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An Empirical Study on Forecasting Stock Returns of Tata Consultancy Services

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Abstract: Forecasting of stock returns is always a vitally important financial notion confronted by investors. Due to existing fluctuations in the stock returns, investors are always keen to show their interest as they want to take the advantage of potential returns from the organization by way of investing in stocks. Hence, it becomes a matter of concern for investors to predict future stock returns so that they can attain their objective of wealth maximization. This reason creates an urge to explore the forecasting of stock returns empirically. This paper employed the ARIMA model, developed by Box and Jenkins in 1970, which relies on the previous values of the variable itself. In the paper, this methodology is applied to the stock returns of one of the top IT companies listed on NSE i.e. Tata Consultancy Services Ltd. Data of daily returns were collected from 1 April 2008 to 31st March 2021. Results concluded that the ARIMA model had a strong capability of forecasting in the short run.

1. Introduction

Forecasting stock returns is always been a topic for discussion in contemporary financial literature. Investors try hard to contemplate possible future returns of a company's given common stock. The question arises of how to identify a probable closest return of a given stock. Traditionally, researchers have made an effort to forecast stock returns by studying the factors which affect a given firm's value or profitability. In the present research paper, an effort has been made to envisage our variable by way of the lagged values of the variable itself. Based on the popular notion of letting the data speak for itself (Gould, 1981). Therefore, ARIMA (Auto-Regressive Integrated Moving Average) technique has been applied to forecast the stock returns based on its previous values and error term. Both statistical and artificial intelligence models have been developed for forecasting the series. Stock price prediction is beneficial for both retail as well institutional investors. The non-stationarity nature of stock prices becomes a hindrance in forecasting the series accurately. In this respect, Autoregressive Integrated Moving Average (ARIMA) model best known as Box-Jenkins Methodology is the most appropriate model. This model was propounded by Box and Jenkins in 1970 after considering the concept of stationarity (Box and Jenkins, 1970). ARIMA is a type of statistical model like other models such as the exponential smoothing model, regression, and Generalized Autoregressive Conditional Heteroscedasticity (Wang et al. 2012). It has become a potent and efficient model, being extensively used in the economics and finance field. ARIMA model transforms the data from non-stationary to stationary before working on it. It is used for capturing linear time series characteristics in the series. It is based on the assumption that time series values contain a linear correlation structure. This model provides a flexible approach to selecting models and estimation of parameters and forecasting.

There have been many studies conducted on different sectors that have applied the ARIMA model for the prediction of various time series variables which might include stock prices as well. However, fewer studies have been conducted on the IT sector to envisage stock returns of IT companies using the ARIMA model. More specifically, no study, as per a review of literature, has been done using the daily stock returns of IT companies. The present work initiates to fill this gap by taking daily stock returns of top IT sector companies in India i.e. TCS.

2. Review of Literature

A study on forecasting the stock price and other series has created interest among academicians and investors. Investors want to invest their hard-earned money which can be a good return. For the same, one of the methods is to forecast the stock return and one can easily evaluate whether it is good or not. The majority of the studies have been found for forecasting the stock return and other series. Smeral (2004) took an initiative to originate long-term prediction of tourism exports and imports for 25 countries by using a new WTTOUR-2001 model for the duration till 2020. Through this research work, the researcher wanted to trace the influence of changes in prices and incomes generated by and in each respective country considered in this model. Papatheodorou and Song (2005) focused on receipts and arrivals of international tourism at nominal, real, and per capita levels. In this research paper, prediction results have been produced from 2001 to 2010 by taking a base period from 1960 to 2000. Moreover, the forecasting has been done in the six major World Tourism Organization regions and the world by applying modern time series techniques. The results concluded that there exist sharp variations among regions' performance and in terms of real and per capita negative tourism growth is not unusual. Therefore, policymakers should measure to raise revenue generation but not at the cost of sustainable tourism development.

Al-Shiab (2006) used the general daily index of the Amman Stock Exchange from 4 January 2004 to 10 August 2004 to examine the univariate ARIMA model. To conduct the test following seven days were considered. Further, to get the best model for describing data, several diagnostic tests were performed, and finally, the best-selected model predicted that the daily index of ASE would increase by 0.195% for seven days beginning on 11 August 2004. However, this prediction was not per the actual performance of ASE. In China, major energy consumption is done by the transport sector. In this study, Zhang (2009) tried to predict the demand for transport energy by applying the partial least square regression (PLSR) method. Further, based on GDP, passenger turnover, urbanization rate, and freight turnover, the demand for transport energy is assessed from 1990 to 2006. The method revealed that the demand for transport energy for 2020 will reach around 433.13 Mtce and 468.26 Mtce, respectively. Consequently, this research provides an effective tool as the resulted figures are very close to the estimations generated by the Energy Research Institute of China.

Devi *et al.* (2013) selected the top four companies out of which Nifty Midcap 50 was selected based on having maximum midcap value for analysis. The historical data of selected companies for the past five years was collected and trained by applying the ARIMA model with different parameters. Further, the accuracy of predicted results was checked using criteria like AIC and BIC. Lastly, an analysis of the trained model was conducted to find the market behavior and trend for future forecasts. Ivanovic *et al.* (2013) attempted to forecast the Crobex on the Zagreb Stock Exchange. The basic motive of this present study was to examine the best ARIMA model for forecasting. Firstly, the researcher conducted a stationarity test on weekly closed prices of Crobex from 1 January 2011 till 1 January 2013. By using the ADF test, ACF & PACF plots data became stationary at first differencing. Further, a suitable ARIMA (16,1,16) model was identified after the evaluation of around 200 models based on R2, SIC, AIC, and HQC. Also, the residuals of the series were tested by using Jarque-Bera. Consequently, results confirmed that the ARIMA model outperformed the naïve model.

Mondal *et al.* (2014) studied 56 stocks from seven different sectors listed on NSE. Researchers collected data for 23 months for the empirical study. Further, AIC was used to select the best ARIMA model. Results indicated that ARIMA provides the best accurate results as above 85% of predictions using the ARIMA model for all sectors were accurate. Moving to specific sectors, forecasting of the FMCG sector was more accurate as compared to the predictions for the Banking and Automobile sectors. The primary objective of this paper was to predict gold prices by using the ARIMA model and two different versions of the wavelet scheme. Khalid *et al.* (2014) collected monthly data on gold prices from Dec 2005 to April 2013 consisting of 221 observations. Researchers evaluated the accuracy of different models based on MAE and MSE and the result favored wavelet neural transformation. In addition, this research utilized the forecast of returns from the above-mentioned various models and compared payoffs to familiar as to which framework will be the best prediction model. Isenah and Olubusoye (2014) used two models in the study namely artificial neural network and ARIMA to forecast Nigeria Stock Market returns. The comparison between ARIMA (3, 0, 1) and two artificial neural networks was done and the results depicted that models based on the artificial neural network were more capable of mimicking log returns closely than the ARIMA-based model. Along with this, results also revealed that simple technical indicators can also be used as predictors for predicting values of future stock market returns instead of extensive market data. Gay (2016) made an effort to investigate the relationship of macroeconomic variables on stock returns of BRIC countries that include Brazil, Russia, India, and China. He made use of the Box-Jenkins method to serve the purpose. The factors are taken into account where the exchange rates and the oil prices. No statistically significant association was found to be there between the given macroeconomic factors and stock returns for any of the BRIC economies. Moreover, no significant link was identified between stock return with its lagged values for any of the four countries. Malik *et al.* (2017) studied the big five banks of Pakistan for their stock price prediction. The stock price data for selected banks were collected from the official website of KSE (Karachi Stock Exchange). Researchers applied the ARIMA model for forecasting and after identification, estimation, and application of multiple diagnostic checks, the best model opted for the prediction of ABL, HBL, and MCB were found to be ARIMA (1, 1, 0). On the contrary, for the prediction of BOP and UBL stocks', ARIMA (1, 1, 1) was coming out to be appropriate. Lastly, its outcome revealed that BOP and MCB had the maximum number of observations whereas HBL ranked lowest in the group.

An attempt was made by Dong and Gong (2017) to build a predictive model of the stock price using the ARIMA model. In the present research, researchers collected stock price data of Apple Inc. from Yahoo! Finance to forecast. Results disclosed that Autoregressive Moving Average (ARIMA) model has a robust capability for short-run prediction as well as is equally competent to other prediction models in guiding investment decisions. Afeef *et al.* (2018) employed the ARIMA methodology to forecast stock prices of a Pakistan-based company namely Oil & Gas Development Company Limited (OGDCL). The researcher considered daily adjusted closing stock prices of OGDCL for almost 15 years starting from 2004 to 2018 with 3632 observations. Results depicted that for prediction in the short-run, ARIMA modeling has great potential. Consequently, it was suggested for investors consider the findings of the study to supplement their aptitude for forecasting. E-commerce is becoming an integral part of society as it serves as a medium for selling and purchasing goods to the mass market. This reason led Carta *et al.* (2019) to forecast the future prices of products. In this research paper, researchers used a combination of sentiment analysis, time series, and reputation. Moreover, researchers exploited a suite of software tools i.e. Price Probe along with the ARIMA model to forecast prices of different products available on E-Commerce sites mainly Amazon. Data related to the prices of products was collected through social media, Google Trends, APIs, and dedicated crawlers. After detailed analysis researchers concluded that the quality of prediction was improved due to the presence of Google Trends information.

As per a detailed review of the literature, it has been observed that the majority of the studies have been conducted at developed countries' stock prices. Hence, there is scope in studying the stock return on Indian Stock price. In the context of the Indian stock market, TCS stock price has been considered to carry in the present study. The present work initiates to fill this gap by taking daily stock returns of top IT sector companies in India i.e. TCS. Tata Consultancy Services Ltd is a global leading IT service, consulting, digital and business solutions organization.

3. Objective of the Study

The main objective of the present study is to forecast the stock return of Tata Consulting Services.

4. Research Methodology

4.1. Data Collection

For the present research work, the daily adjusted closing price of Tata Consultancy Services Ltd. has been taken from 1 April 2008 to 31st March 2021. The data has been collected from CMIE PROWESS. After collecting the daily stock price, it is converted into a log return. Data of daily return was collected which are the logarithmic differences of prices of two successive times, that is, Ri t = log (P it / P it-

1). An Autoregressive Integrated Moving Average (ARIMA) is employed in the present study to forecast the stock return of TCS using RStudio.

4.2. Tools

ARIMA model is explained in the Box-Jenkins methodology. This methodology is used to identify a potential model out of a general class of models. In addition, it uses both the techniques of autoregressive (AR) and moving average (MR) for forecasting as well as tries to search for the best combination of the two techniques. ARIMA stands for Auto-Regressive Integrated Moving Average. It is a method of modeling the data of time series for predicting or forecasting the future data points in the series. It is done based on its past value as well as past values of the error term. ARIMA model believes that information is hidden in the past of the series; Yt-1, Yt-2, and so on, or in the residuals of the series; et-1, et-2, and so on. Here, Yt represents the response variable at time t and e represents the error term.

This model was initially introduced by two statisticians namely George P Box and Gwilym Jenkins in their book "Time Series Analysis: Forecasting and Control" (Box and Jenkins, 1970). That's why it is also known as the Box-Jenkins methodology. To get better results from the model, it is suggested by researchers to work on at least 100 observations or more. The prime problem in the ARIMA model is the identification of lag values of a variable along with the lag value of the error term which can effectively forecast the future value of the variable.

ARIMA models are generally expressed like "ARIMA (p, d, q)", here the three terms are defined as follows:

- "AR" in ARIMA is called an Autoregressive term in the model. "AR" in the model assumes that a time series is a function of its past values; that's *Yt= f(Yt-1, Yt-2, …)*.
- "I" in ARIMA is called the integrated feature of a time series which means how many times a series is to be differenced to make it stationary. If a time series becomes stationary after a second differencing it is called integrated of order two." I" also takes care of the difference to make a time series stationary.
- "MA" in ARIMA represents the Moving Average term in the model. It assumes that a time series is a function of its errors that's – *Yt= f(et-1, et-2, …)*

The creators of the model, Box, and Jenkins, have focused on the principle of parsimony which emphasizes keeping the model as simple and concise as possible. Of course, a model with a huge number of regresses would forecast better results in time series (as R^2 will be high) but at the cost of a lessening degree of freedom. For the prediction of time series, both the model developers proposed a four-tier model. Hence, the model is widely known as the Box-Jenkins methodology whereas the economic terminology for such kind of model prediction is known as ARIMA modeling.

The four steps of the ARIMA model are:

- **Model Identification:** In this preliminary stage, the researcher firstly transforms the series to stabilize variance by taking log or differencing to obtain stationary series. After following this process, the best suitable ARIMA model, including the autoregressive processes (p) affecting a time series variable, the number of times the series to be differenced to make it stationary(d), and the number of moving average processes (q), for the time series has been ascertained.

- **Parameter estimation:** In the next stage of ARIMA modeling, the estimations of parameters of the potential model are made.
- **Diagnostic Checking:** In the third step of the process, the assumptions of autocorrelation and normality of residuals are checked.
- **Forecasting:** Finally, in the last step of the methodology, the future or the next value of the time series is forecasted or computed mathematically to check how near the forecasted value is in comparison to the actual value as well as the accuracy of the forecasted results were identified by considering the error variance. While using the time series econometric framework, it is advisable to extricate information related to a variable that can be gathered from the variable itself (Asteriou and Hall, 2007). Hence the autoregressive integrated moving average model (ARIMA) which is also known as the Box-Jenkins methodology has been implemented in the study. The general equation of an ARMA model (Asteriou and Hall, 2007) is as follows:

$$Yt = \varphi 1Yt\text{-}1 + \varphi 2Yt\text{-}2 + \text{-} \text{-} + \varphi pYt\text{-}p + \varepsilon t + \theta 1\varepsilon t\text{-}1 + \theta 2\varepsilon t\text{-}2 + \text{-} \text{-} + \theta q\varepsilon t\text{-}q$$

Here, Yt is the predicted value of the variable, Yt-1, Yt-2,…..Yt-p is the lagged value of the autoregressive term (AR), ε_t is the error term, ε_{t-1}, ε_{t-2}, - - -, and ε_{t-q} are the lagged values of the moving average (MA) or error terms, φ and θ are the coefficients of the regressors. But under this process, variables of time series are assumed to be weakly stationary. The meaning of stationarity implies that the mean and variance of the time series are constant and its covariance is time-invariant (Gujrati and Porter, 2004). Applying the ARMA process to non-stationary data will provide no results. Therefore, the most appropriate and efficient ARIMA model was applied to daily stock returns of TCS collected from 1 April 2008 till 31st March 2021 to forecast more accurate results of stock returns.

5. Data Analysis and Findings

5.1. Descriptive Statistics

Table 1: Descriptive Statistics

	TCS
Mean	0.0777
Maximum	14.4065
Minimum	-11.3063
Std. Dev.	1.9793

Source: Author's Own Compilation

It has been observed from table 1: Descriptive Statistics, the minimum and maximum values of TCS stock returns stand at -11.3063 and 14.4065 respectively. The minimum value of stock returns depicts that shareholders lost 11.31% in stock returns on the contrary some of them have gained up to 14.40% as stock returns. The mean value of TCS returns comes out to be 0.0777 which is an indication that approximately TCS is generating 0.07% stock returns during the period of study. The variation in the stock returns can be seen in the value of the standard deviation which stood at 1.9793. This implies very little volatility and deviation in stock returns from the mean.

5.2. Trend Analysis of TCS Stock Prices

The TCS stock prices depict that it did not follow any specific trend. The TCS prices stood around 212 on 1st Apr'08 and it declined for 1 year straight. It was due to the global slowdown. From April'2009 till September'14, stock price shooted from 200 to 1400 levels. It shows the strong performance of the company during the period. However, from September, 14 till December, 17 stocks were in the consolidation phase where they traded in a particular range only. There is a breakout in share after January'18. It achieves its lime time of Rs 1587 on 24th Jan'18.

5.3. Unit Root Test

As the series seems to be non-stationary, to make it stationary first of all stock prices of TCS have been converted into stock returns by using the following formula:

$$\mathbf{SR = ln(p2/p1)*100}$$

Where,

Ln = Lognormal

P2 = Price as of 31st March

P1 = Price as of 1st April

Further, to check the stationarity of the TCS stock returns series, the researcher applied ADF test statistics on the level at a 5% significance level. The hypothesis for the same is mentioned under:

H0: The series is non-stationary or the series has the presence of unit root.H1: The series is stationary or the series does not have the presence of a unit root.

The results of the ADF test which has been employed on the log-normal stock return series of TCS depict the ADF value as -31.65182 and probability value as 0.00 which is less than .05, this blatant the stationarity of series at first difference as well as the Durbin-Watson value 2.00 confirms the absence of autocorrelation in the series.

5.4. Model Identification

After achieving the results of stationarity in the series through log normal stock returns values, the researcher stepped further and introduced the Box-Jenkins methodology. The initial step in the process is to identify an appropriate model. To locate the best-fitting ARIMA model for the stock returns of TCS, the function "auto.arima" has been applied in R Studio. After applying the function best model has been estimated which identified the number of AR and MA terms on which returns of TCS depend. Finally, the ARIMA model (2, 0, 2) came out to be the best fit model for the prediction of TCS stock returns. In the estimated model, the value of AR comes out to be 2 which explains that stock returns of TCS can be forecasted by considering stock returns of the previous two days whereas I stand as 0 which shows the stationarity of natural log returns series at first differencing. Moreover, the value of MA comes out to be 2 which represents that stock returns of TCS are affected by the error term of the previous two days.

5.5. Model Estimation

Using R studio, the following are the estimated parameters based on the model identified:

Table 2: ARIMA Model

Parameters	*ar1*	*ar2*	*ma1*	*ma2*	*Intercept*
Constant	0.9679	-0.5148	-0.9523	0.4376	0.0775
s.e.	0.1339	0.1878	0.1393	0.1935	0.0351
t-value	7.2285	-2.7412	-6.8363	2.2615	2.208
p-value	0.0000	0.0000	0.0000	0.0000	0.0000
sigma^2 estimated as 3.875, log likelihood = -5183.86, aic = 10379.73					

	ME	*RMSEMAE*	*MASE*	
Training set	0.000215725	1.968436	1.364479	0.7032506

Source: Author's Own Compilation

ARIMA Model depicted in table 2, the coefficients depict the AR and MR terms of the ARIMA model whereas S.E shows the standard error. The mathematical equation of the ARIMA model is

$$Yt = 0.0775 + 0.9679\ Yt\text{-}1\ -0.5148\ Yt\text{-}2 + 0.0351 - 0.9523\ \varepsilon_{t-1} + 0.4376\ \varepsilon_{t-2}$$

Here the p-value of each coefficient has been examined to determine whether or not the parameters are significantly significant. As a result, it has been discovered that p-values of coefficients ar1, ar2, ma1, and ma2 are found to be significant as their value comes out to be less than .05. Moreover, the above table 2 also shows the Akaike Information Criterion (aic) 10379.73 which helps to identify the best number of parameters and lags to be estimated in the ARIMA(p,d,q) models. The Akaike Information Criterion (aic) was developed by HirotuguAkaike (Akaike, 1974). In addition, results of ME, RMSE, MAE, MASE, and ACF1 have been shown in table 2 to facilitate the process of best model selection.

5.6. Residual Diagnostic

For the best forecasting model or to ensure the appropriateness of the model, it is mandatory to diagnose the leftover residuals generated from the model. If these are left unchecked then, it may lead to the problem of autocorrelation. Consequently, autocorrelation will decrease the accuracy and lead to misinterpretation of data (Pillai, 2017). Therefore, the assumption of the presence of autocorrelation among the residuals has been diagnosed by preparing correlograms of both autocorrelations as well as

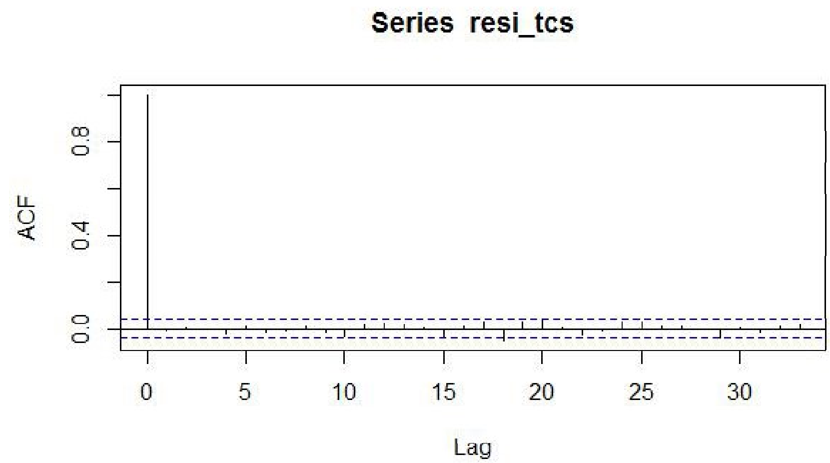

Figure 1: Plot of ACF

Source: Author's Own Compilation

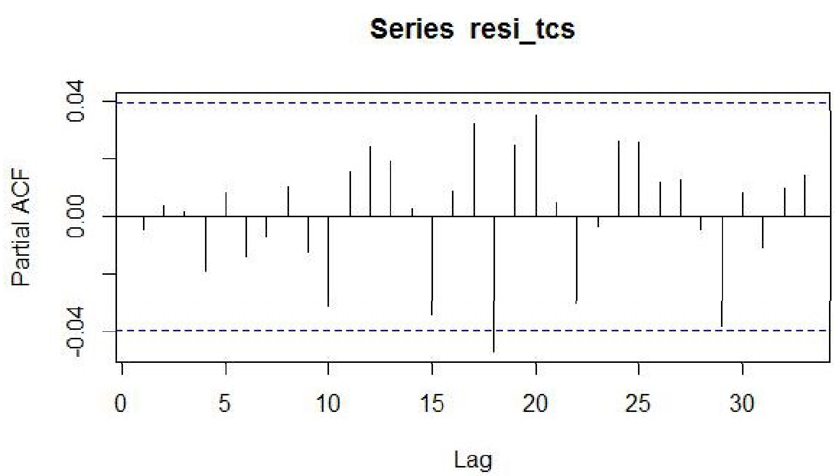

Figure 2: Plot of PACF

Source: Author's Own Compilation

partial autocorrelation. Moreover, the residuals should be white noise as well as uncorrelated and purely random to consider the generated model as a fit model.

As per figure 1 of ACF, it can be observed that the first lag in the series is significant while the rests of the errors are white noise. The autocorrelation check of the residuals indicates that the model is good as well as residuals have constant variance, and zero means and are also uncorrelated.

Further, it is identified from figure 2 of Partial ACF that lag 18 just crosses the significant limit but all other lags of PACF lie within the significance limit and move around zero. Hence, it can be concluded that our selected model is a perfect fit for forecasting.

5.6.1. Autocorrelation

Further, the assumption of autocorrelation has been also diagnosed through the Ljung-Box test. This test is used in ARIMA modeling to test that the residuals obtained from the ARIMA model do not contain any autocorrelation (Davidson, James (2000)).

H0: There exists no autocorrelation

H1: There exists autocorrelation

Table 3: Results of the Ljung Box Test

X- Squared	*Df*	*p-value*
0.084143	2	0.9588

Source: Author's Own Compilation

The results of the Ljung-Box test shown in table 3 reveals that the p-value is greater than .05 which leads to acceptance of the null hypothesis and concludes that there exists no autocorrelation or that the residuals obtained from the selected model are independent of each other.

5.6.2. Normality Test

The second assumption of normality of residuals was satisfied by using the Jarque-Bera test. This test is named after Carlos Jarque and Anil K. Bera. If it is far from zero then it signals that the data do not have a normal distribution. The following is the assumption to check the normality of residuals.

H0: Series is normally distributed

H_1: Series is not normally distributed

Table 4: Results of Jarque-Bera Test

X- Squared	*Df*	*p-value*
3429.8	2	<2.2e-16

Source: Author's Own Compilation

The p-value of the Jarque-Bera test came out to be <2.2e-16 which is less than .05 which leads to no acceptance of the null hypothesis and thus concludes that data is not normally distributed. The normality plot of residuals is presented in above figure 3also evident the same.

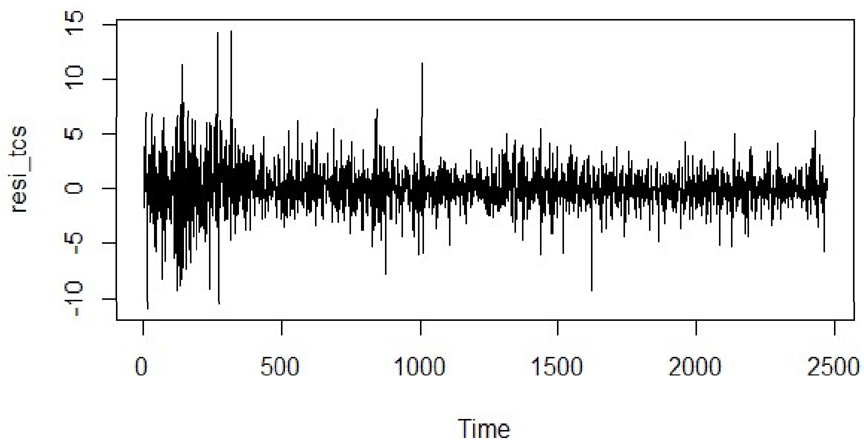

Figure 3: Residuals Normality Plot

Source: Author's Own Compilation

5.7. Forecasting

Lastly, by using ARIMA (2, 0, 2) model, the researcher forecasted the next seven days' log normal returns of TCS. The daily stock returns are compared with the returns generated by the best fit ARIMA (2, 0, 2) model which are shown in table5 along with the calculated value of S.E.

Table 5: Forecasted Returns of TCS

Date	*Actual Returns %*	*Forecast Returns %*	*SE%*
1 April 2021	2.101202187	1.574224631	0.526978
5 April 2021	0.054974129	1.200475726	-1.1455
6 April 2021	-0.012366544	1.007152253	-1.01952
7 April 2021	1.603752983	0.883844137	0.719909
8 April 2021	-0.259298145	0.796254172	-1.05555
9 April 2021	-0.898851852	0.729985132	-1.62884
12 April 2021	0.467457987	0.677663266	-0.21021

Source: Author's Own Compilation

After 1^{st} April 2021, no trading was carried out on 2^{nd}, 3^{rd}, and 4^{th} April 2021. Hence, the actual return of the next working day i.e. 5^{th} April 2021 has been taken into consideration. Similarly, due to non-working days on 10^{th} and 11^{th} April 2021, following the next 12^{th} April has been considered. Table 5 represents actual stock returns and forecasted stock returns of TCS along with its standard error. The results depict that only on 1^{st} April & 7^{th} April 2021, the value was under forecasted by 0.53% and 0.71% respectively, except this day remaining all the returns from 5^{th} April 2021 till 12^{th} April 2021 have been over forecasted. The range of over-forecasted values lies between 0.21% to 1.62% which confirms that the model is precise or the best fit for prediction. To confirm the accuracy of the model, the researcher applied a one-sample t-test. The result of the test signifies that the standard deviation of the accuracy of forecasting of TCS is not too high and we are getting an above 95% accuracy in prediction for TCS stock returns. Moreover, the p-value is coming out to be more than .05 i.e. the null hypothesis will be accepted which is, that the changes in the accuracy of prediction of stock returns of TCS are insignificant.

Table 6: One-Sample Statistics

	N	*Mean*	*Std. Deviation*	*Std. Error Mean*
TCS	7	-.544676	.9020675	.3409495

Source: Author's Own Compilation

Table 7:Results of One-Sample t-Test

	T	*Df*	*Sig. (2-tailed)*	*Mean Difference*	*95% Confidence Interval of the Difference*	
					Lower	*Upper*
TCS	-1.598	6	.161	-.5446761	-1.378949	.289597

Source: Author's Own Compilation

6. Conclusion

6.1. Research Outcomes

The basic objective of the present study is to forecast a stock return of the Tata Consultancy Service (TCS). It is found that ARIMA (2,0,2) model is the best-fitted model to forecast the log-normal stock returns of TCS. The results depict that only on 1st April & 7th April 2021, the value was under forecasted by 0.53% and 0.71% respectively, except this day remaining all the returns from 5th April 2021 till 12th April 2021 have been over forecasted. The range of over-forecasted values lies between 0.21% to 1.62% which confirms that the model is precise or the best fit for prediction. Moreover, the results of one sample t-test signify that the standard deviation of the accuracy of forecasting of TCS is not too high and we are getting an above 95% accuracy in prediction for TCS stock returns and the changes in the accuracy of prediction of stock returns of TCS is insignificant. From the above findings, it can be concluded that the ARIMA model has sufficient potential to predict future values in the short run.

6.2. Implication and Limitation of the Study

The study implies that it is expected to be worthful for prospective investors by guiding them to invest or disinvest in a particular stock at the correct time. Present research work is restricted to the ARIMA model for forecasting but numerous other models are also available.

6.3. Future Scope of Research

The research work was conducted only to study the forecast of one company. The future study can be done by extending to other companies or sectors along with comparisons among them. Present research work forecasted only stock returns whereas forecasting of different variables can also be done in the future. Future studies can also be conducted on other models to forecast stock returns except for ARIMA.

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