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FORECASTING THE PERFORMANCE OF EFFICIENT INDIAN EQUITY MUTUAL FUNDS PORTFOLIO USING AUTO-REGRESSIVE INTEGRATED MOVING AVERAGE MODEL

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ABSTRACT

Mutual funds are one of the safest options to invest money in the stock market or to buy assets. Past and present analysis of the mutual fund investing scenario is very crucial to gain an insight about the future performance. This paper aims to forecast the Net Asset Values of an efficient Indian Equity Mutual Funds portfolio using the Auto-Regressive Integrated Moving Average model. The Equity Mutual funds which are operational on or before January 2015 are considered and their monthly Net Asset Values are collected from January 2015 – December 2019. The portfolio is constructed by allocating weightage to the funds ensuring minimum risk. The stationarity of the Net Asset Value for each fund constituting the portfolio is tested using the Augmented Dickey-Fuller test. An appropriate Auto-Regressive Integrated Moving Average model is fitted to each of these funds and the models are validated using the Ljung Box test. The models with the lowest Akaike's Information Criteria value and significant coefficients are selected as the appropriate model. The Net Asset Values for the first six months of the year 2020 are forecasted for each fund using the selected model and the forecasts are found to be quite appropriate. Thus, this study will help investors in their future investments.

KEYWORDS: Equity Mutual Fund, Auto-Regressive Integrated Moving Average model, Augmented Dickey-Fuller test, Ljung Box test, Akaike's Information Criteria.

1. INTRODUCTION

Mutual Funds (MF) are one of the most popular investment solutions in India among Corporate, household, and Private Investors. As of April 30, 2022, the size of the Indian MF market was approximately INR 38.04 trillion, and in the previous ten years, the corpus size has expanded up to five times (Association of Mutual Funds in India, 2020). It suggests a staggering 500 percent growth in just 10 years, which denotes people's interest in investing in MFs. The fact that most investors seek bigger returns but do not want to accept the risk of investing in the stock market is one of the factors driving interest in an MF. They believe it is safer to make a market investment indirectly through some reliable MFs. The declining interest rate on the

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bank's fixed deposits could be another factor (RBI, 2018). The effective yield from fixed deposits is quite low due to the high rate of inflation. People in general therefore research various investment options that will provide decent returns with a few uncertainties as feasible. In general, investing in individual stocks has the potential to yield good returns but also carries the risk of an unlimited loss. The global spread of COVID-19 is one of the most convincing examples. The lockdown in many parts of the world dramatically restricted economic activity, which caused share prices to drop globally (Chang et al. 2021). COVID-19 was an unanticipated event that had an impact on practically every industry. However, certain industries have benefited from the sudden uptick in consumer demand for their goods. It means that choosing different industries to invest in is desirable if you want to lower your investment risk. However, it becomes challenging for an individual investor to manage a diverse portfolio while keeping track of the numerous companies belonging to the various sectors. Therefore, for many retail investors, a mutual fund is the ideal choice to maintain an investment in the stock market with a diversified portfolio. It is expertly handled by fund managers, who take money from investors and invest it in a variety of stocks, bonds, and other products of the money market to generate a profit. They build their portfolio using sophisticated statistical methods to achieve the ideal balance between returns and risk.

The popularity of predicting mutual fund returns stems from the possibility that investors will be better advised if the future market value of the equities can be accurately forecasted. The predictability of the system, which in turn helps investors get ready for trading and investing in the mutual fund business, is crucial to the benefits of both. To forecast time series data, several statistical techniques have been developed and among all of these, the Auto-Regressive Integrated Moving Average (ARIMA) by Box and Jenkins is possibly the most used model. ARIMA has been used to build forecasting models in various domains. A forecasting comparison between the ARIMA methodology and the neural network method was done by Mutar and Ilias (2010). They demonstrated that the feed-forward artificial neural network provided less accurate forecasts than the ARIMA approach did. Tuama (2012) forecasted the prevalence of malignant tumor patients in the province of Anbar using the ARIMA methodology. The analysis's findings indicated that an integrated autoregressive model of order two is the appropriate model. Maternal mortality is modeled and predicted using the ARIMA model (Sarpong, 2013). The study's findings demonstrated that the ARIMA (1, 0, 2) model can accurately predict quarterly maternal mortality rates. Box-Jenkins models were employed by Ghafil (2013) to forecast the output of electrical energy. The analyses' findings demonstrated that ARIMA (1, 0, and 2) was the most effective model. Wan (2013) used arrest and sentencing data to forecast prison populations using the ARIMA methodology. The findings suggested that although modeling predicts an increase in the number of prisoners on remand, this tendency should be more than compensated by a drop in the number of prisoners serving sentences during the ensuing months. Pang and McElroy (2014) forecasted mortality and fertility by gender and ethnicity/race using the ARIMA approach. The analyses' findings are generated using the data during the period 1989-2009 and it is found that a model without drift generates more reliable estimates for total rates. Brajesh and Shekhar (2015) forecasted the population of accidental fatality in India using statistical models. The study's findings

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demonstrated that ARIMA outperformed damped trend exponential smoothing in terms of model validation. This will make it easier for policymakers to prevent future occurrences of this kind. For predicting India's rice production, Chaudhuri et al. (2020) employed ARIMA, while Nath et al. (2019) suggested the same model for forecasting wheat production in India. To predict future stock indices, which are crucial to the development of the Indian economy, Banerjee (2014) utilized the ARIMA model. Using a half-hourly demand date, Asad (2012) forecasts the daily electricity demand at its peak. He claimed that the ARIMA model created using data from the previous three months is the best model for predicting events two to seven days in the future, while the ARIMA model created using data from the prior six months is the best model for predicting events one day in the future. In a selected area of research in California, USA, Alghamdi et al. (2016) employed the ARIMA model to assess and predict the traffic flow measurements, obtained on an hourly basis. The residual from their model shows excellent performance in forecasting traffic situations in the future. The top 4 firms in the NSE-Nifty Mid Cap 50 were predicted using the ARIMA model by Devi et al. (2013). The ARIMA model was used by Fattah et al. (2018) to forecast demand in a food firm. Qader (2016) used the ARIMA model to predict the Iraqi census using 61 observations from the annual census from 1950 to 2010. According to his research, Iraq's population will grow by 33.58 percent over the following ten years

From the existing literature, we found the application of the ARIMA model in forecasting time series data in different domains. However, forecasting the NAV of Mutual funds in the Indian market is neither well documented nor explained in the finance literature. Thus, our study attempts to forecast the NAV of the efficient Indian Equity Mutual Funds using the appropriate ARIMA model.

2. RESEARCH METHODOLOGY

The methodology is divided into two parts

i) Selection of the funds constituting the portfolio

ii) Forecasting the NAV of the selected funds.

A. Selection of the funds

All the Indian Equity Mutual funds which are operational on or before January 2015 have been considered for the study and their monthly NAV are collected from January 2015 to December 2019. The monthly returns are then calculated as

$R_t = (NAV_t - NAV_{t-1}) / NAV_{t-1}$, t = 2, 3… 60 (Baliyan and Rathi, 2019)

Where R_t: Return for month t and NAV_t and NAV_{t-1}: Net asset value for month t and t-1 respectively.

The funds which have positive average return and negative skewness of return are considered. Next, we select those funds whose standard deviation (SD) is less than the combined SD and whose beta is greater than the average beta. This is done by drawing the Investor's Perception Map taking SD on X-axis and beta on Y-axis. The funds that fall in the second quadrant of the

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Investor's Perception Map are selected. The portfolio is then constructed by allocating weights to these selected funds ensuring minimum risk using a nonlinear optimization technique Generalized Reduced Gradient. According to Modern Portfolio Theory (Markowitz, 1952), the portfolio risk is given by $\sigma = \{\sum \mathrm{Var}\ (w_i.\ R_i)\}^{1/2} = \{\sum w_i^2.\ \sigma_i^2 + \sum\sum w_i.\ w_j.\sigma_{ij}\}^{1/2}$ where R_i and R_j are the monthly returns of the ith and jth fund, w_i and w_j are the proportion of the portfolio invested in the ith and jth fund, $\sigma_i^2 = \mathrm{Var}(R_i)$, and $\sigma_{ij} = \mathrm{Cov}(R_i, R_j)$. The efficiency of these selected funds in the portfolio is measured using a nonparametric mathematical programming model Data Envelopment Analysis.

B. Forecasting

After selecting the portfolio, we try to forecast the performance of the selected funds constituting the portfolio. The first task is to check whether the data is suitable for time series analysis. Durbin-Watson suggested a test that gives us a clear picture of the data set type. The statistic is given by $DW = 2[1-\rho_1]$, where ρ_1 is the 1st order autocorrelation and $0 \leq DW \leq 4$. If the value of DW lies in the interval [0, 1.5] or [2.5, 4], the data is considered to be longitudinal and hence time series analysis can be performed; otherwise, we have cross-sectional data and regression analysis is to be applied. The first step of the time series analysis is to verify whether the data is stationary.

A time series Xt is defined as stationary if the joint probability distribution of $X_{t1}, \ldots, X_{tm}$ is the same as that of $X_{t1+h}, \ldots, X_{tm+h}$, $h > 0$. More generally, if, E(Xt) is independent of t and the auto covariance function of X_t and X_{t-h} depends only on the lag differences h i.e. the variance is constant. To make a forecasting model in time series analysis, a stationary time series is required for better prediction. The Augmented Dickey-Fuller (ADF) test is performed to verify the stationarity of each fund. It tests the presence of unit root in a time series, hence checking its stationarity. Given the data in hand, it is necessary to test for every fund whether the data is stationary after having plotted them to confirm our visual interpretation. Here the hypotheses are H_0: The series is nonstationary (unit root is present) v/s H_1: the series is stationary. The null hypothesis is rejected at 5% level of significance if the computed p-value is less than 0.05. If the series becomes non-stationary, transformation techniques such as differencing and logging can be used to make it stationary.

Auto-Regressive Integrated Moving Average (ARIMA): ARIMA models are perhaps the most common and widely used stochastic models for forecasting a stationary time series. An "ARIMA (p,d,q)" model is a non-seasonal ARIMA model where p refers to the number of AR terms, d denotes the number of times the data is differenced and q is the number of MA terms. Exponential Smoothing, AR, and random–trend models are all variations on ARIMA models. In general, a non-seasonal stationary time series can be described as a sum of the past values and the errors, denoted as

$$X_t = \mu + \alpha_1 X_{t-1} + \ldots + \alpha_p X_{t-p} + e_t + \beta_1 e_{t-1} + \ldots + \beta_q e_{t-q}$$

Where X_t is the actual value, e_t is the error term at time t, and μ is the constant. Here α_i, (i= 1, 2... p) and βj (j = 1,2,..,q) and are called the model parameters. The terms p and q are integers. p represents the autocorrelation term whereas q represents the error term.

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ARIMA model is constructed based on four steps- Identification, Estimation, Diagnostics, and Forecasts. At first Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF) graphs are used to determine the order of AR and the MA value. ACF at lag h is the simple correlation between Y_t and Y_{t-h} and PACF is the correlation between Y_t and Y_{t-h} when the effects of the intervening lags are removed.

These graphs for the differenced series help us to comprehend the associations between observations at various lags, hence indicating the values of parameters p and q that we may consider while fitting AR (p) and MA (q) models. It is done by noting the cut-offs in ACF and PACF graphs of the stationary series. But this is only a tentative model selection procedure, and we need to take various combinations of (p, d, and q) to obtain the best possible model based on goodness of fit criteria.

The following table presents the nature of the different models concerning ACF and PACF:

(Insert Table 1 here)

The best model among the possible combinations of models is chosen using Akaike's Information Criteria (AIC) after calculating the parameters p, d, and q. Lesser the AIC, the better the model.

The model is then validated by the Ljung Box test. The null hypothesis that the fitted model is good is accepted at 5 % level of significance if the observed p-value is greater than 0.05.

Finally, Forecasting is done based on the best-selected model for six months for each fund.

3. RESULTS AND DISCUSSION

Considering the funds which have positive average returns and negative skewness of returns, we have 68 funds. The average and SD of monthly returns and the beta values of these 68 funds are given in Table 2.

(Insert Table 2 here)

The investor's perception map is prepared by taking SD on X-axis and beta on Y-axis with its origin at average beta (0.622) and combined SD (0.045).

(Insert Fig: 1 here)

The funds which fall in the second quadrant of the map are given in the following table.

(Insert Table 3 here)

The weightage of the funds constituting the portfolio is given in Table 3.

(Insert Table 4 here)

The efficiency and relative efficiency of each of these funds and their ranks are given in the following table.

(Insert Table 5 here)

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The DW statistic for each series is respectively 0.247, 0.190, 0.186, and 0.172 which signifies that we have time-series data with high positive autocorrelation for each fund. The NAV of the four funds namely, ICICI Prudential Nifty Next 50 Index (G) (Fund 1), HDFC Top 100 Fund Direct (G) (Fund 2), HDFC Top 100 Fund (G) (Fund 3), and ABSL Mid Cap Fund (G) (Fund 4) is plotted with time.

(Insert Fig 2 here)

From the graph, it is seen that the mean and variance of each series are not constant over time and hence the series are non-stationary. The ADF test is performed to confirm the visual inspection.

(Insert Table 6 here)

As the p-values of the ADF test for all the funds are greater than 0.05, we accept the null hypothesis at the 5% level and hence conclude that all the funds exhibit non-stationarity. The first difference of each series is taken to make them stationary.

(Insert Table 7 here)

Here it is observed that the p-values of the ADF test for differenced series for all the funds are much smaller than 0.05, and hence we strongly reject the null hypothesis at 5% significance level and conclude that the first-order difference of all the funds exhibit stationarity. Hence in fitting ARIMA (p, d, q) model, we take d = 1 for all the funds. To find the appropriate value of p and q for each, their PACF and ACF graphs are drawn.

(Insert Fig 3 here)

The PACF cuts off after lag 1 for all the series, hence the autoregressive component (p) of the ARIMA (p, d, q) model is of order 1 for all the funds. However, we are unable to draw any firm conclusions regarding the MA component (q) of the model because the ACF fades out after many lags in all the series. The trial-and-error method is implemented by trying out different values of q for which AIC is minimum and the coefficients are significant. ARIMA (1, 1, 1) is the appropriate model for the first three funds while ARIMA (1, 1, 0) is suitable for Fund 4. The best fitted ARIMA model for the funds along with estimated parameters and some diagnostic measures are given in the following table

(Insert Table 8 here)

To validate the model for each fund, the Ljung Box test is performed

(Insert Table 9 here)

For each fund, the p-value of the Ljung Box test is greater than 0.05. Thus, we accept the null hypothesis at the 5% level and conclude that the fitted model is good for respective funds.

The residuals of a model are the left-over part after the model is fit and its analysis is an integral part of building a time series model. The main objective of the residuals is to check whether a model has sufficiently captured all the information in the data or not. The residuals of a good forecasting model must approximately follow a normal distribution and to check that, the

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Shapiro – Wilk's test is carried out. The null hypothesis for this test is that the data is normally distributed, and the alternative is the data is not normally distributed. The p-values of the test obtained for all the funds are greater than 0.05 and hence we accept the null hypothesis at 5% level of significance and conclude that the residuals of the models for all the funds follow the normal distribution.

(Insert Table 10 here)

The ADF test is also performed on the residuals and the p-value for all the funds is 0.01, implying that the residuals of the fitted models for each fund are stationary. Moreover, from the residual ACFs, it is observed that the spikes of residual ACF are on both sides of the horizontal axis in a random pattern and falls within the control band as the lag increase, gradually decreasing to zero, which ensures that the fitted model is appropriate.

(Insert Fig 4 here)

Using the respective model, the NAV of each fund is forecasted for the first six months of 2020. The forecasted NAV along with their upper and lower control limits are presented in the following table.

(Insert Table 11 here)

The observed, fitted, and forecasted values of each fund are presented in the following figure.

(Insert Fig 5 here)

4. CONCLUSION

Mutual Funds are one of the most preferred investment options for investors. Forecasting of mutual funds is now a popular trend since good stock market value predictions will help investors make better decisions. This study attempts to forecast the NAV of four efficient Equity Mutual Funds, HDFC Top 100 Fund (G), HDFC Top 100 Fund Direct (G), ICICI Prudential Nifty Next 50 Index (G), and ABSL Mid Cap Fund (G) having minimum risk, using ARIMA model. The presence of autocorrelation for each fund is established by the Durbin Watson test statistic which leads us to the adoption of time series analysis. The NAV is then plotted over time and all the funds show an increasing trend suggesting nonstationary, which is confirmed by the ADF test. The series is then differenced to make stationary. ARIMA models which have the lowest AIC value and significant coefficients are selected as the best models and have been fitted individually for each fund. While ARIMA (1, 1, and 1) is found appropriate for HDFC Top 100 Fund (G), HDFC Top 100 Fund Direct (G), and ICICI Prudential Nifty Next 50 Index (G), ARIMA (1, 1, 0) is suitable for ABSL Mid Cap Fund (G). The larger p-values obtained using the Ljung Box test indicate that all the fitted models are good and appropriate. The NAV of each fund is then forecasted for the period of January'2020 – June'2020 using respective models. We find that the observed NAV for each fund for March'2020 and April'2020 collected from the secondary database does not fall within the control limit of the forecasted value, which suggests the effect of the pandemic COVID 19 on these funds. However as Mutual Funds are professionally managed by Fund managers who

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invest the money in different sectors, the NAV of all these funds steadily increases from May 2020. This study paves the way for some further scope of research. We attempt to create new models by combining qualitative and quantitative methods in order to produce accurate forecasts and more dependable predictions. We can make use of advanced models using the neural network approach or LSTM approach to compare it with the results obtained using ARIMA.

REFERENCES

1. Abdulgader, Q. M. (2016). Time Series Forecasting Using Arima Methodology with Application on Census Data in Iraq. Science Journal of University of Zakho, 4(2), 258-268.
2. Alghamdi, T., Elgazzar, K., Bayoumi, M., Sharaf, T., & Shah, S. (2019, June). Forecasting traffic congestion using ARIMA modeling. In 2019 15th international wireless communications & mobile computing conference (IWCMC) (pp. 1227-1232). IEEE.
3. As' ad, M. (2012). Finding the best ARIMA model to forecast daily peak electricity demand.
4. Baliyan, M., Rathi, P. (2017). Performance Evaluation of Emerging Mutual Fund. SSARSC International Journal of Management (Vol. 3, Issue. 1)
5. Banerjee, D. (2014, January). Forecasting of Indian stock market using time-series ARIMA model. In 2014 2nd international conference on business and information management (ICBIM) (pp. 131-135). IEEE.
6. Brajesh & Shekhar, C. (2015). Accidental mortality in India: Statistical models for forecasting. International Journal of Humanities and Social Science Invention, 4, 35-45.
7. Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). Time series analysis: forecasting and control. John Wiley & Sons.
8. Brockwell, P. J., & Davis, R. A. (Eds.). (2002). Introduction to time series and forecasting. New York, NY: Springer New York.
9. Contreras, J., Espinola, R., Nogales, F. J., & Conejo, A. J. (2003). ARIMA models to predict next-day electricity prices. IEEE transactions on power systems, 18(3), 1014-1020.
10. Chang, C. P., Feng, G. F., & Zheng, M. (2021). Government fighting pandemic, stock market return, and COVID-19 virus outbreak. Emerging Markets Finance and Trade, 57(8), 2389-2406.
11. Chatfield, C. (2003). The analysis of time series: an introduction. Chapman and hall/CRC.
12. Chaudhuri, T., Verma, P., & Khetan, M. (2020). Modeling and Forecasting of Rice Production in Some Major States of India using ARIMA. International Journal for Research in Applied Science & Engineering Technology (IJRASET) ISSN, 2321-9653.
13. Devi, B. U., Sundar, D., & Alli, P. (2013). An effective time series analysis for stock trend prediction using ARIMA model for nifty midcap-50. International Journal of Data Mining & Knowledge Management Process, 3(1), 65.
14. Fattah, J., Ezzine, L., Aman, Z., El Moussami, H., & Lachhab, A. (2018). Forecasting of demand using ARIMA model. International Journal of Engineering Business Management, 10, 1847979018808673.
15. Ghafil, A. A. (2013). Using Box-Jenkins (ARIMA) models for forecasting the production of electric power. Journal of Karbala University, 11, 196-207.
16. Gujarati, D. N. (2003). Basic Econometrics” fourth edition McGraw-Hill. New York.

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17. Ljung, G. M., & Box, G. E. (1978). On a measure of lack of fit in time series models. Biometrika, 65(2), 297-303.
18. Makridakis, S., Wheelwright, S. C., & Hyndman, R. J. (2008). Forecasting methods and applications. John wiley & sons.
19. Markowitz, Harry. (1952). Portfolio Selection. Journal of Finance 7, no 1, 77-91.
20. Mutar, D. R., & Ilias II, I. I. (2010). Analysis and modeling time series of water flow into Mosul city: A comparative study. Iraqi Journal of Statistical Sciences, 10, 1-32.
21. Nath, B., Dhakre, D. S., & Bhattacharya, D. (2019). Forecasting wheat production in India: An ARIMA modelling approach. Journal of Pharmacognosy and Phytochemistry, 8(1), 2158-2165.
22. Pang O. and McElroy T. (2014). Forecasting Fertility and Mortality by Race/Ethnicity and Gender. Center for Statistical Research & Methodology, 3, 1-55.
23. Sarpong, S. A. (2013). Modeling and forecasting maternal mortality; an application of ARIMA models. International Journal of Applied, 3(1), 19-28.
24. Shumway, R. H. (86). Stoffe, r DS (2000) Time series analysis and its application.
25. Tuama, S. A. (2012). Using Analysis of Time Series to Forecast numbers of The Patients Malignant Tumors in Anbar Provinc with. AL-Anbar University journal of Economic and Administration Sciences, 4(8).
26. Wan, W. Y. (2013). Forecasting prison populations using sentencing and arrest data.
27. Zakria, M., & Muhammad, F. (2009). Forecasting the population of Pakistan using ARIMA models. Pakistan Journal of Agricultural Sciences, 46(3), 214-223.
28. www.amfiindia.com
29. www.groww.in
30. www.rbi.org.in

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Table 1: ACF-PACF characteristics

Model	ACF	PACF
AR (p)	Dies down	Cut off after lag p
MA (q)	Cut off after lag q	Dies down
ARMA (p, q)	Dies down	Dies down

Table 2: Average monthly returns, SD of monthly returns, and Beta value of 68 funds.

Category	Funds	Average	SD	Beta
Large Cap Funds	SBI Blue Chip Fund - Direct (G)	0.014868	0.041443	0.658539
Large Cap Funds	Reliance Large Cap Fund - RP (G)	0.014277	0.037656	0.60235

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Large Cap Funds	ABSL Frontline Equity-Direct (D)	0.013313	0.033714	0.580891
Large Cap Funds	ICICI Pru Nifty Next 50 Index - D (G)	0.013728	0.032179	0.571592
Large Cap Funds	ICICI Pru Nifty Next 50 Index (G)	0.014506	0.041426	0.658206
Large Cap Funds	ICICI Pru Bluechip Fund (G)	0.012301	0.031688	0.529681
Large Cap Funds	Kotak Bluechip Fund - D (G)	0.012632	0.033825	0.574684
Large Cap Funds	JM Core 11 Fund (G)	0.0153	0.047082	0.8192
Large Cap Funds	JM Core 11 Fund -Direct (G)	0.0153	0.047082	0.8192
Large Cap Funds	ABSL Frontline Equity (G)	0.012493	0.033685	0.580259
Large Cap Funds	UTI Master share Master Share - Direct (G)	0.012131	0.032874	0.542438
Large Cap Funds	CR Bluechip Equity Fund - D (G)	0.01214	0.034107	0.572809
Large Cap Funds	HDFC Top 100 Fund - D (G)	0.01308	0.039406	0.658634
Large Cap Funds	Franklin (I) Bluechip - Direct (G)	0.01141	0.031154	0.512189
Large Cap Funds	UTI Master share Master Share (G)	0.01162	0.0329	0.542906
Large Cap Funds	Essel Large Cap Equity - D (G)	0.011409	0.032604	0.514123
Large Cap Funds	L&T India Large Cap - Direct (G)	0.011674	0.034198	0.572865
Large Cap Funds	HDFC Top 100 Fund (G)	0.012496	0.039391	0.658372
Large Cap Funds	Franklin India Bluechip (G)	0.010688	0.031136	0.511939
Large Cap Funds	Taurus Largecap Equity Fund (D)	0.013134	0.048601	0.745632
Large Cap Funds	Edelweiss Large Cap - Direct (D)	0.008152	0.03597	0.575496
Large Cap Funds	SBI Blue Chip Fund (D)	0.007536	0.034549	0.541003
Large Cap Funds	HDFC Top 100 Fund - D (D)	0.005254	0.042615	0.593174
Large Cap Funds	Franklin (I) Bluechip - Direct (D)	0.004749	0.035567	0.502461
Large Cap Funds	HDFC Top 100 Fund (D)	0.00449	0.042855	0.592424
Large Cap Funds	ICICI Pru Bluechip Fund (D)	0.004542	0.039138	0.56721
Mid Cap Funds	L&T Midcap Fund -Direct (G)	0.020221	0.043211	0.653715
Mid Cap Funds	L&T Midcap Fund (G)	0.0195	0.043177	0.653369
Mid Cap Funds	ABSL Midcap Fund -Direct (G)	0.016938	0.042749	0.651341
Mid Cap Funds	UTI Mid Cap - Direct (G)	0.017347	0.044407	0.651568
Mid Cap Funds	DSP Mid Cap - Direct (G)	0.017816	0.046341	0.651359
Mid Cap Funds	DSP Mid Cap - Direct (D)	0.017815	0.046341	0.651363
Mid Cap Funds	Tata Mid Cap Growth - Direct (G)	0.017712	0.046525	0.69897
Mid Cap Funds	Taurus Discovery (Midcap) - D (G)	0.016973	0.044086	0.664267
Mid Cap Funds	DSP Mid Cap - Regular (G)	0.017178	0.046321	0.650938
Mid Cap Funds	ABSL Midcap Fund (G)	0.016202	0.042706	0.650442
Mid Cap Funds	UTI Mid Cap (G)	0.016618	0.044421	0.651682
Mid Cap Funds	Tata Mid Cap Growth Fund (G)	0.017043	0.046506	0.698486
Mid Cap Funds	Tata Mid Cap Growth - Direct (D)	0.016465	0.046689	0.686439
Mid Cap Funds	Taurus Discovery (Midcap) - D (D)	0.014981	0.045466	0.645417
Mid Cap Funds	Taurus Discovery (Midcap) (D)	0.014634	0.045483	0.64676
Mid Cap Funds	L&T Midcap Fund -Direct (D)	0.013459	0.046244	0.755207
Mid Cap Funds	Tata Mid Cap Growth Fund (D)	0.013134	0.048601	0.745632
Mid Cap Funds	Invesco India Midcap - D (D)	0.011181	0.04475	0.55091
Mid Cap Funds	UTI Mid Cap (I)	0.011564	0.049773	0.730908
Mid Cap Funds	DSP Mid Cap - Regular (D)	0.008457	0.047627	0.576107
Small Cap Funds	SBI Small Cap Fund - D (G)	0.024281	0.050545	0.600671
Small-Cap Funds	SBI Small Cap Fund (G)	0.023265	0.050543	0.60127
Small Cap Funds	Reliance Small Cap - Direct (G)	0.022386	0.053152	0.725037
Small Cap Funds	Franklin (I) Smaller Co -Direct (G)	0.018934	0.041964	0.606868
Small Cap Funds	Axis Small Cap Fund - Direct (G)	0.018092	0.040727	0.549612

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Small Cap Funds	Reliance Small Cap Fund (G)	0.021501	0.053116	0.724158
Small Cap Funds	DSP Small Cap Fund - Direct (G)	0.019976	0.049643	0.69403
Small Cap Funds	DSP Small Cap Fund - Direct (D)	0.019973	0.049637	0.693933
Small Cap Funds	DSP Small Cap Fund - Regular (G)	0.019468	0.049582	0.693587
Small Cap Funds	DSP Small Cap Fund - Regular (D)	0.019469	0.049584	0.693585
Small Cap Funds	HSBC Small Cap Equity Fund - Direct (G)	0.017159	0.052693	0.835492
Small Cap Funds	HSBC Small Cap Equity Fund (G)	0.016535	0.05266	0.834984
Small Cap Funds	SBI Small Cap Fund - D (D)	0.018379	0.062259	0.663595
Small Cap Funds	Reliance Small Cap - Direct (D)	0.017052	0.058628	0.789795
Small Cap Funds	Kotak Small Cap Fund - D (D)	0.013841	0.043145	0.600917
Small Cap Funds	Reliance Small Cap Fund (D)	0.01601	0.058787	0.791523
Small Cap Funds	HSBC Small Cap Equity Fund - Direct (D)	0.015045	0.057491	0.884842
Small Cap Funds	SBI Small Cap Fund (D)	0.015066	0.064483	0.661169
Small Cap Funds	Quant Small Cap Fund - D (G)	0.006053	0.008307	0.079899
Small Cap Funds	Quant Small Cap Fund (G)	0.005979	0.008349	0.08022
Small Cap Funds	ICICI Pru Small cap Fund - RP (D)	0.004276	0.046816	0.641856
Small Cap Funds	Quant Small Cap Fund - D (D)	0.003632	0.009746	0.05251

Table 3: List of funds belonging to the second quadrant along with their SD and beta

Category	Funds	SD	Beta
Large Cap Fund	ICICI Pru Nifty Next 50 Index - D (G)	0.041443	0.658539
Large Cap Fund	ICICI Prudential Nifty Next 50 Index (G)	0.041426	0.658206
Large Cap Fund	HDFC Top 100 Fund - Direct (G)	0.039406	0.658634
Large Cap Fund	HDFC Top 100 Fund (G)	0.039391	0.658372
Mid Cap Fund	L&T Midcap Fund -Direct (G)	0.043211	0.653715
Mid Cap Fund	L&T Midcap Fund (G)	0.043177	0.653369
Mid Cap Fund	ABSL Midcap Fund -Direct (G)	0.042749	0.651341
Mid Cap Fund	Taurus Discovery (Midcap) - Direct (G)	0.044086	0.664267
Mid Cap Fund	ABSL Midcap Fund (G)	0.042706	0.650442
Mid Cap Fund	UTI Mid Cap (G)	0.044421	0.651682

Table 4: Weights of the funds using GRG

Funds	Weights
ICICI Pru Nifty Next 50 Index - D (G)	0
ICICI Prudential Nifty Next 50 Index (G)	12%
HDFC Top 100 Fund - Direct (G)	36%
HDFC Top 100 Fund (G)	41%
DSP Mid Cap Fund -Direct (G)	0
L&T Mid Cap Fund (G)	0
ABSL Mid Cap Fund -Direct (G)	0
Taurus Discovery (Mid Cap) - Direct (G)	0
ABSL Mid Cap Fund (G)	11%
UTI Mid Cap Fund (G)	0

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Table 5: Relative Efficiency scores of the funds and their ranks

Funds	SD (input)	Beta (output)	Efficiency	Relative Efficiency	Ranking
ICICI Pru Nifty Next 50 Index - D (G)	0.04144	0.65854	15.89023	0.950711	3
ICICI Pru Nifty Next 50 Index (G)	0.04143	0.65821	15.88872	0.95062	4
HDFC Top 100 Fund - Direct (G)	0.03941	0.65863	16.71405	1	1
HDFC Top 100 Fund (G)	0.03939	0.65837	16.71377	0.999983	2
DSP Mid Cap Fund -Direct (G)	0.04321	0.65372	15.12844	0.905133	8
L&T Mid Cap Fund (G)	0.04318	0.65337	15.13234	0.905366	7
ABSL Mid Cap Fund -Direct (G)	0.04275	0.65134	15.2364	0.911593	5
Taurus Discovery (Mid Cap) – D (G)	0.04409	0.66427	15.06753	0.901489	9
ABSL Mid Cap Fund (G)	0.04271	0.65044	15.23069	0.911251	6
UTI Mid Cap (G)	0.04442	0.65168	14.67058	0.87774	10

Table 6: ADF test results for the funds

Funds	P – value
Fund 1	0.4736
Fund 2	0.4821
Fund 3	0.4449
Fund 4	0.2211

Table 7: ADF test result for the differenced series

Funds	P – value
Fund 1	0.01
Fund 2	0.01
Fund 3	0.01
Fund 4	0.011

Table 8: Best fitted ARIMA model for each funds along with estimated parameters and diagnostic measures

Fund	Best fitted model	Estimated parameter(Constant, AR, MA)	Sig. (p value) (Constant,AR, MA)	AIC	Normalized BIC	R square	RMSE	MAPE
Fund 1	ARIMA (1,1,1)	.027, -0.753, -0.992	.041, 0, 0	144.59	-0.244	0.971	0.798	3.13
Fund 2	ARIMA (1,1,1)	4.065, -0.734, -0.893	0.04, 0.02, 0	481.12	5.411	0.962	13.69	3.01
Fund 3	ARIMA (1,1,1)	3.775, -0.734, -0.89	0.05, 0.002, 0	478.45	5.39	0.958	13.38	3.01
Fund 4	ARIMA (1,1,0)	0.015, 0.282	0.046, 0.03	433.67	4.716	0.97	9.87	3.12

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Table 9: Ljung-Box test results

Fund	Ljung-Box test Statistic value	P – value
Fund 1	10.322	0.849
Fund 2	9.97	0.868
Fund 3	10.09	0.862
Fund 4	12.129	0.792

Table 10: Shapiro – Wilk's Test Results

Fund	Shapiro–Wilk's test Statistic value	P-value
Fund 1	0.981	0.456
Fund 2	0.984	0.61
Fund 3	0.983	0.567
Fund 4	0.973	0.215

Table 11: Forecasted values along with their control limits

Funds		Jan'2020	Feb'2020	March'2020	Apr'2020	May'2020	Jun'2020
Fund 1	Forecast	24.53	24.98	25.12	25.50	25.71	26.05
	U	26.28	27.81	28.55	29.58	30.28	31.14
	L	22.82	22.26	21.87	21.66	21.43	21.31
Fund 2	Forecast	475.38	482.49	484.32	490.03	492.89	497.84
	U	502.75	524.39	535.00	549.37	559.00	570.61
	L	448.01	440.60	433.64	430.69	426.77	425.06
Fund 3	Forecast	456.65	463.37	464.98	470.35	472.96	477.59
	U	483.41	504.32	514.53	528.35	537.58	548.72
	L	429.89	422.42	415.44	412.34	408.33	406.45
Fund 4	Forecast	285.76	290.42	295.27	300.24	305.30	310.44
	U	309.95	331.15	350.09	367.61	384.28	400.43
	L	263.02	253.57	247.17	242.58	239.17	236.56

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Figures

Figure 1: Investor's Perception Map

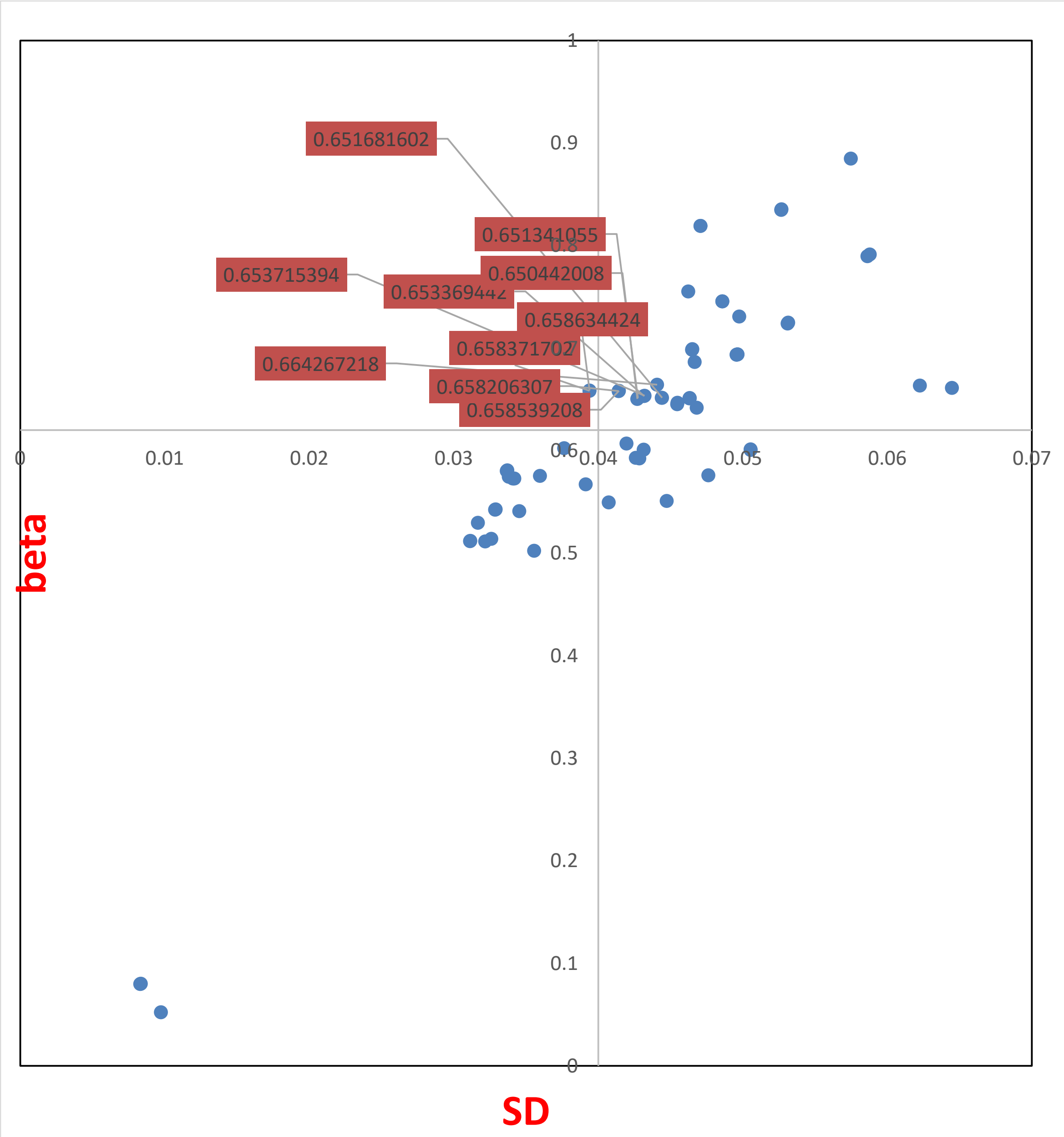

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Fig 2: Time series plots of the four funds

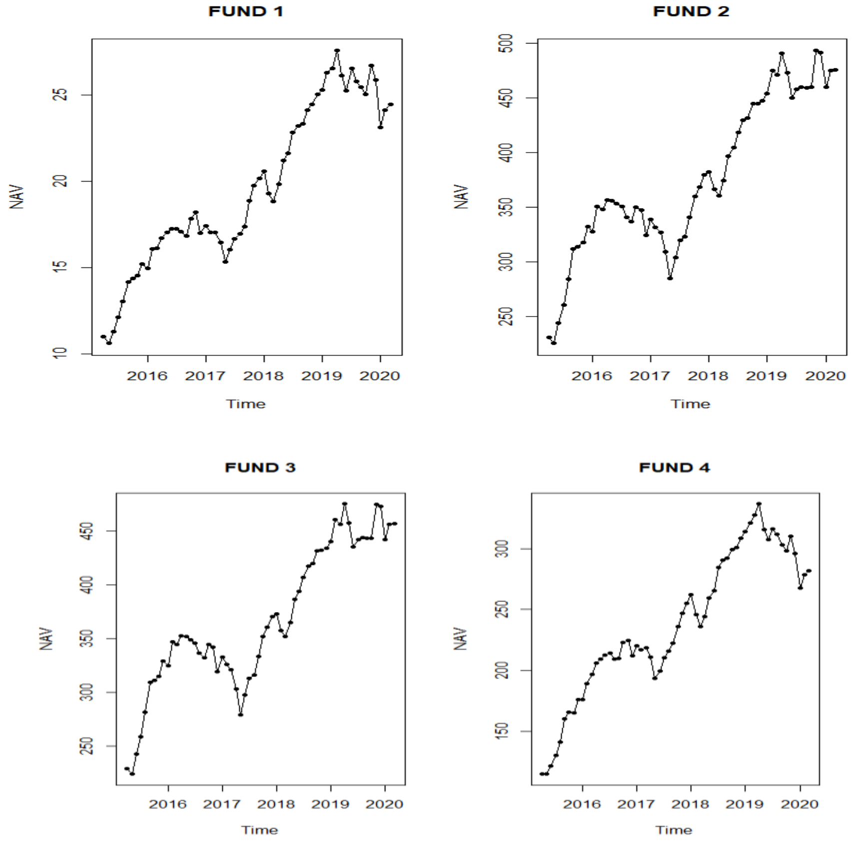
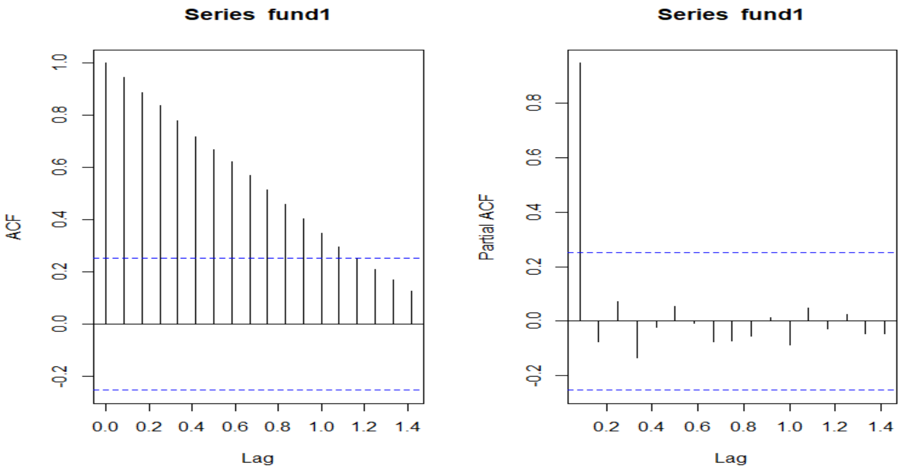


Fig 3: Graphs of ACF and PACF of each fund



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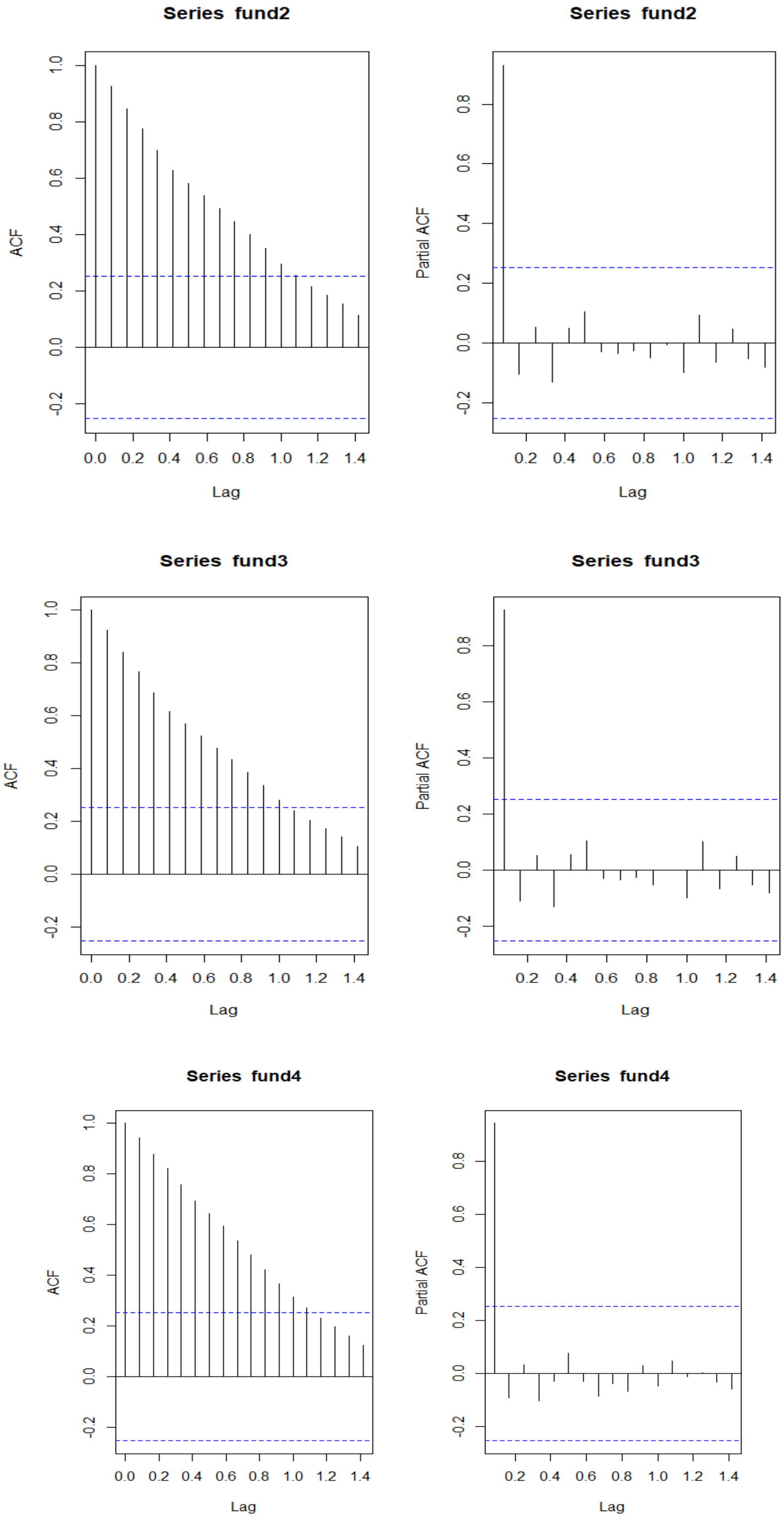

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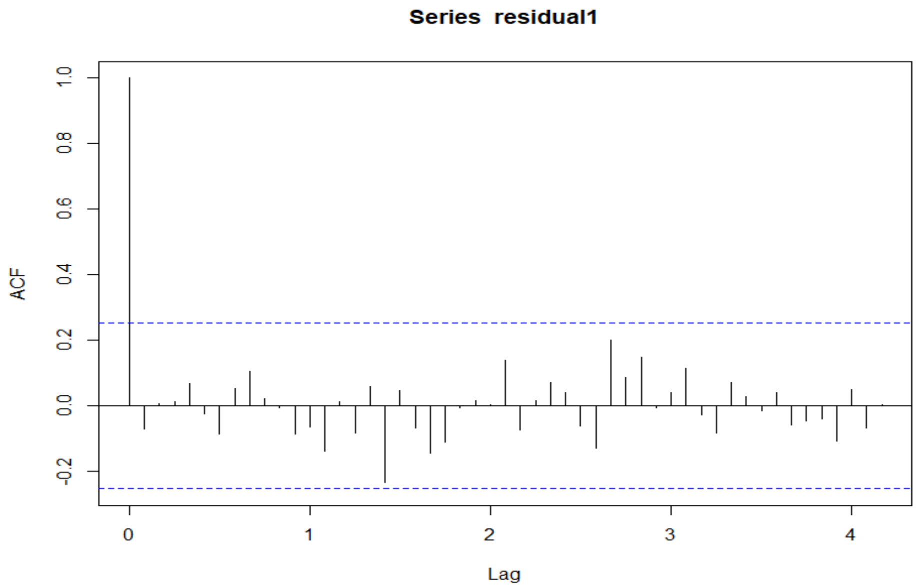
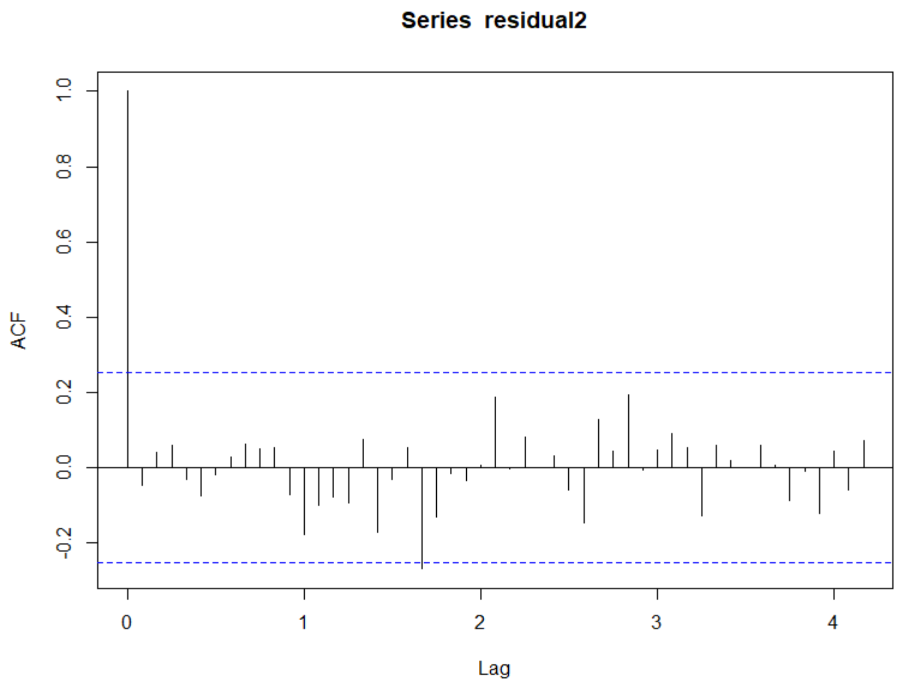
Fig 4: Residual ACFs of the four series





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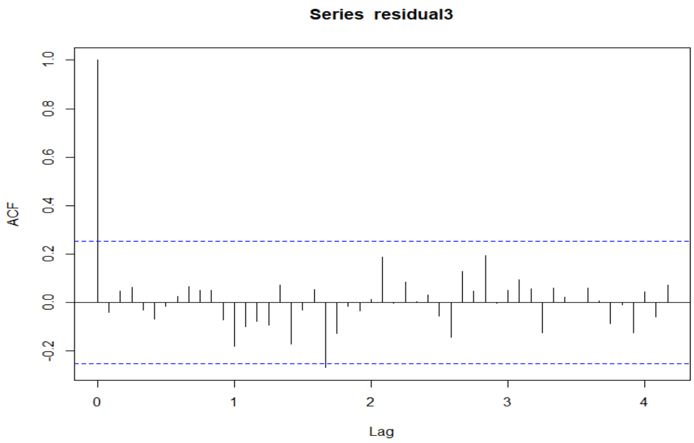


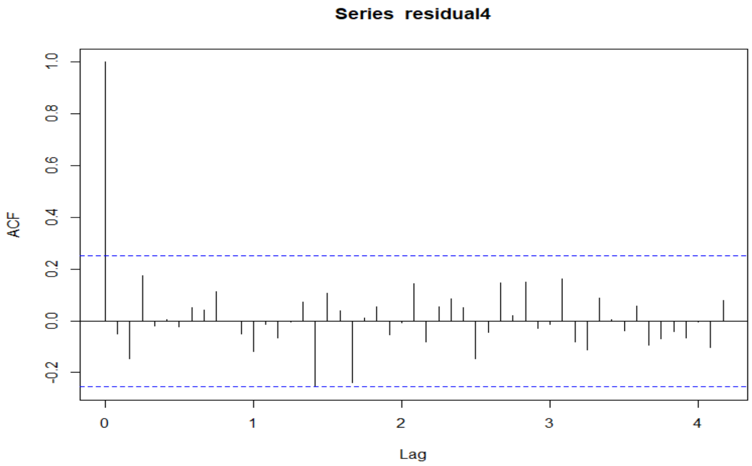
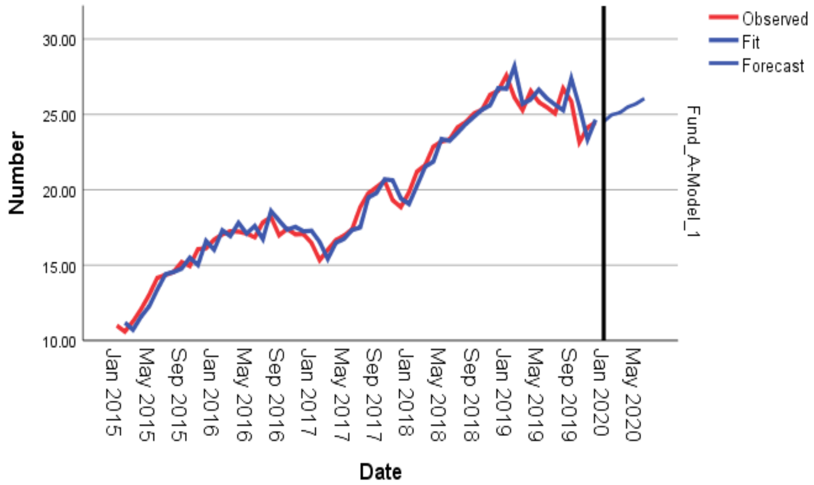


Fig 5: Observed, Fitted and Forecasted values for each fund



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