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Prediction Model of The Net Asset Returns of Indian Equity Fund of Mutual Funds With Application of ARMA

KEYWORDS: Auto Correlation Function (ACF), Partial Autocorrelation Function (PACF), Net Asset Value (NAV), Forecasts, Stationarity.

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ABSTRACT *As return is the central focus of any investment, finance researchers all the times have shown interest in doing modeling and forecasting of assets returns. Fund of Mutual funds are fast growing as India's investment vehicle of choice. As there are a variety of investors in all types fund of fund schemes, the competition among them is very intense and the investors choose funds on the forecasting of NAV returns and thus there is a need to identify right model for forecasting. Among various forecasting methods, ARMA method is considered one of the most useful extrapolation methods for forecasting the stock returns. In this paper, some of the Fund of Mutual Funds in India has been modeled using Box-Jenkins autoregressive moving average (ARMA) methodology. The modeling has been attempted on daily returns of four Growth oriented schemes. The NAV data from 1st April 2007 to 29th February 2015 have been collected from the respective AMC websites. Validity of the models was tested using the future NAV returns of the fund of mutual funds with that of forecasted. The analysis showed that all the schemes in the forecasted sample showed the sustainable return.*

INTRODUCTION

Mutual Fund Industry is experiencing rapid growth in the form of Fund of Funds. Fund of funds are particular investment vehicles to invest in more than two mutual funds. Ordinarily, it holds many funds in it. Globally, several FOFs pick the best breed of funds from across different fund houses and put them into one. These are called multi-manager fund of funds. The Fund of Funds distinguishes themselves from Mutual Funds in the sense that they invest in shares of Mutual Funds rather than investing in individual securities.

Fund of Fund as a financial product can be beneficial for retail and institutional investors due to their distinct features. With FOFs, the retail investors can easily get exposure to sectors, asset classes, markets, and products. FOFs pool fund from large diverse investor, and invest in best managed Mutual Funds so that investors get the best of the capability of various fund managers. They invest in funds of high demand, those offer discount to cost, loads and management fees etc., Retail investors don't have access to sophisticated data systems or information system and even if such access are at disposal, retail investors may find it difficult to take appropriate investment decisions. The large and growing Fund of mutual funds have attracted majority of capital in FOFs. Fund of Fund advantage is diversification within the family house and out of the family house in the mutual fund industry. Fund of mutual funds as a sophisticated financial product deliver precious service to the investors by screening the mutual fund market, performing due diligence process, and by selecting the most correct investment decisions.

Fund of Funds provide an efficient alternative solution to diversify investment through mutual funds. Indeed, they have become the most common means of access for investors who are looking for diversified exposure to mutual funds, but who do not have the resources to research, monitor, and manage multiple mutual funds. The FOFs manager has two functions: One is to seek out investors, educate them on the investment benefits, accumulate the assets from investors, and report on and explain investment activities and performance: the second is to follow the mutual fund industry, determine strategy weightings, conduct due diligence, and select individual fund managers expected to outperform. However predicting the returns becomes the most challenging task for the fund managers. At the same time the success of funds rests on the forecasting ability of the fund managers. The fund managers thus, try to find the appropriate modeling technique to predict the fund returns.

Autoregressive-moving-average (ARMA) model is one of the mathematical models of the persistence, or autocorrelation, in a time series. There are several possible reasons for fitting ARMA models to the time series data. Modeling can provide an understanding to the physical system by enlightening something about the physical procedure that builds persistence into the series. ARMA models use to predict behavior of a time series from past values. Such a prediction can be used as a baseline to evaluate the possible importance of the variables to the system. ARMA models are broadly used for prediction of economic and industrial time series.

Given the rapid growth and potential benefits for this category of funds, this study may shed some light on whether FOFs popularity is justified. In this paper we have used the simple ARMA models for forecasting. The paper is organized as follows. The first section deals with introduction and review of some basics of time-series analysis of FOFs returns. In the next sections the discussion on the models of forecasting considered in the present study which are linear univariate models, autoregressive, moving average, and a combination of both as these build the basis for a model-based forecast. Thereafter we present the forecasting methodology, which concludes the theoretical part followed by data analysis and conclusion.

OBJECTIVE:

This paper attempts to find the appropriate model which fits the present data series and thus can be used for pre-

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diction and would be able to help investors in taking decision.

Review of Related Literature

Fernando Garcia et al., (2012) used the econometric model for estimation of both returns and conditional volatility in financial assets. They made a comparison of traditional approach with Back Propagation neural network. They used Ibex-35 stock market index and proved that neural network achieved significantly better performance in predicting conditional volatility, but not so different results when predicted the financial returns. **Divakar Chitturi (2010)** used fixed window prediction and Moving Window prediction methodologies for the forecasting S & P 500 index, for various time intervals to indentify the patterns in different periods.

Mark M. Carhart (2000) showed for equity mutual funds the last day returns are positive and the following day is negative effect. **Andrea Frazzini ET, al., (2008)** used mutual funds flows as a measure of individual investors' sentiment for different stocks and found that high sentiment predicts low future returns. They showed high sentiment stock tend to be growth stocks and also associated with high corporate issuance. They concluded that the higher returns earned at the short horizon are not effectively captured by individual investors.

An empirical analysis about factor based non parametric risk management for hedge funds and fund of funds was done by **T.R.J. Goodworth and C.M. Jones (2007).** They described about factor based analysis of hedge fund returns to form a risk evaluation framework that should estimate tail risk. They concluded the quantitative portfolio construction and to ensure maximum portfolio diversification, time dependent factor exposure, implied risk profiles, active style analysis and standard deviation based on VAR measures. **Kartik Patel (2007),** examined fund of funds as a function of the number of fund manager in the portfolio, the risk underperformed the benchmark. They used two methods like naïve diversification and strategy diversification. They found that the objective beat the bench mark with a high confidence and a diversified fund of funds with an absolute return mandated.

T.Colon ET, al., (2007) explained the random matrix theory and fund of funds portfolio optimization with various hedge fund Indices. They accustomed to cleaned correlation matrix leads to a 35 % development between the realized and predicted risk of portfolio. **Emily Denvir and Elaine Hutson (2004)** they examined the performance and diversification benefits of fund of hedge funds. They examined the most fund of hedge funds distributions are not negatively skewed**. Lee Hee Soo, (2012)** investigated risk and return in hedge funds and fund of hedge funds: A cross sectional approach. This study examined risk return measure through cross sectional distinction in hedge funds and fund of hedge funds returns.

Noel. Amenc, et.al., (2003) investigated the predictability in hedge funds returns. They provided evidence of predictability in hedge funds and discussed the implication of dynamic style-allocations, explore a multi-style, multi-class combination for an equity-oriented portfolio. **William J.Bertin and laurie prather (2008)** analysed management structure and the performance of fund of hedge funds. They analysed performance of fund of funds in terms of fund management structure and gives a systematic approach for selecting the best fund of funds. **Mila Getmansky (2004)** analysed net flows into individual funds are affected by past fund performance, current performance, past flows, past standard deviation of return and past assets. Linear relationship between current flows and past fund performance was projected and analysed. Review of literature reveals that there is death of studies on modeling of Fund of Funds returns. Hence attempt has been made explore the same in this study.

METHEDOLOGY

General ARMA model was first introduced by Peter Whittle (1951). Latter George P.E. Box (1971) popularized. ARMA model is a tool for understanding, analyzing and forecasting a time series. The model comprise of two parts, an autoregressive (AR) part and a moving average (MA) part. The model is generally referred to as the ARMA (*p*,*q*) model, where *p* is the order of the autoregressive and *q* is the order of the moving average.

The art of ARMA modeling involves the following steps:

Model Identification: The first step in ARMA modeling is to checking of stationarity of the series and identifying the order of the parameters. First is to identify the order of integration on the basis of visual inspection of time series plot, correlogram and unitroot testing. The structure of autocorrelation and partial autocorrelation and the significant autocorrelations among the coefficients provide the evidence of the stationarity. Theoretically, both an AR (p) process and an MA (q) process in the time series should be based on the behavior of the correlogram. The Identification is sometimes done by looking at plots of the ACF and partial autocorrelation function (PACF). Sometimes identification is done by an automatic iterative procedure -- fitting many different possible model structures and orders and using a goodness-of-fit statistic to select the best model.

Estimation: At this stage, one or more models are tentatively chosen which apparently provide statistically satisfactory demonstration of the available data. Then precise estimates of the model by least squares are advocated by Box &Jenkins.

Diagnostics: For the Diagnosis step different models can be obtained for various combinations of AR and MA individually and collectively. For the models obtained, the most preferred diagnostic tests used.

Residual ACF

Box pierce Chi-square tests

Next step is diagnostic checking or verification (Anderson 1976). Two important elements of checking are to ensure residuals to be random, and estimated parameters to be statistically significant. Generally the fitting procedure is guided by the priniciple of parsimony, which identifies the simplest model to be the best suitable model. A different approach of identifying ARMA models is by trial and error and use of a goodness-of-fit statistic. In this process, a suite of models are fitted, and goodness-of-fit statistics are computed. Akaike's Final Prediction Error (FPE) and Information Theoretic Criterion (AIC) are the two statistical measures value for goodness-of-fit of an ARMA (*p*,*q*) model. Goodness of fit could be expected to be measured by some function of the variance of the model residuals: the fit improves as the residuals become smaller. Both the FPE and AIC are functions of the variance of residuals.

Forecasting: ARMA models are employed basically to forecast the corresponding variable. There are two types of forecasts-sample forecasts and post sample forecasts. The

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first one is used to develop confidence in the model and the second to generate genuine forecasts for future planning. ARMA model of fund of fund return series can be used to yield both these types of forecasts.

DATA ANALYSIS

The data used for the analysis pertained to four schemes of the Indian fund of mutual funds of two AMCs. ARMA models were used for the data and the future nav returns were forecasted using eviews. The data of the sample FoFs were collected from the respective AMC web sites from 1st April 2007 to 29th February 2015 and the returns were calculated from the respective schemes NAV price. All the four schemes were GROWTH oriented equity fund of funds. The returns were calculated from the daily NAV of the schemes. The return of the fund of funds NAV was determined as

$R_t = (P_t / P_t\text{-}1)$

Where: r_t- the return of the scheme portfolio

P_t, P_{t-1} – the price of a portfolio at the moment t, t-1 respectively.

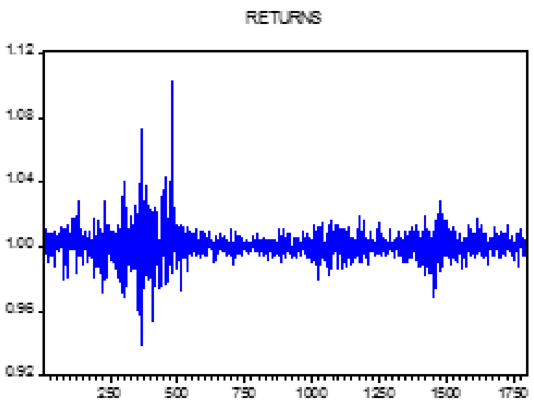
FRANKLIN TEMPLETON ASSET MANAGEMENT (INDIA), PVT LTD.

NAME OF THE SCHEME: FRANKLIN INDIA DYNAMIC PE RATIO FOF (G) FUND: ARMA (1,1) MODEL

Sample period: 3/4/2007 to 27/2/2015.

Forecast period: 01/3/2015 to 12/9/2015(total of 201 days)

Graph 1: Stationarity of FOFs NAV returns



Note: Graph identification of stationarity of the FI dynamic PE Ratio FOF (G) time series.

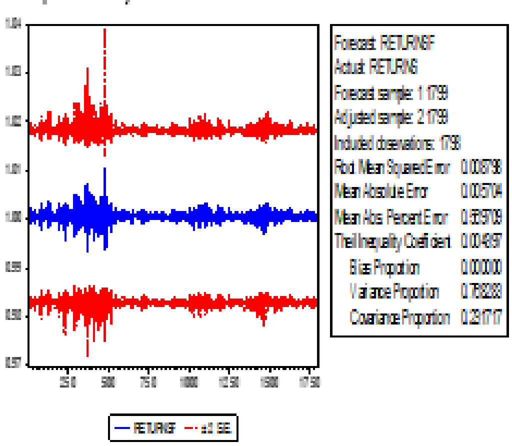
Table 1: Stationarity of FOFs NAV returns

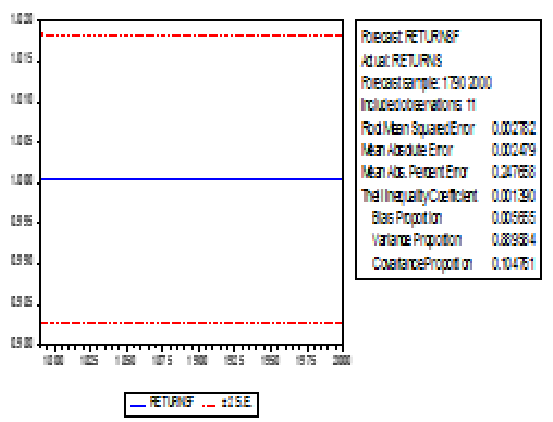
Null Hypothesis: RETURNS has a unit root
Exogenous: Constant

		t-Statistic	Prob
Augmented Dickey-Fuller test statistic		-7.23	0.00
Test critical values:	1% level	-3.43	
	5% level	-2.86	
	10% level	-2.57	

Note: the table shows the stationarity ADF test value greater than critical value at 1%, 5% and 10% level

Graph:2 Dynamic and static forecasts





Note:Static uses actual rather than forecasted values. These are also called 1-step ahead or rolling forecasts.

Note: Dynamics calculates forecasts for the period after the 1st period in the sample by using the previously forecasted values of the lagged left-hand variable. Dynamic forecasts called n-step ahead forecasts.

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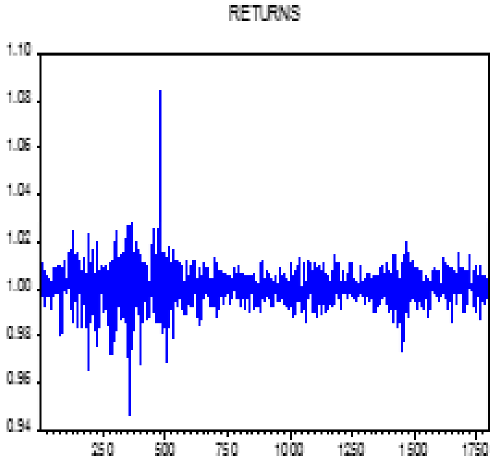
(2) FRANKLIN TEMPLETON ASSET MANAGEMENT (INDIA), PVT LTD. NAME OF THE SCHEME: FRANKLIN INDIA LIFE STAGE FOF 30 (G) FUND: ARMA (1,1) MODEL

Sample period: 3/4/2007 to 27/2/2015.

Forecast period: 01/3/2015 to 12/9/2015(total of 201 days)

Graph 1: **Stationarity of FOFs NAV returns**



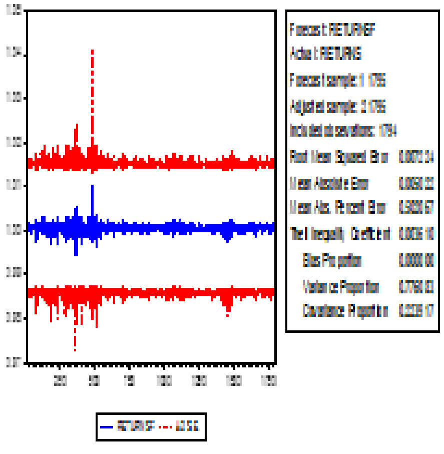
Note: Graph identification of stationarity of the FI life stage FOF 30 (G)

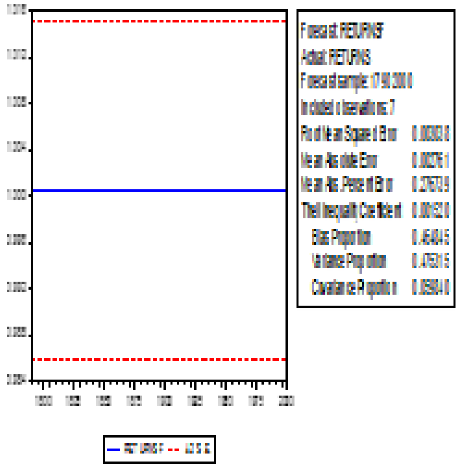
Table:2 Stationarity of FOFs NAV returns
Null Hypothesis: RETURNS has a unit root
Exogenous: Constant

		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-8.56	0.00
Test critical values:	1% level	-3.43	
	5% level	-2.86	
	10% level	-2.56	

Note: the table shows the stationarity ADF test value greater than critical value at 1%, 5% and 10% level time series

Graph:4 Dynamic and static forecasts





Note:Static uses actual rather than forecasted values. These are also called 1-step ahead or rolling forecasts.

Note: Dynamics calculates forecasts for the period after the 1st period in the sample by using the previously forecasted values of the lagged left-hand variable. Dynamic forecasts called n-step ahead forecasts.

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(3) FRANKLIN TEMPLETON ASSET MANAGEMENT(INDIA) PVT LTD.

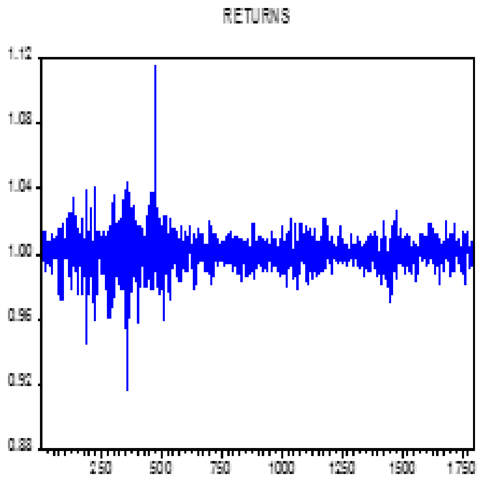
NAME OF THE SCHEME: FRANKLIN INDIA LIFE STAGE FOF 20 (G)

FUND ARMA (1,1) MODEL

Sample period: 3/4/2007 to 27/2/2015.

Forecast period: 01/3/2015 to 12/9/2015(total of 201 days)

Graph:5 **Stationarity of FOFs NAV return series**



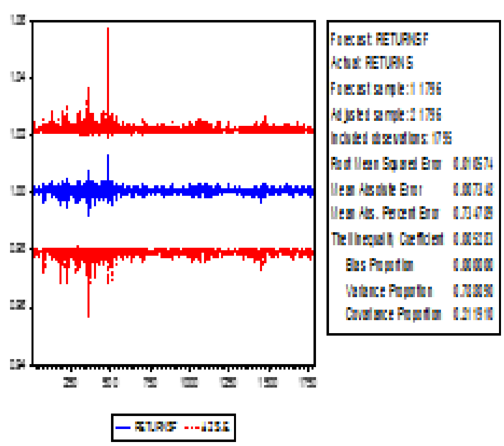
Note: Graph identification of stationarity of the FI life stage FOF 20 (G) time series.

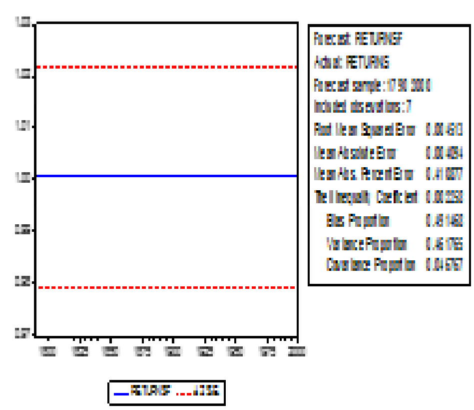
Table: 3 Stationarity of FOFs NAV returns
Null Hypothesis: RETURNS has a unit root
Exogenous: Constant

		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-8.63	0.00
Test critical values:	1% level	-3.44	
	5% level	-2.86	
	10% level	-2.57	

Note: the table shows the stationarity ADF test value greater than critical value at 1%, 5% & 10% level.

Graph:6 Dynamic and static forecasts





Note:Static uses actual rather than forecasted values. These are also called 1-step ahead or rolling forecasts.

Note: Dynamics calculaates forecasts for the period after the 1st period in the amplebyusing the previously forecasted values of the lagged left-hand variable. Dynamic forecasts called n- step ahead forecasts

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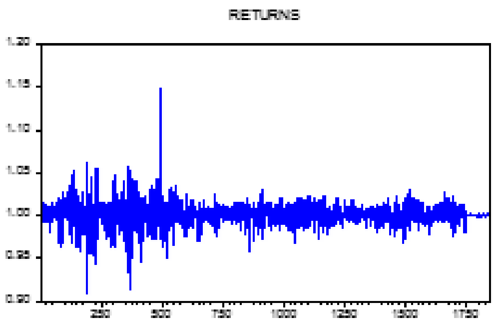
(4) KOTAK MAHINDRA ASSET MANAGEMENT (INDIA) PVT. LTD.
NAME OF THE SCHEME: KOTACK ASSET ALLOCATOR FUND (G): ARMA (1, 1) MODEL

Sample period: 3/4/2007 to 27/2/2015.

Forecast period: 01/3/2015 to 12/9/2015(total of 201 days)

Graph:7 **Stationarity of FOFs NAV return series**



Note: Graph identification of stationarity of the Kotack asset allocator fund (G) time series.

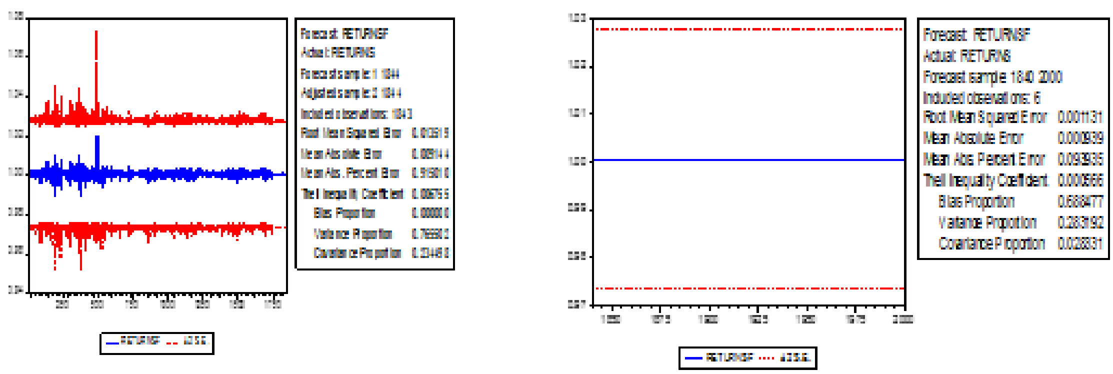
Table:4 Stationarity of FOFs NAV returns

Null Hypothesis: RETURNS has a unit root
Exogenous: Constant

		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-29.39	0.00
Test critical values:	1% level	-3.44	
	5% level	-2.86	
	10% level	-2.57	

Note: The table shows the stationarity ADF test value greater than critical value at 1%, 5% and 10% level

Graph:8 Dynamic and static forecasts



Note:Static uses actual rather than forecasted values. These are also called 1-step ahead or rolling forecasts.

Note: Dynamics calculates forecasts for the period after the 1st period in the sample by using the previously forecasted values of the lagged left-hand variable. Dynamic forecasts called n-step ahead forecasts.

Table 1,2,3 & 4 depict, the results of all the four schemes sampled time series stationarity of fund of fund NAV returns. Table 1 to 4 yields results of ADF test for level series (no differencing). To test the stationary, we used ADF (augmented Dickey-fuller) test and which indicated that the FOFs NAV returns were stationarity. In all model ADF test value was greater than Critical value. Next step followed was the values were plotted in graph for stationary identification. Time series under study were plotted. Such plots give initial clue about the possible nature of the fund of funds returns time series. We computed the FOFs return series correlogram which consists of ACF and PACF values. We also calculated the Ljung-Box Q-statistics. We observed the patterns of the ACF and PACF, and then determined the parameter values p &q for ARMA model. The correlogram for ACF and PACF at level found the series to be stationary and it was plotted in graph. All the four schemes of fund of funds models contained one autoregressive term and one moving-average term of order one, thus we used an ARMA(1,1) time series models. The p&q values for ARMA model were stationary at (1,1). This gave an

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initial indication whether parsimonious ARMA model can be useful to predict the daily returns of fund of funds. The potential models were identified using the autocorrelation function (ACF) and the Potential autocorrelation function (PACF) and finally the best model was selected.

To find the best model out of all the estimated models we considered the AKAIKEE, SCHWARZ information criteria. Since these information criteria guide us towards the best goodness of fit model for forecasting the one with lowest values. In our study these two criteria are negative hence we took highest negative values for this criterion. Next, the estimated model was used to forecast the returns of the Fund of Funds. There are two types of forecasts that was forecasts for future dates from the same date are called dynamic forecasts and static forecasts are a sequence of one-step ahead forecasts. In graph 2,4,6 & 8 the middle line represents the forecasts value of fund of funds returns. In the final stage we calculated RMSE, MAE and Thiel Inequality Co-efficient values for in sample and out of sample forecasts of FOFs return series.

Table: 5 Statistically significant forecasted values.

NAME OF FUND SCHEME	DWS	AIC	SC	MAPE	RMSE
FI D PE RATIO FOF(G)	2.00067	-6.652515	-6.615988	*0.008798 **0.247658	*0.008798 **0.002782
FI LIFE STAGE FOF 30 (G)	1.99393	-7.019412	-7.016021	*0.502067 **0.276739	*0.007224 **0.003038
FI LIFE STAGE FOF 20(G)	1.99314	-6.257545	-6.248366	*0.734789 **0.410877	*0.010574 **0.004513
KOTAK ASSET ALL.FOF(G)	1.99985	-5.766137	-5.757153	*9.915010 **0.093935	*0.013519 **0.001131

***INSAMPLE MAPE AND RMSE ** OUT OF SAMPLE MAPE AND RMSE**

The smaller the RMSE, MAE and Theil Inequalities co-efficient values better the model for forecasting of fund of fund returns. Thereafter, in sample forecast of return dynamics model was conducted and the forecasts performance was evaluated using RMSE, MAE and Theil Inequality co-efficient. The result suggested that the model were appropriate for forecasting.

CONCLUSION

In this paper the data has been collected from AMFI websites. The historical data for the 7 years period since 2007 to 2014 were taken into account for analysis. The Box-Jenkins methodology was used to identify the model. The AIC & SIC test criteria was applied against the data represented to select the best model. The best model was derived for all the four fund of funds schemes. The MAPE, RMSC & % error accuracy is applied to determine the discrimination between the actual historical data and the forecasted data. This paper inferences were drawn based on the minimum error percentage obtained through the above said performance measures. The future forecasts of each scheme for the next 201 days also were highlighted in this paper.

Appreciating the return exposures of Fund of funds is an important area of research, there is always a need for understand the return structure while making investment management decisions involving mutual funds. In this context, an attempt was made to provide, useful information to investors dealing with portfolio constructions and risk return management related issues by modeling the returns. At a more general level, this study indicates whether a fund can be forecasted correctly or not and, when applied on an ongoing basis, it enables investors to address issues like fund of funds drift. This paper presents the performance of ARMA model in estimating the future returns of FOFs, the sample contained a significant number of observation to an extent of 1795. From the results it can be concluded that there are no significant difference in their sample schemes of the returns. The results of forecasting indicated that the future returns of FOFs were as planned. The Fund of Funds maintained their status through diversification. Hence the return process are continued in the long run, thus FOFs proved better than the other traditional fund which is evident from our forecasting results of RMSE, MAE values. The major examined how well our forecasting is able to explain the in-sample and out-of-sample (dynamic and static) prediction of fund of fund schemes return themselves and ARMA model proved its suitability. It is hoped that more innovative approaches about fund strategies will be conducted to bring the hidden information about the Fund of Mutual Funds.

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