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SHORT-TERM FORECASTING OF STOCK PRICES OF INDIAN BANKS UNDER NIFTY-50 DURING COVID-19 PANDEMIC WITH HIGH-FREQUENCY DATA

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Abstract: THE OUTBREAK OF THIS PANDEMIC IS AN UNFAMILIAR SHOCK TO THE WHOLE INDIAN ECONOMY AS WELL, AND AS A RESULT THE INDIAN STOCK MARKET IS SEVERELY AFFECTED TOO. AS THE FINANCIAL MARKETS ARE AFFECTED BY THE PANDEMIC, THE STOCK PRICES OF INDIAN BANKS CANNOT BE THE EXCEPTIONAL ONE. IT IS INTERESTING TO KNOW WHETHER EFFECTIVE FORECASTING OF STOCK PRICES OF BANKS IS POSSIBLE DURING THE COVID-19 BY APPLYING ARIMA WITH AND WITHOUT DRIFT USING HIGH-FREQUENCY DATA RELATED TO 10-MINUTE CLOSING STOCK PRICES DATA OF INDIAN BANKS LISTED UNDER NIFTY 50,WHICH IS NOT YET BEEN EXPLORED BY ANY RESEARCHER. MOREOVER, THE EFFICACY OF THE FORECASTING MODELS HAS BEEN VERIFIED BY USING A SIMPLE METHOD BASED ON COEFFICIENT OF VARIATION. IT IS FOUND THAT THE ERROR MARGIN IN FORECASTING IS LESS WITH DRIFT MODELS FORAXIS, HDFC, ICICI, INDUSIND AND KOTAK

MAHINDRA BANK IN CASE OF STATE BANK OF INDIA ERROR MARGIN IS LESS IN WITHOUT DRIFT MODELS. THOUGH THE MODEL FOR AXIS, HDFC AND KOTAK MAHINDRA BANK WITHOUT DRIFT SHOWS MORE VARIATIONS BUT IT MAY BE MORE RELIABLE AS ALL THE COEFFICIENT OF INDEPENDENT TERMS ARE SIGNIFICANT I.E. LESS THAN 0.05.

Keywords: COVID-19, HIGH-FREQUENCY DATA, INDIAN BANKS, NIFTY, SHORT-TERM FORECASTING, ARIMA WITH DRIFT, ARIMA WITHOUT DRIFT

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1. INTRODUCTION

The outbreak of COVID-19 which triggered crisis in global financial economy is of special interest. Efforts to contain the spread of this disease such as quarantine and restrictions on mobility of labour are slowing down the world economy (Salisu & Vo, 2020).The outbreak of this pandemic is an unfamiliar shock to the whole Indian economy as well, and as a result the Indian stock market is severely affected too. Financial markets in India are witnessing sharp volatility currently due to the fallout in global markets. The fall is in line with the global benchmark indices as the domestic market usually tracks the major global indices and the high volatility is likely to continue in the near future (Raja Ram, 2020) . The all-encompassing lockdown enunciated on 24th March 2020 by the Prime Minister of India as a precautionary measure against COVID-19, followed by subsequent extensions, has resulted in a standstill of all economic activities in the country. This has also led to impact on the banking sector of India as well. The pandemic has been affecting the financial services sector in multiple ways — from business continuity issues and operational considerations to the overall financial outlook (Shah, 2020). Banks, working with skeletal staff, are keeping branches open across the country and are focusing on cash withdrawals, cheque clearing, remittances and government transactions. They gearing up to deal with the huge requests for deferring the loan repayments and have to figure out how to reach the Direct Benefit Transfer announced by the government to intended beneficiaries. All banks are ensuring that their branches are kept open, ATMs filled up & are working. Banking correspondents are active. Social distancing is respected & sanitizers are provided where necessary (Economic Times Bureau, 2020). But one the biggest concern for banks is that the impending outbreak of the virus is likely to severely impact the recovery process. Due to the shutdown and its subsequent extensions many businesses are affected because of which they made defaults in repayment of loans within stipulated time. This is also one the reason that stock prices of Indian banks are affected during COVID-19.

In addition to that, the stock markets recorded several shock waves starting with February 2020, whereas the financial volatility continued to increase in the context of COVID-19 uncertainty (Albulescu, 2020) . In the presence of stock markets price bubbles, the COVID-19 impact on the financial system could not be ignored. Few early researches focussed on impact of COVID-19 on stock market (Raja Ram, 2020), (Ashraf, 2020)(Zhang, Hu, & Ji, 2020) on the other hand only few papers underline the COVID-19 impact on financial volatility (Hartwell, 2018) (Meher, Hawaldar, Mohapatra, & Sarea, 2020) and due to high volatility it is difficult to forecast the stock prices during the pandemic. As the financial markets are affected by the pandemic,the stock prices of Indian banks cannot be the exceptional one. Now this will be interesting to know whether effective short-term forecasting of stock prices of Indian banks will be possible during the COVID-19 using the ARIMA model including drift and excluding with high-frequency data which is not yet been explored by any researcher. Moreover, by using the models short-term forecasting of stock prices of Indian Banks has been done for 10 trading days. Again the paper also attempts to proposed a simple method based on coefficient of variation to check the efficacy and accuracy of the formulated models.

2. REVIEW OF LITERATURE

The review of literature part has been divided into two parts. The first part highlights some of the important research works related to forecasting, high frequency data or ARIMA and the second part deals with the few of the important recent studies related to COVID-19 and stock markets.

A paper shows the examples of high-frequency time series arise in many fields of applications, like daily sales in stores, energy consumptions by hours in office buildings, daily cash flows in organisations, etc. where ARIMA has been applied for forecasting (Guy, 2009). Some more practical applications of ARIMA with high-frequency data where the authors proposed a methodology of combining Seasonal ARIMA and data assimilation to predict 15-min, hourly, and daily water demand either offline (using historical or real-time data) and concluded the suggested methodology showed a better performance using weekly seasonality(Arandia, et al., 2014).Again, a study predicted the performance of Ethereum cryptocurrency exchange rate using ARIMA with high-frequency data from 22nd January 2018, 00:00 until 23rd January 2018, 08:45 (Bakar & Rosbi, 2019).Furthermore, few researches are based on advancement in ARIMA model like a paper aims to modify the traditional ARIMA model by using the machine-derived deep learning long short-term memory (LSTM) model using high-frequency data for forecasting. (Li, Han, & Song, 2020)Similarly a study used, proposed a partitioning-interpolation (PI) based hybrid ARIMA-GARCH model for selected Indian stocks from 2002 to 2007, having improved prediction accuracy over the other models like ARIMA, GARCH and Artificial Neural Network (Narendra Babu & Eswara Reddy, 2014) Moreover, a study makes a comparison between recent available model of the area, providing generalized modelling for the stock market analysis and prediction and realization of the model using fundamental and generalized ARIMA and found hybrid model gives better forecasting results. (Shrivastav & Kumar, 2018) Similarly, a paper proposed a hybrid ARIMA with help of wavelet transform decomposition using six months' daily data of S&P BSE information technology, and predicted the 10 days' step ahead future values and comparative analysis has been done between ordinary model and proposed models. (Valvi & Shah, 2018) A diversion from ARIMA, a study proposed a structured method to specify an observable high-frequency model, on the basis of the low-frequency sample properties to model and forecast a vector of time series sampled at different frequencies (Casals, Jerez, & Sotoca, 2005)A study using high frequency trading data of Kweichow Moutai Co Ltd from January 4th, 2013 to February 26th, 2014 found both ARIMA model and

ARIMA GARCH model cannot fit the data of mid-quote price well rather ARFIMA and regression model can be fitted. (Yifan, et al., 2016)

Some of the important researches related to COVID-19 and financial market where an article explores the problems associated with the onset of the economic crisis and the outbreak of COVID-19 in countries with small open economies (SOE) and proved that the key challenges the SOE countries will face are primarily the devaluation of the national currency, the massive closure of small and micro businesses, the growth of social problems, etc. (Abuselidze & Slobodianyk, 2020) Again a paper evaluates the health news predictability of stock returns since the emergence of COVID-19 by evaluating the stock returns behaviour of top 20 most affected countries and found that the model that incorporates health news index performs better (Salisu & Vo, 2020)Furthermore, in a study, authors applied wavelet methods to daily data of COVID-19 world deaths and daily Bitcoin prices from 31th December 2019 to 29th April 2020 and found that the levels of COVID-19 caused arise in Bitcoin prices and proved whether Bitcoin is a safe haven investment. (Goodell & Goutte, 2020) Similarly, a paper investigates the impact of COVID-19 official announcements on the financial volatility using S&P 500 realized volatility as a proxy for the US financial markets' volatility and compared the impact of data reported at global level and in the US. (Albulescu, 2020) Nevertheless, a study related to the relationship banking in Germany during COVID-19 where the authors found that by providing liquidity Hausbanks can support business clients to survive the social shutdown and hence cushion the economic impacts of the pandemics. (Flogel & Gartner, 2020) Moreover, a paper investigates the reaction of financial markets globally in terms of their decline and volatility as Coronavirus epicentre moved from China to Europe and then to USwhich affected even relatively safer commodities in US. (Ali, Alam, & Rizvi, 2020) Again, an existing study shows the impact of COVID-19 on the price volatility of Crude Oil and Natural Gas of MCX India using EGARCH where the presence of leverage affect has been proved in the price volatility of crude oil in India but not in Natural Gas. (Meher, Hawaldar, Mohapatra, & Sarea, 2020) Similar to that a working paper shows the leverage effect of COVID-19 on Stock Price Volatility of Companies under NIFTY Energy using 1-minute closing price from 15th October, 2019 to 15th May, 2020 where the authors formulate asymmetric volatility models by using EGARCH and TGARCH. (Meher, Gil, & Deebom, Leverage Effect of COVID-19 on Stock Price Volatility of Companies under NIFTY Energy using Highfrequency Data, 2020)

The recent studies related to the pandemic, have not yet thrown any light on using the high-frequency data to formulate forecasting models for stock prices of Indian Banks so that the investors interested in financial service sector could develop better investment portfolio for their investment in gaining better profit and reducing loss. Hence, this research gap is considered as the most viable one.

3. RESEARCH METHODOLOGY

The study is Empirical in nature. Secondary data have been used in this study. The secondary data involves the 10-Minute closing stock prices of Banks which are listed in NIFTY 50 of India. The high-frequency data related to 10-minute closing prices of shares of the banks are ranging from 28th July, 2020 to 27th October, 2020 (3 months) which have been downloaded from kotaksecurities.com. Wherever required, attempt has been made to make the irregular or unbalanced data into regular and balanced data i.e. 39 data points in a day for period of 3 months (66 trading days). There are 6banks which are listed under NIFTY 50 namely Axis Bank Ltd., Housing Development and Financial Corporation (HDFC) Bank Ltd., ICICI Bank Ltd., IndusInd Bank, Kotak Mahindra Bank Ltd. and State Bank of India. All these banksunder NIFTY 50 have been selected for the purpose of modelling and analysing. The total sample size or data points for each bank is 2,574 i.e. 3 months (66 trading days) @ 39 data points on each day. Required number of differencing has been done to make the data stationary and Augmented Dickey Fuller Test has been used to check the stationarity of the data. Autoregressive Integrated Moving Average (ARIMA) has been used to formulate the model for each company for the purpose of forecasting share price. Correlogram of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) would be plotted to determine the different AR and MA terms. For the purpose of formulating forecasting models of selected banks, E-Views 10 has been used.

4. NEED OF THE STUDY

The affairs of the study could provide feasible forecasting models that can assist those investors having basic knowledge on algorithms, to run the developed models to study and forecast the stock prices of Indian banks during COVID-19 situation. Moreover, this study helps investors to develop better investment portfolio for their investment in gaining better profit and reducing risk because by using the 10-minute wise data in formulating forecasting models helps not only for short-term investment but also for high-frequency trading. The study could act as a base for those scholars or researchers in future who wish to formulate any hybrid forecasting models using high-frequency data with advanced statistical tools and softwares during this pandemic COVID-19.

5. LIMITATIONS OF THE STUDY

- The study is limited to 6 Indian Banks of NIFTY 50, India only by using only last 3 months' data i.e. from 28th July, 2020 to 27th October, 2020 as obtaining high-frequency data is costly and only these 3 months' data was affordable.
- Conducting this kind of research can only be possible if proper funding to obtain such kind of data will be available. Moreover, appropriate applications, software and computer system are required to run such minute wise data for the purpose of modelling. Taking into consideration these limitations the study has been conducted.

6. ANALYSIS, RESULTS AND DISCUSSION

For the purpose of short-term forecasting of stock prices of Indian Banks under NIFTY 50 ARIMA model has been used which is a generalization of an autoregressive moving average (ARMA) model. An ARMA model expresses the conditional mean of Y_t as a function of both past observations Y_{t-1}, Y_{t-2}, Y_{t-p} and past innovations, $\varepsilon_{t-1}..\varepsilon_{t-q}$. The number of past observations that Y_t depends on, p, is the AR degree. The number of past innovations that Y_t depends on, q, is the MA degree.

In general, these models are denoted by ARMA (p, q). The form of the ARMA (p, q) model is

$$\mathrm{Y}_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots. + \beta_p Y_{t-p} + \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \ldots. + \phi_q \varepsilon_{t-q}$$

$\boldsymbol{\alpha}$= Constant term $\boldsymbol{\beta_1 \ldots. \beta_p}$ = AR – Nonseasonal Autoregressive (AR) coefficients

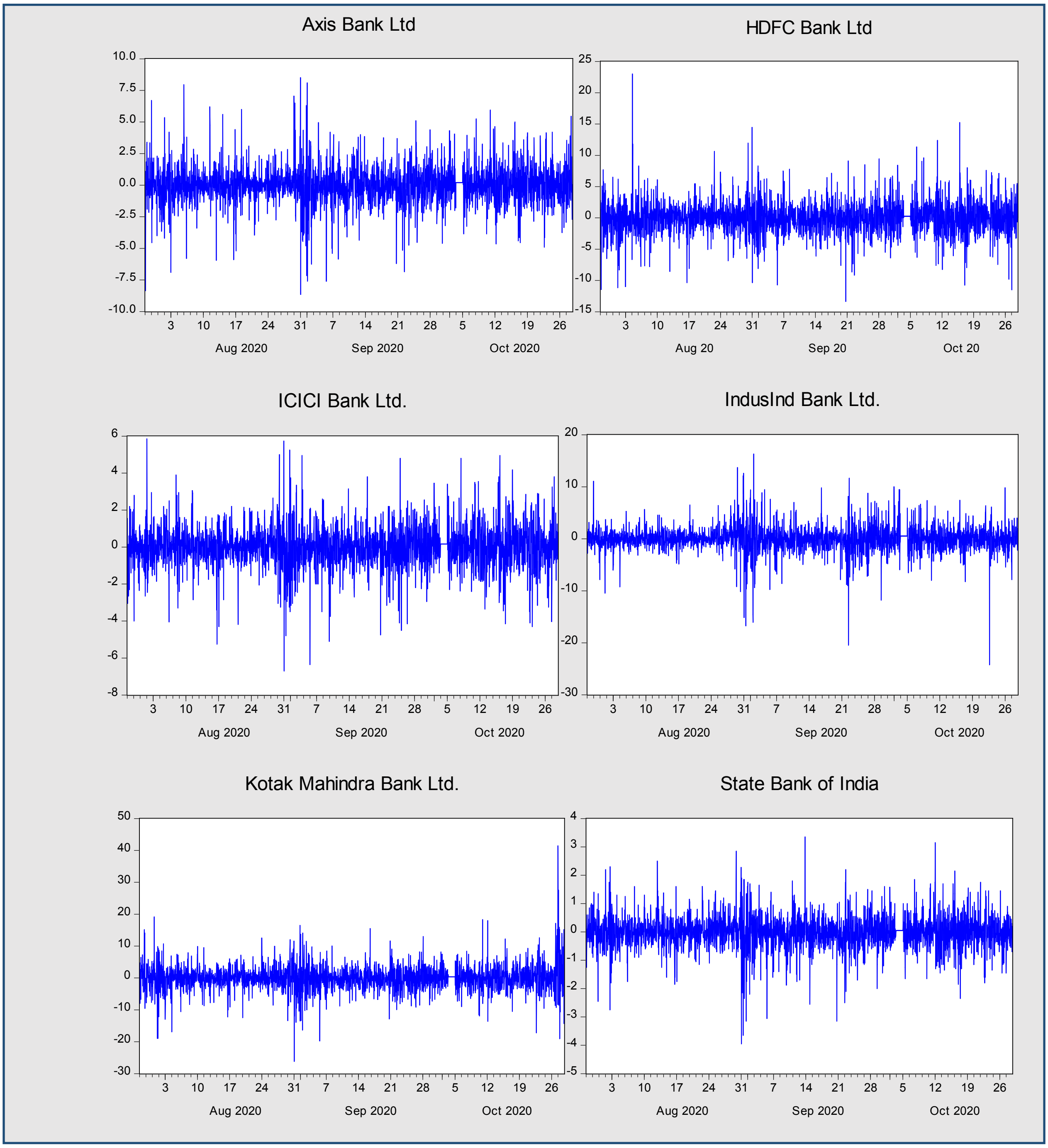
$\phi_1 \ldots \phi_q$ = MA - Nonseasonal Moving Average (MA) coefficients

$Y_{t-1} \ldots Y_{t-p}$ = Nonseasonal AR Lags corresponding to nonzero

$\mathcal{E}_{t-1} \ldots \mathcal{E}_{t-q}$ = MALags – Lags corresponding to nonzero, nonseasonal MA coefficients

For the purpose of formulating ARIMA Model, the data related to 10-Minutes closing prices of shares of all the six banks i.e. Axis Bank Ltd., Housing Development and Financial Corporation (HDFC) Bank Ltd., ICICI Bank Ltd., IndusInd Bank, Kotak Mahindra Bank Ltd. and State Bank of India have been differentiated once to make the data stationary. After first level of differencing the data of the six banks could be visualise through line graphs mentioned in Figure 1.

Figure No. 1. Line graphs of 10-Minute Closing Prices of Six Banks under NIFTY 50 after Differentiating Once



Source : Authors' Computation through E-Views 10

While visualising the line graphs in Figure 1, it can be observed that the data of all the banks have become stationary after first level of differencing. But in order to assure statistically the stationarity of the data has been examined with the help of a unit root test named Augmented Dickey Fuller Test with the inclusion of test equation with Intercept, with both Trend and Intercept and without Trend and Intercept and found that all the data of six companies are stationary as the probability values in all the cases are significant even at 1% level of significance.After making the data stationary, ARIMA model have been framedwith different AR and MA terms for each company, the procedure, results and analysis of which are mentioned in the subsequent part of the paper in a company wise pattern.

6.1. Axis Bank Ltd.

Axis Bank Limited is an Indian private sector bank head quartered in Mumbai, Maharashtra with 3,485 domestic branches (including extension counters) and 14,332 ATMs across the country as on 30 September 2017, the network of Axis Bank spreads across 2,033 cities and towns, enabling the bank to reach out to a large cross-section of customers with an array of products and services.It is the third largest private sector bank in India. The Bank operates in four segments, namely treasury which includes, retail banking which includes lending to individuals or small businesses, corporate or wholesale banking and other banking business. It also includes liability products, card services, Internet banking, automated teller machines (ATM) services, depository, financial advisory services, and non-resident Indian (NRI) services.The bank also has nine overseas offices with branches at Singapore, Hong Kong, Dubai (at the DIFC), Shanghai and Colombo; representative offices at Dubai, Abu Dhabi and Dhaka and an overseas subsidiary at London, UK. The market capitalisation of Axis Bank Ltd. was Rs. 1.36 trillion on 31st October, 2020 and listed under NIFTY 50. Hence, there is a possibility that this bank might be affected during the pandemic.

For framing ARIMA of Axis Bank Ltd. the Correlogram of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) have been plotted to determine the different significant AR and MA terms.By analysing the correlogram it has been found that the spikes in ACF and PACF are significant at 1, 36, 46, 109, 113, 114, 186, 190 and 197 lags. By considering these 9 lags, 81 models have been formulated.These 81 models have been compared among each other on the basis of lowest Akaike Information Criterion (AIC), Schwarz Criterion, Volatility (SIGMASQ) and highest Adjusted R Squared, and 3 best models have been selected, the results of which are given in the Table No. 1. All these selected 3 modelshave significant coefficients as the Significance value of AR and MA terms are less than 0.05.

Table 1. Results of best 3 ARIMA Models out of 81 Models for Axis Bank Ltd.

ARIMA (p, d, q)	**AIC**	**Schwarz Criterion**	**SIGMASQ**	**Adjusted R Squared**
ARIMA (1, 1, 36)	3.731240	3.740339	2.435615	0.008946
ARIMA (1, 1, 190)	3.732437	3.741536	2.438099	0.007935
ARIMA (36, 1, 1)	3.731094	3.740193	2.435236	0.009100

Source : Authors' Computation through E-Views 10

The above table 1 represents the best 5 selected ARIMA models of Axis Bank Ltd. By comparing these 3 models, it has been found that the ARIMA(36, 1, 1) has least AIC, Schwarz Criterion and SIGMASQ and highest Adjusted R squared, hence this could be the better model among these three models. But there is also a possibility that some residuals have not yet been considered in the above models, hence, it is necessary to check the residual diagnostic. For this, again the correlogram of Q statistics has been plotted and by observing the significant spikes, different AR and MA terms have been inculcated and experimented to adjust the models in order to achieve a better model with higher adjusted R squared and least AIC, Schwarz Criterion and Volatility. Again that model has been adjusted by removing the drift (constant) if it's coefficient is not significant. The results of the most suitable model with drift and without drift is mentioned in Table 2.

Table 2. Results of Selected Model With Drift and Without Drift for Axis Bank Ltd.

Dependent Variable: D(AXIS)	
Method: Least Squares	
Date: 11/02/20 Time: 13:39	
Sample: 7/28/2020 09:20 10/27/2020 15:30	
Included observations: 2573	
Convergence achieved after 29 iterations	Convergence achieved after 24 iterations
Coefficient covariance computed using outer product of gradients	

	WITH DRIFT				WITHOUT DRIFT			
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Coefficient	Std. Error	t-Statistic	Prob.
C	0.027146	0.038519	0.704731	0.4810	-	-	-	-
AR(20)	0.045939	0.018741	2.451187	0.0143	0.046089	0.018757	2.457127	0.0141
AR(22)	-0.270673	0.098331	-2.752682	0.0060	-0.269699	0.098091	-2.749483	0.0060
AR(28)	0.041019	0.018024	2.275766	0.0229	0.041173	0.018020	2.284920	0.0224
AR(36)	0.063523	0.014852	4.277074	0.0000	0.063669	0.014815	4.297624	0.0000
AR(46)	-0.042421	0.018423	-2.302660	0.0214	-0.042296	0.018424	-2.295653	0.0218
AR(113)	0.051878	0.018576	2.792681	0.0053	0.052087	0.018567	2.805422	0.0051
AR(190)	0.047578	0.017012	2.796785	0.0052	0.047880	0.016997	2.816989	0.0049
AR(193)	-0.039637	0.019467	-2.036114	0.0418	-0.039414	0.019460	-2.025376	0.0429
MA(1)	0.074328	0.013014	5.711430	0.0000	0.074466	0.012898	5.773582	0.0000
MA(13)	0.044844	0.018066	2.482317	0.0131	0.045004	0.018029	2.496196	0.0126
MA(22)	0.325216	0.097197	3.345927	0.0008	0.324391	0.096989	3.344609	0.0008
MA(52)	-0.045367	0.018724	-2.422899	0.0155	-0.045292	0.018732	-2.417913	0.0157
MA(177)	-0.040580	0.020098	-2.019083	0.0436	-0.040362	0.020088	-2.009189	0.0446
MA(194)	-0.039757	0.019371	-2.052384	0.0402	-0.039634	0.019389	-2.044172	0.0410
MA(200)	0.045054	0.020835	2.162417	0.0307	0.045214	0.020836	2.170013	0.0301
SIGMASQ	2.373270	0.039853	59.55057	0.0000	2.373750	0.039839	59.58407	0.0000

	WITH DRIFT	WITHOUT DRIFT
• R-squared	0.035441	0.035245
• Adjusted R-squared	0.029403	0.029586
• S.E. of regression	1.545657	1.545511
• Sum squared resid	6106.425	6107.660
• Log likelihood	-4764.282	-4764.543
• F-statistic	5.869656	NA
• Prob(F-statistic)	0.000000	NA
• Mean dependent var	0.027303	0.027303
• S.D. dependent var	1.568894	1.568894
• Akaike info criterion	3.716504	3.715929
• Schwarz criterion	3.755174	3.752325

Source : Authors' Computation through E-Views 10

By observing the table 2 it has been found that all the coefficients of AR and MA terms in the model with drift are significant except the coefficient of drift hence the model is further formulated without drift. The model without drift has all significant coefficient, higher Adjusted R Squared but it has higher volatility(SIGMASQ). Both the models are mentioned below.

Short-term Forecasting Model with Drift

$$\begin{aligned} D(Y_t) = {} & 0.027146 + 0.045939Y_{t-20} - 0.270673Y_{t-22} + 0.041019Y_{t-28} + 0.063523Y_{t-36} \\ & - 0.042421Y_{t-46} + 0.051878Y_{t-113} + 0.047578Y_{t-190} - 0.039636Y_{t-193} \\ & + 0.074328\varepsilon_{t-1} + 0.044844\varepsilon_{t-13} + 0.325215\varepsilon_{t-22} - 0.045367\varepsilon_{t-52} \\ & - 0.040580\varepsilon_{t-177} - 0.039756\varepsilon_{t-194} + 0.045054\varepsilon_{t-200} \end{aligned}$$

Short-term Forecasting Model without Drift

$$\begin{aligned} D(Y_t) = {} & 0.046089Y_{t-20} - 0.269699Y_{t-22} + 0.041173Y_{t-28} + 0.063669Y_{t-36} \\ & - 0.042296Y_{t-46} + 0.052087Y_{t-113} + 0.047880Y_{t-190} - 0.039414Y_{t-193} \\ & + 0.074466\varepsilon_{t-1} + 0.045004\varepsilon_{t-13} + 0.324391\varepsilon_{t-22} - 0.045292\varepsilon_{t-52} \\ & - 0.040362\varepsilon_{t-177} - 0.039634\varepsilon_{t-194} + 0.045214\varepsilon_{t-200} \end{aligned}$$

The above two models have been used for forecasting the stock prices of Axis Bank Ltd. which have been mentioned in the forecasting section. Moreover, the efficacy of both the models has been verified using a simple method based on coefficient of variation i.e. the percentage of square root of the average of the squares of deviations of forecasted values from actual values on average price of the stock during forecasted period which is mentioned in efficacy of the models section.

6.2. HDFC Bank Ltd.

HDFC Bank was incorporated in August 1994 with its registered office in Mumbai, India. As of September 30, 2020, the Bank had a nationwide distribution network 5,430 branches and 15,292 ATMs in 2,848 cities/towns. The Housing Development Finance Corporation Limited (HDFC) was amongst the first to receive an 'in principle' approval from the Reserve Bank of India (RBI) to set up a bank in the private sector, as part of RBI's liberalisation of the Indian Banking Industry in 1994. HDFC is India's premier housing finance company and enjoys an impeccable track record in India as well as in international markets. Since its inception in 1977, the Corporation has maintained a consistent and healthy growth in its operations to remain the market leader in mortgages. HDFC has developed significant expertise in retail mortgage loans to different market segments and also has a large corporate client base for its housing related credit facilities. The market capitalisation of the bank was Rs. 6.09 trillion on 31st October, 2020 and listed under NIFTY 50. Hence, there a high possibility that this bank might be affected during the pandemic.

For framing ARIMA of HDFC Bank Ltd. the Correlogram of ACF and PACF have been plotted to determine the different AR and MA terms. By analysing the correlogram it has been found that the spikes in ACF and PACF are significant at 1, 2, 18, 28, 29, 30, 31, 104 and 199. By considering these 9 lags, 81 models have been formulated. These 81 models have been compared among each other on the basis of lowest AIC, Schwarz Criterion, Volatility (SIGMASQ) and highest Adjusted R Squared, and 3 best models have been selected, the results of which are given in the Table No. 3. All these selected 3models have significant coefficients as the Significance value of AR and MA terms are less than 0.05.

Table No. 3. Results of best 3 ARIMA Models out of 81 Models for HDFC Bank Ltd.

ARIMA (p, d, q)	AIC	Schwarz Criterion	SIGMASQ	Adjusted R Squared
ARIMA (1, 1, 199)	4.831041	4.840139	7.313883	0.005775
ARIMA (104, 1, 1)	4.831954	4.841053	7.322002	0.004672

ARIMA (199, 1, 1)	4.830855	4.839953	7.312578	0.005953

Source : Authors' Computation through E-Views 10

Table 3 represents the best 3 selected ARIMA models of HDFC Bank Ltd. By comparing these 3 models, it has been found that the ARIMA(199, 1, 1) has least AIC, Schwarz Criterion and SIGMASQ and highest Adjusted R squared, hence this could be the better model among these five. But there is also a possibility that some residuals have not yet been considered in the above models, hence, it is necessary to check the residual diagnostic. For this, again the correlogram of Q statistics has been plotted and by observing the significant spikes, different AR and MA terms have been inculcated and experimented to adjust the models in order to achieve a better model with higher adjusted R squared and least AIC, Schwarz Criterion and Volatility. Again the developed model has been adjusted by removing the drift if it's coefficient is not significant. The results of the most suitable model with drift and without drift is mentioned in Table 4.

Table 4. Results of Selected Model With Drift and Without Drift for HDFC Bank Ltd.

Dependent Variable: D(HDFC) Method: Least Squares Date: 11/02/20 Time: 22:51 Sample: 7/28/2020 09:20 10/27/2020 15:30 Included observations: 2573 Convergence achieved after 21 iterations Coefficient covariance computed using outer product of gradients					Convergence achieved after 24 iterations			
	WITH DRIFT				**WITHOUT DRIFT**			
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Coefficient	Std. Error	t-Statistic	Prob.
C	0.056830	0.058558	0.970495	0.3319	-	-	-	-
AR(2)	-0.032112	0.013675	-2.348193	0.0189	-0.031669	0.013623	-2.324742	0.0202
AR(18)	0.044535	0.019346	2.302006	0.0214	0.044931	0.019332	2.324191	0.0202
AR(31)	-0.039265	0.017769	-2.209731	0.0272	-0.038895	0.017721	-2.194836	0.0283
AR(115)	0.037466	0.018284	2.049072	0.0406	0.037954	0.018268	2.077647	0.0378
AR(193)	-0.049613	0.019656	-2.524060	0.0117	-0.048886	0.019630	-2.490426	0.0128
AR(199)	0.060277	0.022616	2.665260	0.0077	0.060963	0.022574	2.700571	0.0070
MA(1)	0.054353	0.014462	3.758364	0.0002	0.054672	0.014407	3.794912	0.0002
MA(37)	0.037518	0.016913	2.218307	0.0266	0.037746	0.016903	2.233043	0.0256
MA(104)	-0.050611	0.021952	-2.305535	0.0212	-0.050073	0.021922	-2.284098	0.0224
MA(150)	0.051488	0.019767	2.604705	0.0092	0.052047	0.019730	2.638010	0.0084
MA(155)	-0.038452	0.018015	-2.134444	0.0329	-0.037893	0.017999	-2.105335	0.0354
MA(156)	-0.037778	0.017031	-2.218170	0.0266	-0.037059	0.016999	-2.180079	0.0293
MA(190)	0.044604	0.020308	2.196350	0.0282	0.045319	0.020316	2.230691	0.0258
SIGMASQ	7.183456	0.122074	58.84509	0.0000	7.186168	0.121213	59.28568	0.0000
	WITH DRIFT				**WITHOUT DRIFT**			
• R-squared	0.024644				0.024276			
• Adjusted R-squared	0.019306				0.019319			
• S.E. of regression	2.688044				2.688026			
• Sum squared resid	18483.03				18490.01			
• Log likelihood	-6189.115				-6189.605			
• F-statistic	4.616621				NA			
• Prob(F-statistic)	0.000000				NA			
• Mean dependent var	0.056899				0.056899			
• S.D. dependent var	2.714373				2.714373			
• Akaike info criterion	4.822476				4.822079			
• Schwarz criterion	4.856596				4.853925			

Source : Authors' Computation through E-Views 10

By observing the table 4 it has been found that all the coefficients of AR and MA terms in the model with drift are significant except the coefficient of drift hence the model is further formulated without drift. The model without drift has all significant coefficient, higher Adjusted R Squared, lower AIC, lower Schwarz criterion but has higher volatility(SIGMASQ). Both the models are mentioned below.

Short-term Forecasting Model with Drift

$$\begin{aligned}D(Y_t) = 0.056830 - 0.032112Y_{t-2} + 0.044535Y_{t-18} - 0.039265Y_{t-31} + 0.037466Y_{t-115}\\ - 0.049613Y_{t-193} + 0.060277Y_{t-199} + 0.054353\varepsilon_{t-1} + 0.037518\varepsilon_{t-37}\\ - 0.050611\varepsilon_{t-104} + 0.051488\varepsilon_{t-150} - 0.038452\varepsilon_{t-155} - 0.037778\varepsilon_{t-156}\\ + 0.044604\varepsilon_{t-190}\end{aligned}$$

Short-term Forecasting Model without Drift

$$\begin{aligned}D(Y_t) =- 0.031669Y_{t-2} + 0.044931Y_{t-18} - 0.038895Y_{t-31} + 0.037954Y_{t-115}\\ - 0.048886Y_{t-193} + 0.060963Y_{t-199} + 0.054672\varepsilon_{t-1} + 0.037746\varepsilon_{t-37}\\ - 0.050073\varepsilon_{t-104} + 0.052047\varepsilon_{t-150} - 0.037893\varepsilon_{t-155} - 0.037059\varepsilon_{t-156}\\ + 0.045319\varepsilon_{t-190}\end{aligned}$$

The above two models have been used for forecasting the stock prices of HDFC Bank Ltd. during COVID-19 which is mentioned in the forecasting section. Moreover, the efficacy of both the models has been verified using a simple method based on coefficient of variation which is mentioned in efficacy of the models section.

6.3. ICICI Bank Ltd

ICICI Bank Limited is an Indian multinational banking and financial services company with its registered office in Vadodara, Gujarat and corporate office in Mumbai, Maharashtra. It offers a wide range of banking products and financial services for corporate and retail customers through a variety of delivery channels and specialised subsidiaries in the areas of investment banking, life, non-life insurance, venture capital and asset management. The bank has a network of 5,275 branches and 15,589 ATMs across India and has a presence in 17 countries. ICICI Bank is India's largest private sector bank by consolidated assets. The bank's equity shares are listed in India on Bombay Stock Exchange and the National Stock Exchange of India Limited and their American Depositary Receipts (ADRs) are listed on the New York Stock Exchange. The market capitalisation of the bank was Rs. 2.54 trillion on 31st October, 2020 and listed under NIFTY 50. There a high possibility that this bank might be affected during the pandemic.

For framing ARIMA of ICICI Bank Ltd. the Correlogram of ACF and PACF have been plotted to determine the different significant AR and MA terms. By analysing the correlogram it has been found that the spikes in ACF and PACF are significant at 11, 18, 23, 114, 150, 190 and 195 lags. By considering these 7 lags, 49 models have been framed by taking different AR and MA terms. These 49 models have been compared among each other on the basis of lowest AIC, Schwarz Criterion, Volatility (SIGMASQ) and highest Adjusted R Squared, and 3 best models have been selected, the results of which are given in the Table No. 5. All the 3models have significant coefficients as the Significance value of AR and MA terms are less than 0.05.

Table. 5Results of best 3 ARIMA Models out of 49 Models for ICICI Bank Ltd.

ARIMA (p, d, q)	**AIC**	**Schwarz Criterion**	**SIGMASQ**	**Adjusted R Squared**
ARIMA (1, 1, 195)	3.166154	3.175253	1.383757	0.016117
ARIMA (23, 1, 1)	3.166073	3.175172	1.384094	0.015878
ARIMA (195, 1, 1)	3.165317	3.174416	1.382544	0.016979

Source : Authors' Computation through E-Views 10

Table 5 represents the best 3 selected ARIMA models of ICICI Bank Ltd. By comparing these five models, it has been found that the ARIMA(195, 1, 1) has least AIC, Schwarz Criterion and SIGMASQ and highest Adjusted R squared, hence this could be the better model among these three models. But there is also a possibility that some residuals have not yet been considered in the above models, hence, it is necessary to check the residual diagnostic. For this, again the correlogram of Q statistics has been plotted and by observing the significant spikes, different AR and MA terms have been inculcated and experimented to adjust the models in order to achieve a better model with higher adjusted R squared and least AIC, Schwarz Criterion and Volatility. Again the developed model has been adjusted by removing the drift if it's coefficient is not significant. The results of the most suitable model with drift and without drift is mentioned in Table 6.

Table 6. Results of Selected Model With Drift and Without Drift for ICICI Bank Ltd.

Dependent Variable: D(ICICI) Method: Least Squares Date: 11/03/20 Time: 13:15 Sample: 7/28/2020 09:20 10/27/2020 15:30 Included observations: 2573 Convergence achieved after 24 iterations Coefficient covariance computed using outer product of gradients					Convergence achieved after 22 iterations			
	WITH DRIFT				**WITHOUT DRIFT**			
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019128	0.028658	0.667449	0.5045	-	-	-	-
AR(195)	0.076401	0.017266	4.424959	0.0000	0.076707	0.017172	4.467013	0.0000
AR(18)	0.042310	0.019259	2.196903	0.0281	0.042503	0.019270	2.205600	0.0275
AR(23)	-0.070634	0.019227	-3.673708	0.0002	-0.070411	0.019237	-3.660243	0.0003
AR(51)	-0.220098	0.089923	-2.447627	0.0144	-0.218676	0.089741	-2.436754	0.0149
AR(70)	0.201973	0.087398	2.310965	0.0209	0.203717	0.087321	2.332975	0.0197
AR(108)	0.037713	0.018017	2.093120	0.0364	0.038036	0.018022	2.110588	0.0349
AR(150)	0.042154	0.020243	2.082435	0.0374	0.042440	0.020238	2.096997	0.0361
AR(190)	0.048419	0.019067	2.539383	0.0112	0.048737	0.019057	2.557354	0.0106
MA(1)	0.120353	0.013603	8.847340	0.0000	0.120499	0.013558	8.887730	0.0000
MA(16)	-0.036021	0.018309	-1.967446	0.0492	-0.035820	0.018292	-1.958242	0.0503
MA(36)	0.046791	0.016995	2.753256	0.0059	0.046957	0.016964	2.768006	0.0057
MA(43)	-0.036931	0.017118	-2.157374	0.0311	-0.036743	0.017111	-2.147268	0.0319
MA(51)	0.191282	0.090242	2.119657	0.0341	0.189999	0.090073	2.109383	0.0350
MA(70)	-0.234887	0.088451	-2.655558	0.0080	-0.236419	0.088377	-2.675103	0.0075
SIGMASQ	1.351179	0.024538	55.06468	0.0000	1.351406	0.024471	55.22393	0.0000

	WITH DRIFT	**WITHOUT DRIFT**
• R-squared	0.040402	0.040240
• Adjusted R-squared	0.034772	0.034987
• S.E. of regression	1.166033	1.165903
• Sum squared resid	3476.583	3477.167
• Log likelihood	-4039.622	-4039.851

• F-statistic	7.177087	NA
• Prob(F-statistic)	0.000000	NA
• Mean dependent var	0.021084	0.021084
• S.D. dependent var	1.186851	1.186851
• Akaike info criterion	3.152446	3.151847
• Schwarz criterion	3.188841	3.185967

Source : Authors' Computation through E-Views 10

By observing the table 6 it has been found that all the coefficients of AR and MA terms in the model with drift are significant except the coefficient of drift hence the model is further formulated without drift. But the model without drift cannot be a better model as all coefficient of AR and MA terms are not significant and hence cannot be considered for forecasting. The developed model with drift is mentioned below.

Short-term Forecasting Model with Drift

$$\begin{aligned} D(Y_t) = {} & 0.019128 + 0.076401Y_{t-195} + 0.042310Y_{t-18} - 0.070634Y_{t-23} - 0.220098Y_{t-51} \\ & + 0.201973Y_{t-70} + 0.037713Y_{t-108} + 0.042154Y_{t-150} + 0.048419Y_{t-190} \\ & + 0.120353\varepsilon_{t-1} - 0.036021\varepsilon_{t-16} + 0.046791\varepsilon_{t-36} - 0.036931\varepsilon_{t-43} \\ & - 0.191282\varepsilon_{t-51} - 0.234887\varepsilon_{t-70} \end{aligned}$$

The above model has been used for forecasting the stock prices of ICICI Bank Ltd. during COVID-19 which is mentioned in the forecasting section. Moreover, the efficacy of both the models has been verified using a simple method based on coefficient of variation which is mentioned in efficacy of the models section.

6.4. IndusInd Bank Ltd.

IndusInd Bank Limited is a new-generation Indian bank headquartered in Pune. The bank offers commercial, transactional and electronic banking products and services. It is the first among the new-generation private banks in India. The bank has specialized in retail banking services and continuously upgrades its support systems by introducing newer technologies. It is also working on expanding its network of branches all across the country along with meeting the global benchmark. As on 31 December 2018, IndusInd Bank had 1,558 branches, and 2453 ATMs spread across different geographical locations of the country. It also has representative offices in London, Dubai and Abu Dhabi. Mumbai has the largest number of bank branches followed by New Delhi and Chennai. The market capitalisation of the bank was Rs. 448.45billion on 31st October, 2020 and listed under NIFTY 50 and there a high possibility that this bank might be affected during the pandemic which also affected its stock prices.

For framing ARIMA of IndusInd Bank Ltd. the Correlogram of ACF and PACF have been plotted to determine the different AR and MA terms. By analysing the correlogram it has been found that the spikes in ACF and PACF are significant at 1, 15, 34, 36, 38, 65, 71, 87, 131 and 193 lags. By considering these 10 lags, 100 models have been framed by taking different AR and MA terms. These 100 models have been compared among each other on the basis of lowest AIC, Schwarz Criterion, Volatility (SIGMASQ) and highest Adjusted R Squared, and 3 best models have been selected, the results of which are given in the Table. 7. All the 3 models have significant coefficients as the Significance value of AR and MA terms are less than 0.05.

Table. 7 Results of best 3ARIMA Models out of 100 Models for IndusInd Bank Ltd.

ARIMA (p, d, q)	**AIC**	**Schwarz Criterion**	**SIGMASQ**	**Adjusted R Squared**
ARIMA (1, 1, 71)	4.714970	4.724068	6.513607	0.014614
ARIMA (1, 1, 87)	4.714849	4.723947	6.512565	0.014771
ARIMA (1, 1, 193)	4.71501	4.724108	6.512631	0.014762

Source : Authors’ Computation through E-Views 10

Table 7 represents the best 3 selected ARIMA models of IndusInd Bank Ltd. By comparing these five models, it has been found that the ARIMA(1, 1, 87) has least AIC, Schwarz Criterion and SIGMASQ and highest Adjusted R squared, hence this could be the better model among these three. But there is also a possibility that some residuals have not yet been considered in the above models, hence, it is necessary to check the residual diagnostic. For this, again the correlogram of Q statistics has been plotted and by observing the significant spikes, different AR and MA terms have been inculcated and experimented to adjust the models in order to achieve a better model with higher adjusted R squared and least AIC, Schwarz Criterion and Volatility. Again the developed model has been adjusted by removing the drift if it’s coefficient is not significant. The results of the most suitable model with drift and without drift is mentioned in Table 8.

Table 8. Results of Selected Model With Drift and Without Drift for IndusInd Bank Ltd.

Dependent Variable: D(INDUS) Method: Least Squares Date: 11/04/20 Time: 23:32 Sample: 7/28/2020 09:20 10/27/2020 15:30 Included observations: 2573 Convergence achieved after 40 iterations Coefficient covariance computed using outer product of gradients					Convergence achieved after 42 iterations			
	WITH DRIFT				**WITHOUT DRIFT**			
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Coefficient	Std. Error	t-Statistic	Prob.
C	0.041446	0.053848	0.769678	0.4416	-	-	-	-
AR(1)	0.110386	0.011363	9.714302	0.0000	0.110908	0.011205	9.897920	0.0000
AR(4)	-0.028174	0.013010	-2.165531	0.0304	-0.027774	0.012990	-2.138146	0.0326
AR(5)	0.182657	0.066444	2.749042	0.0060	0.182031	0.066445	2.739585	0.0062
AR(21)	0.341139	0.073125	4.665163	0.0000	0.339255	0.073003	4.647151	0.0000
AR(36)	0.049956	0.016893	2.957248	0.0031	0.050237	0.016871	2.977704	0.0029
AR(38)	-0.034966	0.015544	-2.249437	0.0246	-0.034769	0.015535	-2.238032	0.0253
AR(57)	-0.042610	0.017072	-2.495920	0.0126	-0.042215	0.016976	-2.486782	0.0130
AR(131)	0.050704	0.019037	2.663441	0.0078	0.051278	0.019023	2.695576	0.0071
AR(156)	-0.039830	0.017394	-2.289948	0.0221	-0.039371	0.017391	-2.263903	0.0237
MA(87)	-0.057881	0.018753	-3.086537	0.0020	-0.057457	0.018807	-3.055024	0.0023
MA(5)	-0.216064	0.069479	-3.109756	0.0019	-0.215069	0.069474	-3.095698	0.0020
MA(19)	0.033055	0.015044	2.197172	0.0281	0.033584	0.014960	2.244940	0.0249
MA(21)	-0.324805	0.073459	-4.421598	0.0000	-0.322442	0.073237	-4.402747	0.0000
MA(31)	0.041496	0.017906	2.317392	0.0206	0.041622	0.017923	2.322252	0.0203
MA(34)	0.042015	0.015935	2.636615	0.0084	0.042732	0.015813	2.702381	0.0069
MA(48)	0.039989	0.016385	2.440563	0.0147	0.040591	0.016345	2.483373	0.0131
MA(70)	-0.035894	0.017078	-2.101816	0.0357	-0.035547	0.017079	-2.081393	0.0375
MA(102)	-0.034268	0.017466	-1.962028	0.0499	-0.033840	0.017515	-1.932059	0.0535
MA(157)	-0.035202	0.016283	-2.161889	0.0307	-0.034574	0.016266	-2.125550	0.0336
MA(188)	-0.038917	0.019115	-2.035919	0.0419	-0.038302	0.019170	-1.998055	0.0458
SIGMASQ	6.318885	0.082520	76.57405	0.0000	6.320561	0.081555	77.50092	0.0000
	WITH DRIFT				**WITHOUT DRIFT**			
• R-squared	0.045187				0.044933			

• Adjusted R-squared	0.037327	0.037449
• S.E. of regression	2.524555	2.524395
• Sum squared resid	16258.49	16262.80
• Log likelihood	-6023.926	-6024.251
• F-statistic	5.748870	NA
• Prob(F-statistic)	0.000000	NA
• Mean dependent var	0.037233	0.037233
• S.D. dependent var	2.573033	2.573033
• Akaike info criterion	4.699515	4.698990
• Schwarz criterion	4.749558	4.746759

Source : Authors’ Computation through E-Views 10

By observing the table 8 it has been found that all the coefficients of AR and MA terms in the model with drift are significant except the coefficient of drift hence the model is further formulated without drift. But the model without drift cannot be a better model as the coefficient of MA(102) is not significant and hence it cannot be considered for forecasting. The developed model with drift is mentioned below.

Short-term Forecasting Model with Drift

$$\begin{aligned}D(Y_t) = {} & 0.041446 + 0.110386Y_{t-1} - 0.028174Y_{t-4} + 0.182657Y_{t-5} + 0.341139Y_{t-21} \\ & + 0.049956Y_{t-36} - 0.034966Y_{t-38} - 0.042610Y_{t-57} + 0.050704Y_{t-131} \\ & - 0.039830Y_{t-156} - 0.057881\varepsilon_{t-87} - 0.216064\varepsilon_{t-5} + 0.033055\varepsilon_{t-19} \\ & - 0.324805\varepsilon_{t-21} + 0.041496\varepsilon_{t-31} + 0.042015\varepsilon_{t-34} + 0.039989\varepsilon_{t-48} \\ & - 0.035894\varepsilon_{t-70} - 0.034268\varepsilon_{t-102} - 0.035202\varepsilon_{t-157} - 0.038917\varepsilon_{t-188}\end{aligned}$$

The above model has been used for forecasting the stock prices of IndusInd Bank Ltd. during COVID-19 which is mentioned in the forecasting section. Moreover, the efficacy of both the models has been verified using a simple method based on coefficient of variation which is mentioned in efficacy of the models section.

6.5. Kotak Mahindra Ltd.

Kotak Mahindra Bank Limited is an Indian private sector bank headquartered in Mumbai, Maharashtra, India. It offers banking products and financial services for corporate and retail customers in the areas of personal finance, investment banking, life insurance, and wealth management. As of April 2019, it is the second largest Indian private sector bank by market capitalization, with 1600 branches & 2519 ATMs. The market capitalisation of the bank was Rs. 2.59trillion on 31st October, 2020 and listed under NIFTY 50 and there a high possibility that this bank might be affected during the pandemic which also affected its stock prices.

For framing ARIMA of Kotak Mahindra Bank Ltd. the Correlogram of ACF and PACF have been plotted to determine the different significant AR and MA terms. By analysing the correlogram it has been found that the spikes in ACF and PACF are significant at 1, 3, 7, 8, 15, 36 and 161 lags. By considering these 7 lags, 49 models have been framed by taking different AR and MA terms. These 49 models have been compared among each other on the basis of lowest AIC, Schwarz Criterion, Volatility (SIGMASQ) and highest Adjusted R Squared, and 3 best models have been selected, the results of which are given in the Table. 9. All the 3 models have significant coefficients as the Significance value of AR and MA terms are less than 0.05.

Table. 9 Results of best 3 ARIMA Models out of 100 Models for Kotak Mahindra Bank Ltd.

ARIMA (p, d, q)	**AIC**	**Schwarz Criterion**	**SIGMASQ**	**Adjusted R Squared**
ARIMA (1, 1, 161)	5.661151	5.670250	16.77500	0.008969
ARIMA (7, 1, 1)	5.661144	5.670243	16.77930	0.008715
ARIMA (161, 1, 1)	5.661015	5.670114	16.77246	0.009120

Source : Authors' Computation through E-Views 10

Table 9 represents the best 3 selected ARIMA models of IndusInd Bank Ltd. By comparing these five models, it has been found that the ARIMA(161, 1, 1) has least AIC, Schwarz Criterion and Volatility (SIGMASQ) and highest Adjusted R squared, hence this could be the better model among these five. But there is also a possibility that some residuals have not yet been considered in the above models, hence, it is necessary to check the residual diagnostic. For this, again the correlogram of Q statistics has been plotted and by observing the significant spikes, different AR and MA terms have been inculcated and experimented to adjust the models in order to achieve a better model with higher adjusted R squared and least AIC, Schwarz Criterion and Volatility. Again the developed model has been adjusted by removing the drift if it's coefficient is not significant. The results of the most suitable model with drift and without drift is mentioned in Table 8.

Table 10. Results of Selected Model With Drift and Without Drift for Kotak Mahindra Bank Ltd.

Dependent Variable: D(KOTAK) Method: Least Squares Date: 11/07/20 Time: 19:50 Sample: 7/28/2020 09:20 10/27/2020 15:30 Included observations: 2573 Convergence achieved after 69 iterations Coefficient covariance computed using outer product of gradients					Convergence achieved after 69 iterations			
	WITH DRIFT				**WITHOUT DRIFT**			
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Coefficient	Std. Error	t-Statistic	Prob.
C	0.067902	0.069250	0.980528	0.3269	-	-	-	-
AR(161)	-0.057894	0.018586	-3.114947	0.0019	-0.057733	0.018575	-3.108076	0.0019
AR(3)	0.620631	0.065957	9.409654	0.0000	0.621342	0.065768	9.447463	0.0000
AR(8)	0.035199	0.011090	3.173985	0.0015	0.035685	0.011050	3.229390	0.0013
AR(10)	-0.034538	0.011996	-2.879105	0.0040	-0.034113	0.012008	-2.841000	0.0045
AR(12)	-0.214082	0.064063	-3.341724	0.0008	-0.212920	0.063966	-3.328614	0.0009
AR(21)	0.129364	0.061197	2.113903	0.0346	0.130311	0.060891	2.140067	0.0324
AR(25)	-0.030212	0.013672	-2.209794	0.0272	-0.029772	0.013641	-2.182544	0.0292
AR(96)	-0.039398	0.017323	-2.274281	0.0230	-0.039346	0.017288	-2.275961	0.0229
AR(97)	-0.035749	0.017787	-2.009901	0.0445	-0.035710	0.017764	-2.010241	0.0445
AR(115)	0.160014	0.067000	2.388268	0.0170	0.159943	0.066903	2.390673	0.0169
MA(1)	0.070469	0.008430	8.359040	0.0000	0.070866	0.008358	8.479294	0.0000
MA(3)	-0.615112	0.067496	-9.113278	0.0000	-0.615338	0.067325	-9.139799	0.0000
MA(12)	0.256558	0.065892	3.893631	0.0001	0.255742	0.065778	3.887967	0.0001
MA(21)	-0.125187	0.063042	-1.985783	0.0472	-0.125731	0.062708	-2.005017	0.0451
MA(115)	-0.182271	0.064552	-2.823647	0.0048	-0.182100	0.064599	-2.818926	0.0049
MA(127)	-0.039649	0.018076	-2.193485	0.0284	-0.039708	0.018090	-2.194998	0.0283
SIGMASQ	16.44813	0.256903	64.02471	0.0000	16.45529	0.256637	64.11901	0.0000
	WITH DRIFT				**WITHOUT DRIFT**			
• R-squared	0.029414				0.028991			
• Adjusted R-squared	0.022956				0.022913			
• S.E. of regression	4.069890				4.069980			

• Sum squared resid	42321.04	42339.47
• Log likelihood	-7254.836	-7255.391
• F-statistic	4.554658	NA
• Prob(F-statistic)	0.000000	NA
• Mean dependent var	0.096813	0.096813
• S.D. dependent var	4.117424	4.117424
• Akaike info criterion	5.653195	5.652850
• Schwarz criterion	5.694140	5.691520

Source : Authors’ Computation through E-Views 10

By observing the table 10 it has been found that all the coefficients of AR and MA terms in the model with drift are significant except the coefficient of drift hence the model is further formulated without drift. But the model without drift cannot be a better model because though all coefficients are significant but there is no improvement in adjusted R squared. The developed model with drift is mentioned below

Short-term Forecasting Model with Drift

$$\begin{aligned} D(Y_t) = 0.067902 - 0.057894Y_{t-161} + 0.620631Y_{t-3} + 0.035199Y_{t-8} - 0.034538Y_{t-10} \\ - 0.214082Y_{t-12} + 0.129364Y_{t-21} - 0.030212Y_{t-25} - 0.039398Y_{t-96} \\ - 0.035749Y_{t-97} + 0.160014Y_{t-115} + 0.070469\varepsilon_{t-1} - 0.615112\varepsilon_{t-3} \\ + 0.256558\varepsilon_{t-12} - 0.125187\varepsilon_{t-21} - 0.182271\varepsilon_{t-115} - 0.039649\varepsilon_{t-127} \end{aligned}$$

Short-term Forecasting Model without Drift

$$\begin{aligned} D(Y_t) =- 0.057733Y_{t-161} + 0.621342Y_{t-3} + 0.035685Y_{t-8} - 0.034113Y_{t-10} \\ - 0.212920Y_{t-12} + 0.130311Y_{t-21} - 0.029772Y_{t-25} - 0.039346Y_{t-96} \\ - 0.035710Y_{t-97} + 0.159943Y_{t-115} + 0.070866\varepsilon_{t-1} - 0.615338\varepsilon_{t-3} \\ + 0.255742\varepsilon_{t-12} - 0.125731\varepsilon_{t-21} - 0.182100\varepsilon_{t-115} - 0.039708\varepsilon_{t-127} \end{aligned}$$

The above models have been used for forecasting the stock prices of Kotak Mahindra Bank Ltd. during COVID-19 which is mentioned in the forecasting section. Moreover, the efficacy of both the models has been verified using a simple method based on coefficient of variation which is mentioned in efficacy of the models section.

6.6. State Bank of India

State Bank of India (SBI) is an Indian multinational, public sector banking and financial services statutory body headquartered in Mumbai, Maharashtra. SBI is the 43rd largest bank in the world and ranked 236th in the Fortune Global 500 list of the world's biggest corporations of 2019.A nationalised bank, it is the largest in India with a 23% market share by assets and a 25% share of the total loan and deposits market. SBI has over 24000 branches and 58,555 ATMs in India. The market capitalisation of the bank was Rs. 1.70 trillion on 31st October, 2020 and listed under NIFTY 50 and there a high possibility that this bank might be affected during the pandemic which also affected its stock prices.

For framing ARIMA for State Bank of India, the Correlogram of ACF and PACF have been plotted to determine the different AR and MA terms. By analysing the correlogram it has been found that the spikes in ACF and PACF are significant at 1, 7, 10, 11, 24, 76, 116 and 156 lags. By considering these 8 lags, 64 models have been formulated. These 64 models have been compared among each other on the basis of lowest AIC, Schwarz Criterion, Volatility (SIGMASQ) and highest Adjusted R Squared, and 3 best models have been selected, the results of which are given in the Table No. 11. All these selected 3models have significant coefficients as the Significance value of AR and MA terms are less than 0.05.

Table. 11 Results of best 5 ARIMA Models out of 64 Models for State Bank of India

ARIMA (p, d, q)	**AIC**	**Schwarz Criterion**	**SIGMASQ**	**Adjusted R Squared**
ARIMA (1, 1, 76)	1.850154	1.859253	0.371241	0.005498
ARIMA (1, 1, 156)	1.850099	1.859198	0.371187	0.005641
ARIMA (156, 1, 1)	1.850265	1.859364	0.371246	0.005482

Source : Authors' Computation through E-Views 10

Table 11 represents the best 3 selected ARIMA models of State Bank of India. By comparing these three, it has been found that the ARIMA(1, 1, 156) has least AIC, Schwarz Criterion and Volatility (SIGMASQ) and highest Adjusted R squared, hence this could be the better model among these three. But there is also a possibility that some residuals have not yet been considered in the above models, hence, it is necessary to check the residual diagnostic. For this, again the correlogram of Q statistics has been plotted and by observing the significant spikes, different AR and MA terms have been inculcated and experimented to adjust the models in order to achieve a better model with higher adjusted R squared and least AIC, Schwarz Criterion and Volatility. Again the developed model has been adjusted by removing the drift if it's coefficient is not significant. The results of the most suitable model with drift and without drift is mentioned in Table 12.

Table 12. Results of Selected Model With Drift and Without Drift for State Bank of India

Dependent Variable: D(SBI) Method: Least Squares Date: 11/06/20 Time: 05:22 Sample: 7/28/2020 09:20 10/27/2020 15:30 Included observations: 2573 Convergence achieved after 30 iterations Coefficient covariance computed using outer product of gradients	Convergence achieved after 33 iterations

	WITH DRIFT				**WITHOUT DRIFT**			
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001937	0.011426	0.169492	0.8654	-	-	-	-
AR(1)	0.068084	0.011894	5.724398	0.0000	0.068106	0.011838	5.753171	0.0000
AR(6)	0.326457	0.089627	3.642416	0.0003	0.326433	0.089550	3.645257	0.0003
AR(141)	0.266192	0.088536	3.006613	0.0027	0.266317	0.088184	3.020012	0.0026
MA(156)	-0.049166	0.016287	-3.018649	0.0026	-0.049153	0.016256	-3.023707	0.0025
MA(6)	-0.377720	0.088633	-4.261617	0.0000	-0.377666	0.088587	-4.263231	0.0000
MA(24)	-0.054630	0.018020	-3.031737	0.0025	-0.054596	0.018018	-3.030103	0.0025
MA(80)	0.036298	0.016568	2.190884	0.0286	0.036338	0.016397	2.216075	0.0268
MA(106)	0.046861	0.017415	2.690867	0.0072	0.046905	0.017373	2.699822	0.0070
MA(115)	-0.041830	0.017762	-2.355056	0.0186	-0.041787	0.017745	-2.354868	0.0186
MA(117)	0.035633	0.016495	2.160229	0.0308	0.035660	0.016468	2.165416	0.0304
MA(141)	-0.241151	0.087141	-2.767354	0.0057	-0.241251	0.086884	-2.776701	0.0055
MA(163)	-0.044393	0.017392	-2.552508	0.0108	-0.044365	0.017392	-2.550826	0.0108
SIGMASQ	0.364372	0.006042	60.30825	0.0000	0.364376	0.006014	60.58445	0.0000

	WITH DRIFT	**WITHOUT DRIFT**
• R-squared	0.025038	0.025026
• Adjusted R-squared	0.020085	0.020456
• S.E. of regression	0.605281	0.605166

• Sum squared resid	937.5279	937.5391
• Log likelihood	-2353.359	-2353.374
• F-statistic	5.055202	NA
• Prob(F-statistic)	0.000000	NA
• Mean dependent var	0.002157	0.002157
• S.D. dependent var	0.611453	0.611453
• Akaike info criterion	1.840154	1.839389
• Schwarz criterion	1.872000	1.868960

Source : Authors’ Computation through E-Views 10

By observing the table 12 it has been found that all the coefficients of AR and MA terms in the model with drift are significant except the coefficient of drift hence the model is further formulated without drift. The model without drift has all significant coefficient, higher Adjusted R Squared, lower AIC, lower Schwarz criterion but has slightly higher SIGMASQ. Both the models are mentioned below.

Short-term Forecasting Model with Drift

$$\begin{aligned} D(Y_t) = {} & 0.001937 + 0.068084Y_{t-1} + 0.326457Y_{t-6} + 0.266192Y_{t-141} - 0.049166\varepsilon_{t-156} \\ & - 0.377720\varepsilon_{t-6} - 0.054630\varepsilon_{t-24} + 0.036298\varepsilon_{t-80} + 0.046861\varepsilon_{t-106} \\ & - 0.041830\varepsilon_{t-115} + 0.035633\varepsilon_{t-117} - 0.241151\varepsilon_{t-141} - 0.044393\varepsilon_{t-163} \end{aligned}$$

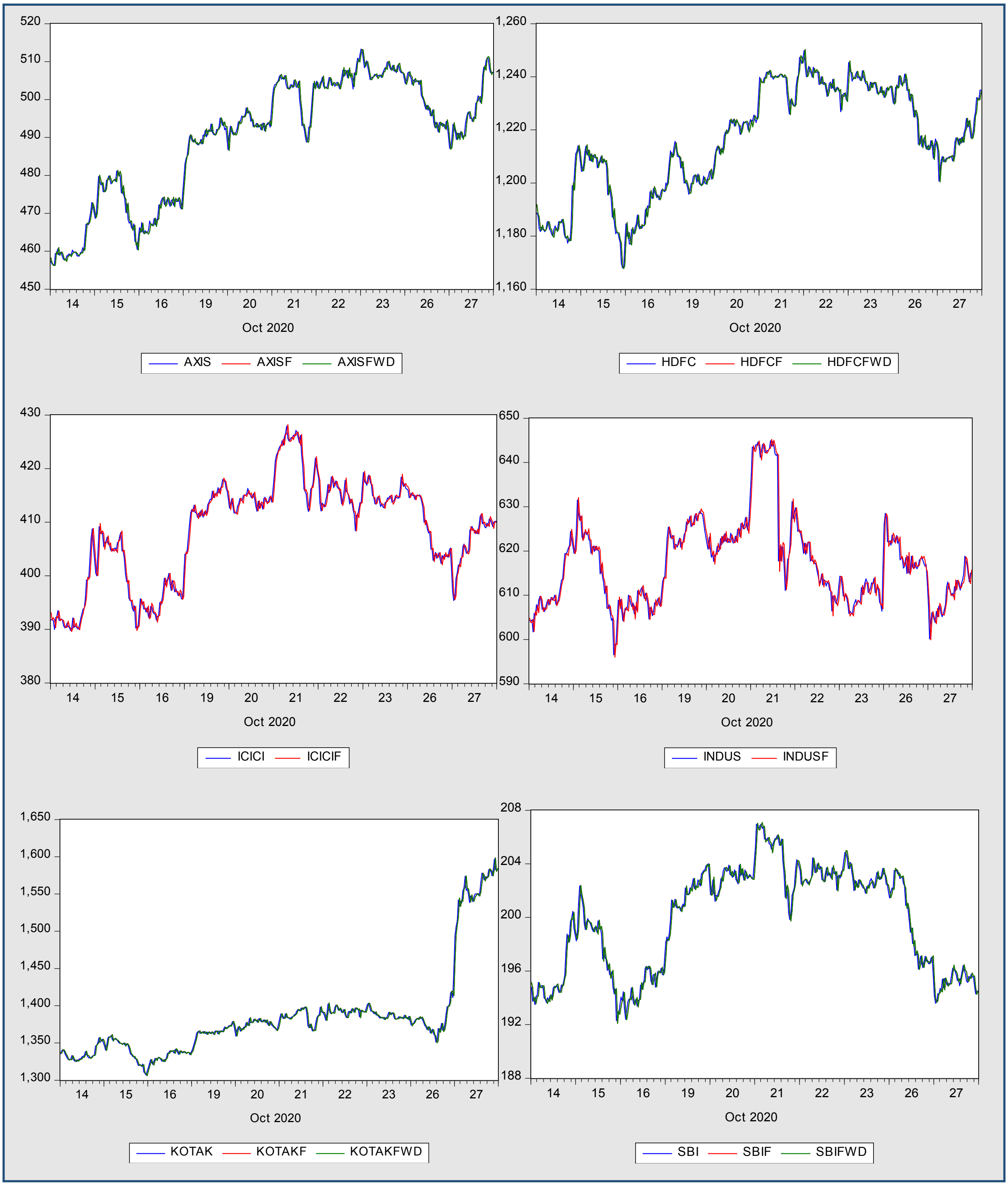
Short-term Forecasting Model without Drift

$$\begin{aligned} D(Y_t) = {} & 0.068106Y_{t-1} + 0.326433Y_{t-6} + 0.266317Y_{t-141} - 0.049153\varepsilon_{t-156} \\ & - 0.377666\varepsilon_{t-6} - 0.054596\varepsilon_{t-24} + 0.036338\varepsilon_{t-80} + 0.046905\varepsilon_{t-106} \\ & - 0.041787\varepsilon_{t-115} + 0.035660\varepsilon_{t-117} - 0.241251\varepsilon_{t-141} - 0.044365\varepsilon_{t-163} \end{aligned}$$

The above models have been used for forecasting the stock prices of State Bank of India during COVID-19 which is mentioned in the forecasting section. Moreover, the efficacy of both the models has been verified using a simple method based on coefficient of variation which is mentioned in efficacy of the models section.

7. FORECASTING OF STOCK PRICES OF BANKS USING THE FORMULATED MODELS

Figure. 2. Line Graphs of Actual and Forecasted Stock Prices of Indian Banks from 14th to 27th October, 2020 (10 trading days)



Source : Authors' Computation through E-Views 10

By using the formulated models forecasting for the period of last 10 trading days i.e. 14th October to 27th October, 2020 (390 data points) has been done. Then the actual stock prices and forecasted values of the models with and without drift of six banks have been plotted in the line graphs which are mentioned in Figure. 2.

The line graphs in Figure 2 depicts that the lines of forecasted prices with and without drift are too close to actual stock prices with minute deviations. This represents that all the models formulated in this paper are suitable for short-term forecasting of the six banks considered in this study. Again, the efficacy of each formulated model has been verifies using a simple method in the succeeding section.

8. EFFICACY OF THE MODELS IN FORECASTING STOCK PRICES OF INDIAN BANKS DURING COVID-19

The efficacy of the model has been verified using the percentage of square root of the average of the squares of deviations of forecasted values from actual values on average stock price during forecasted period which is a simple method based on coefficient of variation. The model having the least Coefficient of Variation performs better in forecasting.

Where,

- Percentage of square root of the average of the squares of deviations of forecasted values from actual values on average stock price during forecasted period = $\frac{\sigma}{\bar{X}} \times 100$
- Deviations from Forecasted Price from Actual Stock Price = D
- Square root of the average of the squares of deviations of forecasted values from actual values = $\sigma = \sqrt{\frac{\sum D^2}{N-1}}$
- Average Stock Price of respective bank during the Forecasted Period = $\bar{X}$

Table. 13. Calculation and Results of Efficacy of Models

Banks	Forecasting Model	$\sum D^2$	N	σ	$\bar{X}$	$\frac{\sigma}{\bar{X}} \times 100$
Axis Bank Ltd.	With Drift	963.9545	390	1.5741	489.95	0.3212895
Axis Bank Ltd.	Without Drift	965.6481	390	1.5755	489.95	0.3215717
HDFC Bank Ltd.	With Drift	3095.8967	390	2.8210	1215.60	0.2320733
HDFC Bank Ltd.	Without Drift	3098.6503	390	2.8223	1215.60	0.2321765
ICICI Bank Ltd.*	With Drift	696.8389	390	1.3384	408.55	0.3275984
IndusInd Bank Ltd.*	With Drift	2334.4854	390	2.4497	617.27	0.3968657
Kotak Mahindra Ltd.	With Drift	11362.0551	390	5.4044	1384.92	0.3902369
Kotak Mahindra Ltd.	Without Drift	11393.9996	390	5.4120	1384.92	0.3907851
SBI	With Drift	134.8767	390	0.5888352	199.81	0.2946970
SBI	Without Drift	134.8767	390	0.5888351	199.81	0.2946969

*Forecasting Models without Drift for ICICI Bank Ltd and IndusInd Bank Ltd. are not considered due to non-significance of all AR and MA terms

Table 13 reveals the efficacy of each formulated model. It can be observed that all the models have less than 0.5% of coefficient of variation which implies that the error margin is minimal in all forecasting models. It is also noted that the error margin is less with drift models as compared to without drift models in all banks except State Bank of India.Though coefficient of variation in without drift models in Axis, HDFC and Kotak MahindraBank is more but these may be more reliable as their all terms are significant.

9. CONCLUSION

From the above results, analysis and observations,it is clear that ARIMA Models with high frequency data can be effectively used for short-term forecasting of stock prices of Indian Banks provided more lags are required to be experimented to frame the models. All the models formulated above have high level of accuracy and can be used for forecasting. The closeness between the actual and forecasted stock prices is evident for this accuracy.Though the model for Axis, HDFC and Kotak Mahindra Bank without drift shows more variations but it may be more reliable as all the coefficient of independent terms are significant i.e. less than 0.05. Moreover, short-term investments and Intraday Trading on the stocks of Indian Banks during COVID-19 can also be a possible by using the models which enables the investors to take appropriate decisions to maximize the profits and minimize the risk. Hence, the study could also encourage investors to invest on stocks of Indian Banks as they can take appropriately calculated risk to maximise their profits from investment using the models. For future researchers, this paper acts as a base to use ARIMA with high frequency data to forecast stock prices of companies of other sectors during this pandemic. Moreover, there is an advanced variant of ARIMA i.e. ARIMA-GARCH, Long Short Term Memory (LSTM), Artificial Neural Network (ANN) and any other improved method with high frequency data can also be used by future researchers to predict stock prices during COVID-19 on short-term basis.

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