) processes inherent in the time series.

4. Results and Findings

Firstly, the time series data on which ARIMA model is to be applied needs to be stationary. Therefore, the time series data regarding liquidity of NSE are tested for stationarity where unit root test i.e. Augmented Dickey Fuller (ADF) test has been applied. If the ADF statistics (calculated value) is less than the critical value then series is non-stationary otherwise stationary. The results of Augmented Dickey Fuller (ADF) test is applied on data given in Table1. It could be stated that data for NSE is integrated at order 1 that is to say I (1). It should be noticed that if a time series data is I (d), it has to be stationary. While applying ADF test on Eviews, one of the option 'level' was chosen which means that'd' equals to zero. The calculated p-values of ADF were less than table p-value of 0.005 which leads to the conclusion that the data of the time series under study is stationary. Furthermore, correlogram was generated which also exhibited that the data of the time series under study is stationary (Table 2).

(Insert Table 1)

Table 2 shows the autocorrelation and partial autocorrelation functions of the residuals, together with the Ljung-Box Q-statistics for high-order serial correlation and also shows the stationarity of the data. If there is no serial correlation in the residuals, the autocorrelations and partial autocorrelations at all lags should be nearly zero, and all Q-statistics should be insignificant with large p-values. To judge the auto correlation of the ARIMA Model Box Pierce Q statistic in the following form has been used.

$$\mathbf{Q= n \sum^{m}_{k=1} p^{\wedge}2_{k} \;\square\; X^{2}_{m}}$$

Where

n= sample size

m= lag length

The computed Q statistics are significant which reveals that residual estimated by the equation is purely non- random and p-value is less than 0.005. The results of Q-statistics are reported in the table 2. Thus, Correlogram is carried out by looking at Autocorrelation (AC) and Partial Autocorrelation (PAC) function coefficients to identify the structure in the data. There are three insignificant spikes of AC as well as PAC function in corrrelogram consisting number of Moving Average and Autoregressive terms. In this case, Correlogram displays AC and PAC functions up to three lag orders. Q -statistics are significant at all lags, indicating significant serial correlation in the residuals.

(Insert Table 2)

The following graph (fig 1) highlights the correlogram of number of securities traded in diagrammatic way which shows the white noise process where mean and variance are constant and serially uncorrelated.

(Insert Figure 1)

Table 3 highlights the different pairs of ARMA Model[1] with AR and MA terms. Each model in the table showing Akaike Information Criteria (AIC) and Root Mean Squared Error (RMSE). To identify a correct model for the study, selection of the model depends on lowest value of AIC and RMSE. In a case, when AIC and RMSE has

[1] Note: ARIMA become ARMA when series get stationary. 'I' in ARIMA means integration which is used to get stationary series. After eliminating 'I', the model will be referred as ARMA.

different model of lowest value, select RMSE's lowest value. As the analysis shows different lowest values of AIC and RMSE, ARMA (2, 3) has a lowest value of RMSE i.e. 57.521. Hence, ARMA (2, 3) would be an appropriate model for the study.

(Insert Table 3)

On the basis of model, the following estimate equation made in Eviews Software:

= **d (nst) c ar(1) ar(2) ma(1) ma(2) ma(7)**

After applying the above equation, estimated results of ARIMA for National Stock Exchange is obtained as follows:

(Insert Table 4)

In the table 4, the estimate of ARIMA Model is reported for NSE where number of securities traded used as a measure of liquidity. This model is a good fit as R-squared= 0.5206 and Adjusted R-Squared= 0.5066 respectively with a very significant F statistics (37.1420). Chawla and Sondhi (2011) focused on how good the estimated regression equation is. For the purpose, there is a measure R-square (explains the variation in dependent variable by independent variable) which also called the coefficient of determination of a regression equation and it takes value between 0 and 1 which indicates the explanatory power of the regression model. Although Durbin-Watson statistics (2.0478) are also significant but for this purpose it is not worth mentioning. Mostly the probability in the result would be insignificant due to the presence of multicollinearity in ARMA modeling and AR (1) and AR (2) tends out to be significant as given in Table 4. Regarding p and q, modeling estimates p=2 and q=3 which considered as a measurement of liquidity. Thus, only ARMA models will be considered further. ARMA (2, 3) is to be used that predicts the second difference of the series equals a linear function of the last three forecast errors:

$$\hat{Y}_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \gamma_1 U_{t-1} + \gamma_2 U_{t-2} + \gamma_3 U_{t-3} \ldots\ldots\ldots\ldots\ldots \quad (1)$$

Where $\hat{Y}_t$ = Predicted Value, α = Constant term, U_{t-1}, U_{t-2} and U_{t-3} are the MA (1), MA (2) and MA (3) coefficients and Y_{t-1} and Y_{t-2} are AR (1) and AR (2) coefficients with lag order 1, 2, 3.

(Insert Table 5)

The above table 5 showed actual and residual values of last three days for the purpose of forecasting liquidity in terms of number of securities traded by using regression equation (1). Hence, the predicted value $\hat{Y}$ (t) of liquidity after making calculations for the model is 7.991. From the constructed model, it can be easily forecast within the period which has taken for the study i.e. April 2000 to March **2019** based on its past behavior. With an ARIMA model, the model predictions compare with the actual values of number of securities and hence, the forecast values are not accurate to that extent i.e. decreasing from the previous month's actual value.

The above results highlighted that the forecast values are not accurate as the actual value in the data. The reason behind is that trend is broken during the year 2005 as shown in Fig. (1) & (2). For the purpose, data has been segregated into two periods i.e. from April 2000 to March 2005 (Period-I) and April 2006 to March **2019** (Period-II) to overcome the limitation of above result. ARIMA Model has been applied on both the periods separately. As the analysis shows different lowest values of AIC and RMSE, ARMA (2, 2) has a lowest value of RMSE for both the periods i.e. 28.90 and 67.25 respectively. Hence, ARMA (2, 2) would be appropriate models for both the periods (Period-I & Period-II).

(Insert Table 6)

On the basis of models, the following estimate equation made in Eviews Software:

= **d (nst1) c ar(1) ar(2) ma(1) ma(2)…………………….(i)**

= d (nst2) c ar(1) ar(2) ma(1) ma(2)…………………….(ii)

After applying the above equations, estimated results of ARIMA for National Stock Exchange in both the periods is obtained as follows:

(Insert Table 7 & 8)

From the table, it is analyzed that both the models are good fit as R-squared= 0.168 (Period-I) & 0.575 (Period-II) respectively and Adjusted R-Squared= 0.1135 & 0.558 respectively with a significant F statistics (3.80 & 34.84 respectively). ARMA modeling and AR (1) = 0.003 & 0.020 respectively and AR (2) = 0.029 & 0.000 respectively tends out to be significant as given in Table 7&8. Regarding p and q, modeling estimates p=2 and q=2 which considered as a measurement of liquidity. Thus, only ARMA models will be considered further. ARMA (2, 2) is to be used that predicts the second difference of the series equals a linear function of the last two forecast errors in segregated data.

(Insert Table 9 & 10)

Table 9& 10 represented actual and residual values of last two days which were taken for the purpose of forecasting liquidity in terms of number of securities traded by using regression equation (1). Hence, the predicted value $\hat{Y}$ (t) of liquidity after making calculations for both the models is 171.75. The model predictions are compared with the actual values of number of securities at NSE during the period. Thus, the forecast values are accurate to that extent i.e. approximately near to previous month's actual value.

5. Conclusion

The paper has revealed that securities traded can best be measured by applying ARIMA Model on segregated data due to trend break with the predicted value of 171.75 as it has been found to be based on its own past behavior and hence the null hypothesis has been rejected. Thus, it has been observed that an ARMA of (2, 2) would be an appropriate model for two periods taken for the study which represented liquidity in terms of number of securities traded. Sample is one of the limitations to the study. Due to small sample of monthly observations of number of securities traded taken in the paper has limited scope to generalize the results. Hence, academic researchers may employ this model on large sample. On the other hand, only one factor i.e. number of securities traded has been considered for measuring the impact of liquidity in stock market. The paper has suggested that other factors like number of transactions, liquidity ratio, market capitalization and turnover to assess the impact over the liquidity.

References

- Abdullah, L. (2012), "ARIMA Model for Gold Bullion Coin Selling Prices Forecasting", *International Journal of Advances in Applied Sciences,* 1(4), 153-158.
- Aggarwal, K.; and Aggarwal, D. (2000), Bull, Bears and the Mouse- An Introduction to Online Stock Tradin*g, Macmillan India*, New Delhi.
- Amihud, A.; and Mendelson, H. (1998), "Liquidity and Asset Pricing: Financial Management Implications", *Financial management*, 5-13.
- Biswal, C. and Kamaiah, B. (2001), "Stock Market Development in India: Is there any trend break?" *Economic and Political Weekly*, 36 (4); Jan-Feb, 377-84.

- Bogdan, S.; Baresa, S.; and Ivanovic, S. (2012), "Measuring Liquidity on Stock Market: Impact on Liquidity Ratio", *Tourism and Hospitality Management*, 18 (2), 183-193.
- Bureau (2013), "Indian stock Markets Trail Peers in Share Turnover Velocity", Retrieved from: www. articles.economictimes.indiatimes.com.
- Chai, D.; Faff, R. and Gharghori, P. (2010), "New evidence on the relation between stock liquidity and measures of trading activity", *International Review of Financial Analysis,* 19 (3); June, 181-192.
- Challa M.L., Malepati V., & Kolusu S. N., Forecasting risk using auto regressive integrated moving average approach: an evidence from S&P BSE Sensex, *Financial Innovation* volume 4, Article number: 24 (2018)
- Chen, Z.; Ibbotson, R.G. and Hu, W.Y. (2010), "Liquidity as an Investment Style", *Zebra Capital Management*, LLC, Sept.
- Chordia, T.; Roll, R. and Subramanyam, A. (2001), "Market Liquidity and Trading Activity", *Journal of Finance*, 56 (2); April, 501-530.
- Corliss, D.J. (2013), "Non-Temporal ARIMA Models in Statistical Research", *Magnify Analytic Solutions,* SAS Global Forum, University of Toledo, 1-10.
- Dang T. L., Ho H. L., Lam C. D., Tran T. T. & Vo X. V., Stock liquidity and capital structure: International evidence, 26 May 2019. https://doi.org/10.1080/23322039.2019.1587804
- Devi, U.; Sundar, D. and Alli, P. (2013), "An Effective Time Series Analysis for Stock Trend Prediction Using ARIMA Model for Nifty Midcap-50*", International Journal of Data Mining & Knowledge Management Process,* 3(1).
- Domowitz, I. (2001), "Liquidity, Transaction Costs, and Reintermediation in Electronic Markets", *eBusiness Research Center,* Working Paper 4, April.
- Flood, M.D.; Liechty, J.C.; and Piontek, T. (2014), "Macroeconomic Patterns in System-Wide Liquidity Regimes", Nov.
- Ghosh, S.K. and Sen, S.S. (2008), "Forecasting Liquidity of BSE and NSE at an aggregate level", *Capital market,* ICFAI University Press, New Delhi.
- Gupta, L.C. and Rohtagi, J.K. (1972), "Stock market Liquidity: How much? For Whom?, *Economic and Political Weekly,*8 (34); August,85-96.
- Hong, H. And Rady, S. (2002), "Strategic trading and learning about liquidity", *Journal of Financial Markets*, 5, 419–450.
- Izzeldin, M.A. (2007), "Trading Volume and the number of trades: A Comparative study using high frequency data". Retrieved from: www. Lums.lancs.ac.uk/publications/viewpdf/004798.

- Jarrett, J.E. and Kyper, E. (2011), "ARIMA Modeling with intervention to forecast and analyse Chinese stock prices", *International Journal of Engineering Business Management*, 3(3), 53-58.
- Kanasro, H.; Jalbani, A. and Junejo, M. (2009), "Stock Market Liquidity: A Case Study of Karachi Stock Exchange", *Pakistan Journal of Commerce and Social Sciences*,3.
- Kilian, L. and Ohanian, L.E. (1998), "Is there a trend break in U.S. GNP? A Macroeconomic Perspective", *Center for Economic Policy Research (CBEPR)*, Jan.
- Kumar, A. (2008) "Determinants of Stock Trading Volume: Evidence from Indian Stock Market, *Indira Gandhi Institute of Development Research (IGIDR)* May. Retrieved from: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=947429.
- Liu, S. (2015), "Investor Sentiment and Stock Market Liquidity", *Journal of Behavioral Finance*, 16(1); Mar, 51-67.
- Mainelli, M. (2007), "Liquidity: Finance in motion or evaporation". Retrieved from: http://www.gresham.ac.uk/lectures-and-events/liquidity-finance-in-motion-or-evaporation.
- Massimb, M.N.; and Phelps, B.D. (1994), "Electronic trading, market structure and liquidity", *Financial Analyst Journal*, 50 (1); Jan-Feb.
- Mondal, P.;Shit L.and Goswami, S.(2014), "Study of Effectiveness of Time Series Modeling (ARIMA) In Forecasting Stock Prices", *International Journal of Computer Science, Engineering and Applications*, 4(2).
- Panayi, E; and Peters, GW. (2015), "Stochastic simulation framework for the Limit Order Book using liquidity motivated agents"; Statistical Finance, Cornell University, Jan.Retreived from: http://arvix.org/abs/
- Prakash, N. (2001), "BSE vs NSE- A Comparative Analysis", *SEBI and Corporate Laws*, Jan, Vol.XXIX, Part I, pp.19-34.
- Sarr, A. and Lybek, T. (2002), "Measuring liquidity in financial markets", *IMF working paper WP/02/232*, Monetary & Exchange Affairs.
- Satish, V.; Saxena, A. and Palmer, M. (2014), "Predicting Intraday trading volume and volume percentages", *Journal of Trading*, 9(3).
- Singh, G. (2004), "Illiquidity in Stock Exchanges: Some Issues", *The Indian Journal of Commerce*, 57(4); Oct-Dec, 71-83.
- Singh, P.L. (1994), "Indian Capital Market: A Functional Analysis", *Kaniksha Publishers Distributors*, New Delhi.
- Sioud, O.B. and Hmaied, D.M. (1998), "The impact of automation, liquidity, volatility, stock returns and efficiency" Evidence from the Tunisian Stock market", *ERF Working Paper 0222*, CESifo Conference Center, Munich.

- Soderberg, J. (2008), "Do Macroeconomic Variables Forecast Changes in Liquidity? An Out-of-Sample Study on the Order-Driven Stock Markets in Scandinavia", *Conference on Liquidity: Concept and Risks*, CEsifo Conference Center, Munich, 17-18 Oct.
- Tetlock, P.C. (2008), "Liquidity and Prediction market efficiency", March. Retreived from: http://ssrn.com/abstract=929916.
- Usha, S. (1996), "Development of Indian Financial Markets- A study of strategic Management and regulatory Mechanisms in relation to Capital Market", *An Unpublished thesis*, Delhi University.
- Wyss, R.V.; Zimmermann, H. and Keel, A. (2004), "Measuring and Predicting Liquidity in the Stock Market", *A Dissertation*, Swiss Institute of Banking and Finance of the University of St. Gallen.
- Ye et.el. (2013), "High-frequency stock trading of little value to investors, general public", Vol.13, *University of Illinois at Urbana-Champaign*. Retreived from:http://www.sciencedaily.com/releases/2013/01/130110111738.htm.
- Zhou, X. and Dionne, G. (2016), "The Dynamics of Exante High-Frequency Liquidity: An Empirical Analysis". Retrieved from: http://www.cirrelt.ca/documents travail/CIRRELT-2016-02.pdf.

Table1: Results of Augumented Dicker Fuller (ADF) test

Null Hypothesis: D(NST) has a unit root			
Exogenous: Constant			
Lag Length: 6 (Automatic - based on AIC, maxlag=13)			
		t-Statistic	**Prob.**
Augmented Dickey-Fuller test statistic		-4.535	0.000*
Test critical values	1% level	-3.468	
	5% level	-2.878	
	10% level	-2.575	

Table2: Correlogram for stationary time series data (2000 to 2019)

AC	PAC	Q-stat	Prob
-0.680	-0.680	84.271	0.000
0.314	-0.278	102.31	0.000
-0.023	0.123	102.41	0.000
-0.121	-0.005	105.10	0.000
0.098	-0.096	106.90	0.000
-0.049	-0.045	107.34	0.000
0.090	0.181	108.87	0.000
-0.096	0.072	110.62	0.000

0.036	-0.113	110.87	0.000
0.074	0.084	111.93	0.000
-0.142	0.051	115.83	0.000
0.177	0.084	121.93	0.000
-0.129	-0.000	125.16	0.000
0.081	0.042	126.45	0.000
-0.051	0.006	126.97	0.000
0.061	0.067	127.71	0.000
-0.061	-0.019	128.46	0.000
0.073	0.056	129.54	0.000
-0.038	0.044	129.84	0.000
0.054	0.113	130.43	0.000
-0.090	-0.060	132.10	0.000
0.137	0.049	136.00	0.000
-0.181	-0.079	142.78	0.000
0.213	0.106	152.29	0.000
-0.131	0.097	155.91	0.000
0.044	-0.011	156.32	0.000
0.022	-0.027	156.42	0.000
-0.078	-0.056	157.71	0.000
0.126	0.109	161.15	0.000
-0.114	0.014	163.97	0.000
0.131	0.064	167.73	0.000
-0.117	-0.055	170.74	0.000
0.034	-0.042	171.00	0.000
0.055	0.004	171.68	0.000
-0.123	-0.029	175.10	0.000
0.195	0.064	183.73	0.000

Source: Compiled from Eviews7 Software

Table 3: Table showing the values of AIC and RMSE

Terms	Akaike Information Criteria (AIC)	Root mean Squared Error (RMSE)
ar(1) ma(1)	11.024	58.937
ar(1) ma(1) ma(2)	11.018	58.430
ar(1) ma(1) ma(2) ma(7)	11.027	58.367
ar(1) ar(2) ma(1)	**11.005**	58.044
ar(1) ar(2 ar (7) ma(1) ma(2)	11.017	57.675
ar(1)ar(2)ma(1)ma(2)	11.006	57.756
ar(1)ar(2)ar(7)ma(1)	11.029	58.378

ar(1)ar(2)ma(1)ma(2) ma(7)	11.010	**57.521**
ar(1)ar(2)ar(7)ma(1)ma(2)ma(7)	11.028	57.663

Source: Compiled from Eviews 7 software

Table 4: Estimated Results of ARIMA for number of securities traded at NSE

Dependent Variable: D(NST)				
Method: Least Squares				
Sample: 2000-2019				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	3.5475	2.6959	1.3158	0.1900
AR(1)	-0.9443	0.2346	-4.0235	0.0001*
AR(2)	-0.4627	0.1504	-3.0768	0.0024*
MA(1)	0.1296	0.2373	0.5461	0.5857
MA(2)	0.2605	0.1221	2.1324	0.3441
MA(7)	0.0905	0.0770	1.1744	0.2419
R-squared	0.5206	**Mean dependent var**		3.7683
Adjusted R-squared	0.5066	**S.D. dependent var**		83.315
S.E. of regression	58.5224	**Akaike info criterion**		11.0100
Sum squared resid	585653.5	**Schwarz criterion**		11.1176
Log likelihood	-968.385	**Hannan-Quinn criter.**		11.0536
F-statistic	37.1420	**Durbin-Watson stat**		2.0478
Prob(F-statistic)	00.0000			

Source: Compiled from Eviews7 software

Table 5: Table showing actual and residual values of number of securities traded from 29 Mar to 31 Mar, 2019

Actual Values	**Residuals**
-6.00	-33.44
-19.00	-23.52
21.00	5.01

Source: Compiled from Eviews 7 Software

Table 6: Table showing the values of AIC and RMSE for two different periods

Terms	**Period-I**		**Period-II**	
	AIC	**RMSE**	**AIC**	**RMSE**
ar(1) ma(1)	29.29	9.68	68.99	11.36
ar(1) ar(2) ma(1)	28.97	9.69	68.27	11.35

ar(1) ar(2) ma(1) ma(2)	28.90	9.71	67.25	11.34
ar(1) ma(1) ma(2)	29.10	9.69	68.91	11.37

Source: Compiled from Eviews 7 Software

Table 7: Estimated Results of ARIMA for number of securities traded at NSE (Period-I)

Dependent Variable: D(NST1)				
Method: Least Squares				
Sample (adjusted): 2000- 2005				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	-3.163135	2.422414	-1.305778	0.1965
AR(1)	-1.000894	0.330370	-3.029619	0.0036
AR(2)	-0.329147	0.301876	-1.090338	0.0299
MA(1)	0.636096	0.346534	1.835595	0.0713
MA(2)	-0.110783	0.338086	-0.327677	0.7443
R-squared	0.168076	**Mean dependent var**		-3.060606
Adjusted R-squared	0.113523	**S.D. dependent var**		31.93401
S.E. of regression	30.06679	**Akaike info criterion**		9.717454
Sum squared resid	55144.73	**Schwarz criterion**		9.883337
Log likelihood	-315.6760	**Hannan-Quinn criter.**		9.783002
F-statistic	3.080997	**Durbin-Watson stat**		2.010058
Prob(F-statistic)	0.022375			

Source: Compiled from Eviews 7 Software

Table 8: Estimated Results of ARIMA for number of securities traded at NSE (Period-II)

Dependent Variable: D(NST2)				
Method: Least Squares				
Sample: 2006- 2019				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	6.657645	1.044150	6.376140	0.0000
AR(1)	0.344370	0.146618	2.348764	0.0207
AR(2)	0.482075	0.099012	4.868858	0.0000
MA(1)	-1.332522	0.162268	-8.211845	0.0000
MA(2)	0.340907	0.157426	2.165505	0.0327
R-squared	0.575082	**Mean dependent var**		7.592593
Adjusted R-squared	0.558581	**S.D. dependent var**		103.6559
S.E. of regression	68.86834	**Akaike info criterion**		11.34746
Sum squared resid	488513.4	**Schwarz criterion**		11.47163
Log likelihood	-607.7629	**Hannan-Quinn criter.**		11.39781
F-statistic	34.84998	**Durbin-Watson stat**		2.039445
Prob(F-statistic)	0.000000			

Table 9: Table showing actual and residual values of number of securities traded for Period-I

Actual Values	**Residuals**
57.08	-36.08
43.96	-62.96

Source: Compiled from Eviews 7 Software

Table 10: Table showing actual and residual values of number of securities traded for Period-II

Actual Values	Residuals
-1.17	-13.82
-17.95	54.95

Source: Compiled from Eviews 7 Software