

Forecasting NEPSE Index: An ARIMA and GARCH Approach

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Abstract

In this study, an attempt has been made to demonstrate the usefulness of univariate time series analysis as both an analytical and forecasting tool for Nepali stock Market. The data set covers the daily closing value of NEPSE index for two and half years starting from the middle of 2012 to end 2015. The forecasting analysis indicates the usefulness of the developed model in explaining the variations, trend and fluctuations in the values of the price index of Nepali stock exchange. Explanation of the fit of the model is described using the Correlogram, Unit Root tests and ARCH tests, which finally confirm that the ARIMA and EGARCH are good in forecasting and predicting daily stock index of Nepal. Furthermore, it is inferred that the daily stock price index contains an autoregressive, seasonal and moving average components; hence, one can predict stock returns through the identified models.

Key Words: Forecasting, NEPSE Index, ARIMA, EGARCH and Univariate Model.

JEL Classification: C22, C53, G13

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I. INTRODUCTION

A stock index or stock market index is a measurement of the value of the selected stock market. It is computed from the prices of listed stocks. Typically a weighted average method is used to construct an index of particular stock exchange. An index is a mathematical construct, so it may not be constructed directly. But many mutual funds and specialized financial institutions attempt to track the stock index to develop specialized investment vehicles such as Index Funds (IFs) and Exchange Traded Funds (ETFs). However, those funds and investment vehicles may not be judged against the overall market.

Stock index is considered as a tool to describe the performance of market which is used by investors and financial managers for estimation and forecasting purpose. It is also used to compare the return on specific stock with that of market return. From macro perspective, stock index can be considered as a barometer of overall economy to gauge the performance of the economy as a whole (Levine and Zervos, 1998). Similarly, stock index also used to gauge the ease of doing business situation of a given nation and as a proxy it reflects investors' sentiment on the state of the economy concerned.

Time series techniques have become the most widely used method for short and medium-term forecasts in practice (Box and Jenkin, 1976). In stock markets, Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models have been used for modelling and forecasting of daily index value and stock price with good results. Ayodele, et. al. (2014) presented extensive process of building stock price predictive model using the ARIMA model. They have used the data obtained from New York Stock Exchange (NYSE) and Nigeria Stock Exchange (NSE) to develop predictive model. Results revealed that the ARIMA model has a strong potential for short-term prediction of stock price.

The experimental results obtained with best ARIMA model demonstrated that it is potential to predict stock prices satisfactory. This could guide investors in stock market to make profitable investment decisions. In the meantime, Yang and Steven (2015) applied the GARCH models using high frequency data of China Shanghai Stock Index (CSI 300). The empirical analysis yields a result that there was a one-way feedback of volatility transmission from the CSI 300 index futures to spot returns. This further suggests index futures market leads the spot market. These results reveal new evidence on the informational efficiency of the CSI 300 index futures market compared to earlier studies.

Different studies, with different sample periods, different asset classes and different performance evaluation criteria, have found that the GARCH model provides the best forecasting performance in financial markets (Sharma, 2015). The results better explain the forecasting performance of seven GARCH-family models for 21 world stock indices including NIFTY of India, with specific attention to the choice of appropriate benchmark and loss criteria and the prevention of data-snooping bias. The GARCH forecasting model contributes in a number of ways since a heavily parameterized model is better able to capture the multiple dimensions of volatility (Yang and Steven, 2015). However, a better in-sample fit may not necessarily translate into a better out-of-sample forecasting

performance. On the out-of-sample forecasting ability, the simpler models often outperform the more complex models (GC, 2008).

Whether this is a permanent or temporary component of the time series requires a more exhaustive study involving long-term modelling of financial time series as exemplified by Ray, Jarrett and Chen (1997) in a study of the Japanese stock market index. One very basic conclusion was that the use of intervention analysis is very useful in explaining the dynamics of the impact of serious interruptions in an economy and the changes in the time series of a price index in a precise and detailed manner. Similarly, Jeffrey and Eric (2011) modelled the stock market price index of China by using the methods of ARIMA-Intervention analysis and produced a fit for one to analyse and draw conclusion concerning how the index behave over time. The results corroborate that daily prices of Chinese equity securities have an autoregressive component.

Aslam and Ramzan (2013) studied the effects of the real effective exchange rate, CPI, per capita income and interest rate on the stock indices of Pakistan. Applying NLS and ARMA techniques revealed that while discount (interest) rates and inflation negatively affected Karachi stock price index, per capita income and real effective exchange rate affected positively. Discount rate impacted stock index the most. This study helps to understand how effectively a country can control its macroeconomic variables for better performance of the stock market (Alenka and Mejra, 2011).

In Nepali context, GC (2008) used volatility models and analysed the volatility of daily return of selected stocks from the period 2003-2009 using GARCH (1, 1) model for the conditional Heteroskedasticity. The study found the distribution of the daily return series for the Nepali stock market to be leptokurtic, non-normal and exhibiting significant time dependencies. The conditional volatility of the NEPSE series was modelled using a random walk model, a non-linear GARCH(1,1) model and three asymmetric models: GJR model, EGARCH(1,1) and PARCH(1,1). The study found that the NEPSE Index returns series exhibits stylized characteristics supported by empirical evidence in different studies, such as volatility clustering, time-varying conditional Heteroskedasticity and leptokurtosis.

Available literature shows that various authors have studied different aspects of the stock market of Nepal. They have employed different financial and statistical methods to analyze the performance of stock market as well as the price of companies listed in NEPSE (Pradhan, 1993). Most of the researchers have focused on the important of dynamic and vibrant stock market for higher economic growth of the country and also depict the positive relationship between the stock market and economic growth.

However, very few studies have touched up-on the issues of scientific analysis and forecasting of stock index as well as price of the companies. Therefore, development and testing of scientific models and tools for forecasting and prediction of stock indices and price of the companies is essential. It has been observed that, of the various problems and challenges of Nepali stock market, inadequate information and lack of tested forecasting models are the majors.

In this backdrop, this paper aims to identify the suitable forecasting univariate model to test an autoregressive, moving average and seasonal components of NEPSE index. This would be helpful in forecasting the daily index value of Nepali stock market. It is believed that the present study will signify the development of tested and validated predictive models which would be assets for Nepali stock market and the stakeholders. Similarly, the findings from the study would serve as the reference while making investment and trading strategies especially for the investors. Moreover, an empirical paper would be added in the literature of financial economics in general and capital market of Nepal in particular.

The reminder of this paper is organized as follows. Section two describes data and methodology. Section three shows the empirical results and the final section draws conclusions and the implication of the study finding.

II. DATA AND METHODOLOGY

In order to achieve the set objectives of this study an analytical research design has been adopted. The research has been designed in such a way that the collection, analysis and interpretation of the secondary data related to the study may be easier and reliable while drawing conclusions.

2.1 Data

The study is concentrated on the secondary market of Nepal and has made an attempt to model the daily NEPSE index so as to capture the trends and patterns in the past and forecasting the future. For this, daily closing data of NEPSE index have been collected from first July 2012 to last December 2015. The source of data includes various yearly and monthly reports of Nepal Stock Exchange Ltd, commonly known as NEPSE. A brief description of NEPSE index is given below.

NEPSE Index

The NEPSE is a value weighted index of all shares listed at the Nepal Stock Exchange and calculated once a day at the closing price. The basic equation of NEPSE index is defined as:

$$NEPSE_t = \frac{M.C_t}{M.C_b} \times IB \quad \dots\dots\dots (1)$$

Where,

- $NEPSE_t$ = NEPSE Index at current time (t)
- $M.C_t$ = Market Capitalization (market value) of all listed stocks at current time (t) period
- $M.C_b$ = Market Capitalization (market value) of all listed stocks at base time (0) period
- IB = NEPSE Index at base period (100)

The standard NEPSE index is designed based on Weighted Market Capitalization (WMC) method, where stocks with the largest MC carries the greatest weight in the index, which is making the value of the index very vulnerable to the price movement of such dominant companies.

2.2 Forecasting Techniques

As the present study is based on the time series data, it is important to check whether a series is stationary or not before using it in a model. A series is said to be stationary if the mean and auto-covariance of the series do not depend on time. Any series that is not stationary is said to be non-stationary and has a problem of unit root. A unit root is a feature of processes that evolve through time that can cause problems in statistical inference involving time series models.

Unit Root Test

Many economic and financial time series exhibit trending behavior or found non-stationary in the mean. Leading examples are stock prices, gold prices, exchange rates and the levels of macroeconomic aggregates like real GDP. An important econometric task is determining the most appropriate form of the trend in the data. For example, in Autoregressive Moving Average (ARMA) and Vector Autoregressive (VAR) modeling the data must be transformed to stationary form prior to analysis. The formal method to test the stationary of a series is the unit root test.

Dickey and Fuller (1979) have explained the following form of basic unit root tests.

Consider a simple autoregressive (AR) 1 process:

$$Y_t = \rho Y_{t-1} + X_t' \delta + \epsilon_t \quad \dots\dots\dots (2)$$

Where, x_t are optional exogenous regressor, which may consist of constant, or a constant and trend, ρ and δ are parameters to be estimated, and ϵ_t is assumed to be white noise.

Series Y is a non-stationary series if $|\rho| \geq 1$, and the variance of Y increases with time and approaches infinity. Series Y has a (trend) stationary process if $|\rho| < 1$. Thus, the hypothesis of (trend) Stationarity can be evaluated by testing whether the absolute value of ρ is strictly less than one or not.

The standard Dickey and Fuller (DF) test is carried out by subtracting Y_{t-1} in both side of the equation 2.

$$\Delta Y_t = \alpha Y_{t-1} + X_t' \delta + \epsilon_t \quad \dots\dots\dots (3)$$

Where, $\alpha = \rho - 1$.

The null and alternative hypotheses may be written as,

$$\begin{aligned} H_0: \alpha &= 0 \\ H_1: \alpha &< 0 \end{aligned}$$

The hypothesis can be evaluated using the conventional t-ratio for α .

$$t_\alpha = \frac{\hat{\alpha}}{S.E(\hat{\alpha})} \dots\dots\dots (4)$$

Where, $\hat{\alpha}$ = the estimated α , and S. E ($\hat{\alpha}$) is the coefficient standard error of $\hat{\alpha}$.

The simple Dickey-Fuller unit root test described above is valid only if the series is an AR (1) process. If the series is correlated at higher order lags, the assumption of white noise disturbances ϵ_t is violated. In order to cope with this issue the Augmented Dickey-Fuller (ADF) test has been constructed with a parametric correction for higher-order autocorrelation by assuming that the series Y follows an AR (p) process. Adding p lagged difference terms of the dependent variable Y the ADF test follows the following process.

$$\Delta Y_t = \alpha Y_{t-1} + X_t' \delta + \beta_1 \Delta Y_{t-1} + \beta_2 \Delta Y_{t-2} + \dots + \beta_p \Delta Y_{t-p} + \vartheta_t \dots\dots\dots (5)$$

This augmented specification is then used to test the above mentioned hypothesis using the t-ratio of (4). An important result obtained by Fuller is that the asymptotic distribution of the t-ratio for α is independent of the number of lag differences included in the ADF regression. Moreover, while the assumption that Y follows an autoregressive (AR) process may seem restrictive. Dickey (1984) demonstrated that the ADF test is asymptotically valid in the presence of a moving average (MA) component, provided that sufficient lag difference terms are included in the test regression.

ARIMA Models

The acronym ARIMA stands for Auto-Regressive Integrated Moving Average. Lags of the stationarized time series in the forecasting equation are called Autoregressive (AR) terms, lags of the forecast errors are called Moving Average (MA) terms, and a time series which needs to be differenced to be made stationary is said to be an integrated (trend differenced) version of a stationary series. Random-walk and random-trend models, autoregressive models, and exponential smoothing models are all special cases of ARIMA models.

A basic non-seasonal ARIMA model is identified as an ARIMA (p, d, q) model.

Where:

- p is the number of autoregressive (AR) term
- d is the number of non-seasonal differences (Trend Difference) needed for making the series stationary, and
- q is the number of lagged forecast errors in the prediction equation (MA) term

Autoregressive (AR) Process

If the predictors consist only of lagged values of Y, it is a pure autoregressive (AR) model, which is just a special case of a regression model. For example, a first-order autoregressive {AR (1)} model for Y is a simple regression model in which the

independent variable is just Y lagged by one period. As the number of lagged period (p) increases the order of autoregressive process also becomes AR (p).

- AR(1) model specification is

$$Y_t = m + a Y_{t-1} + u_t \quad \text{..... (6)}$$

Where, $u_t \sim N(0, \sigma^2)$ (random error)

- AR(p) Process is :

$$Y_t = a_1 Y_{t-1} + \dots + a_p Y_{t-p} + u_t \quad \text{..... (7)}$$

Moving Average (MA) Process

In a pure MA process, a variable is expressed solely in terms of the current and previous white noise disturbances.

- MA (1) Process:

$$Y_t = u_t + \beta u_{t-1} \quad \text{..... (8)}$$

Where, $u_t \sim N(0, \sigma^2)$ (random error)

If $|\beta| < 1$, then, u_t can be considered as the sum of Geometric Progression (GP) series.

Thus, a MA (1) process can be expressed as an infinite order of AR with geometrically declining weights.

- MA(q) Process:

$$Y_t = u_t + \beta_1 u_{t-1} + \beta_2 u_{t-2} + \dots + \beta_q u_{t-q} \quad \text{..... (9)}$$

GARCH Models

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) process is an econometric model developed in 1982 by Robert Engle. There are several models under GARCH family. The GARCH process is often preferred by financial modeling professionals because it provides a more real-world context than other forms of ARIMA models when trying to predict the prices and rates of financial instruments. If an ARMA model is assumed for the error variance, the model becomes GARCH model (Bollerslev, 1986).

The GARCH model is a weighted average of past squared residuals, but it has declining weights that never go completely to zero. It gives parsimonious models that are easy to estimate and, even in its simplest form, has proven surprisingly successful in predicting conditional variances. The most widely used GARCH model asserts that the best predictor of the variance in the next period is a weighted average of the long-run average

variance. The variance predicted for this period, and the new information in this period is captured by the most recent squared residual.

GARCH (p, q) Model

The GARCH (p, q) model estimates conditional variance as a function of weighted average of the past squared residuals till q lagged term, and lagged conditional variance till p terms. Consider a regression or auto-regression model:

$$Y_t = a + \beta_1 X_t + u_t; \quad \text{OR} \quad Y_t = \beta_2 Y_{t-1} + u_t \quad \dots\dots\dots (10)$$

Where, $u_t \sim N(0, \sigma^2)$ and σ^2 is not constant but changes over time and dependent on the past history.

$$u_t = \epsilon_t \sqrt{h_t}; \quad h_t = \sigma^2$$

Where, ϵ_t is white noise and $\sim N(0, 1)$ and h_t is the systematic variance which changes over time, a scaling factor.

The GARCH (1, 1) model can be written as

$$h_t = \gamma_0 + \gamma_1 u_{t-1}^2 + \delta_1 h_{t-1} \quad \dots\dots\dots (11)$$

The GARCH (p, q) model can be written as

$$h_t = \gamma_0 + \sum_{i=1}^p \delta_i h_{t-i} + \sum_{j=1}^q \gamma_j u_{t-j}^2 \quad \dots\dots\dots (12)$$

Now h_t depends both on past values of the shocks/error, which are captured by the lagged squared residual terms, and on past values of itself, which is captured by lagged h_t terms. The (12) is called Variance Equation.

Where; $\gamma_0 > 0, \delta_i > 0, \gamma_j > 0$ (non-negativity conditions) and $\delta_i + \gamma_j < 1$

III. EMPIRICAL ANALYSIS

In this chapter, an attempt has been made to estimate univariate models of ARIMA and GARCH family in order to identify the autoregressive, seasonal and cyclic components of NEPSE index with an aim of forecasting the index by its past behaviors. The results are discussed below.

From the ADF tests it has been found the data series which is taken into consideration for this study was non-stationary at level. However, the series has become stationary at first difference. This has been proved as the null hypotheses that there is unit root in the data series was rejected at 5 % level of significance as indicated by probability (Mackinnon P-value) of the variable. The results of the ADF tests have been presented in the following table.

Table 1: Augmented Dickey-Fuller (ADF) Tests

Variable	At Level		At First Difference	
	t-statistics	p-value*	t-statistics	p-value*
Nepse Index	-0.456	0.9843	-8.646	0.0000

* Mackinnon (1996) one sided p-values.

ARIMA Model

Since the data series of NEPSE index was stationary at first difference as indicated by unit root test the AR (1) process has been identified. Similarly, the seasonality factor has also been identified from the Autocorrelation Function (ACF) of Correlogram of first differenced series NEPSE (-1). Since the daily data of NEPSE index are being used in this study the seasonal process SAR (5) has been identified and adjusted by generating new series i.e. D (NEPSE, 0, 5). In the meantime, cyclical or moving average (MA) process has also been identified. From the Partial Autocorrelation Function (PACF) of newly generated seasonality adjusted series D (NEPSE, 0, 5) regressors (explanatory variables) AR (1), MA (1), SAR (5), SAR (10), SMA (7) and SMA (15) have been selected. The interpretation of selected regressors is as follows:

- **AR(1)** : NEPSE index of period t affected by its value at $t - 1$ period
- **MA(1)** : NEPSE index of period t affected by the random error of period t and $t - 1$
- **SAR (5) and SAR (10)** : NEPSE index of period t affected by its value at $t - 5$ and $t - 10$ period as well (seasonality effect)
- **SMA (7) and SMA (15)** : NEPSE index of period t affected by the random error of period $t - 7$ and $t - 15$ as well (seasonality effect)

Once the predictors are identified, an ARIMA model has been estimated for seasonality adjusted series of NEPSE. In the model, all the coefficients of predictors are less than one hence the Stationarity and invertibility conditions are satisfied. Similarly, all the coefficients are statistically significant at 5 % level of significance as indicated by the corresponding probability values. It has been found the model is better estimated in terms of standard error of regression, adjusted R^2 , AIC and SIC criteria.

The Correlogram of seasonality adjusted NEPSE index (Table-2) and the result of model estimation (Table-3) are presented below.

Table 2: Correlogram of Seasonality Adjusted NEPSE Index

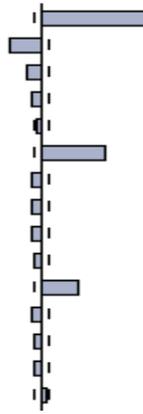
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
		1	0.836	0.836	767.98	0.000
		2	0.630	-0.233	1203.5	0.000
		3	0.424	-0.108	1401.0	0.000
		4	0.240	-0.068	1464.6	0.000
		5	0.095	-0.030	1474.6	0.000
		6	0.126	0.467	1492.2	0.000
		7	0.182	-0.081	1528.8	0.000
		8	0.222	-0.080	1583.1	0.000
		9	0.230	-0.074	1641.5	0.000
		10	0.208	-0.064	1689.5	0.000
		11	0.164	0.270	1719.4	0.000
		12	0.116	-0.066	1734.2	0.000
		13	0.080	-0.056	1741.4	0.000
		14	0.060	-0.064	1745.5	0.000
		15	0.073	0.041	1751.3	0.000

Table 3: Results of ARIMA Model Estimation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.339505	2.677288	1.620859	0.1058
AR(1)	0.993463	0.007359	134.9942	0.0000
SAR(5)	-0.975167	0.022452	-43.43322	0.0000
SAR(10)	-0.903429	0.038069	-23.73120	0.0000
MA(1)	0.194895	0.032322	6.029880	0.0000
SMA(7)	0.064618	0.021244	3.041710	0.0025
SMA(15)	-0.936798	0.399171	-2.346860	0.0194
SIGMASQ	36.73636	1.787062	20.55684	0.0000
R-squared	0.865985	Mean dependent var		4.362643
Adjusted R-squared	0.863598	S.D. dependent var		16.57732
S.E. of regression	6.122432	Akaike info criterion		6.532269
Sum squared resid	14731.28	Schwarz criterion		6.611949
Log likelihood	-1301.720	Hannan-Quinn criter.		6.563820
F-statistic	362.7882	Durbin-Watson stat		1.960934
Prob(F-statistic)	0.000000			

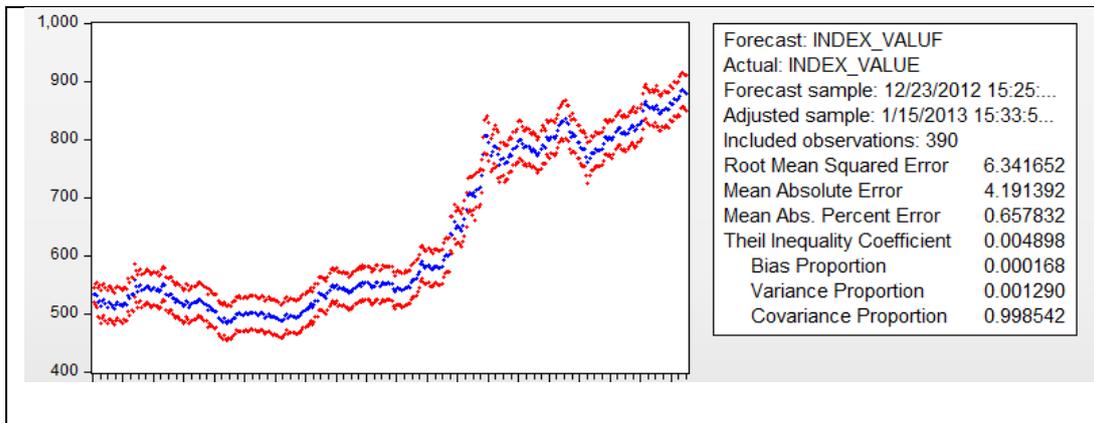
Likewise, Correlogram (Q-stat) of residuals has shown that the series has become completely random/white noise, which is presented in the following table-4. Thus the model has been selected for forecasting the daily NEPSE Index.

Table 4: The Correlogram (Q-stat) of Residuals

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 0.019	0.019	0.1505	
		2 0.071	0.070	2.1713	
		3 -0.029	-0.031	2.5028	
		4 -0.011	-0.015	2.5530	
		5 -0.025	-0.021	2.8141	
		6 0.003	0.005	2.8179	
		7 0.032	0.034	3.2297	0.072
		8 0.024	0.021	3.4696	0.176
		9 -0.008	-0.014	3.4928	0.322
		10 0.036	0.035	4.0240	0.403
		11 0.084	0.087	6.9195	0.227
		12 0.008	0.002	6.9488	0.326
		13 -0.020	-0.031	7.1189	0.417
		14 -0.108	-0.106	12.014	0.151
		15 -0.030	-0.021	12.401	0.192
		16 0.023	0.044	12.619	0.246
		17 0.088	0.086	15.880	0.146
		18 -0.084	-0.108	18.864	0.092
		19 0.039	0.021	19.507	0.108
		20 0.049	0.073	20.508	0.115
		21 0.065	0.067	22.300	0.100
		22 0.100	0.094	26.551	0.047
		23 -0.003	-0.027	26.556	0.065
		24 -0.055	-0.069	27.841	0.065

Now it has been proved that all the trend differencing, cyclical (moving average) and seasonal factors have been captured by the selected ARIMA model and the series has become random. Therefore, we can use the model to forecast daily NEPSE index. Accordingly, a within the sample (static) forecasting has been performed. The result of forecast shows that the Root Mean Squared Error (RMSE) and Mean Absolute

The static forecasting of the NEPSE index by ARIMA model



GARCH Model

Standard GARCH models assume that positive and negative error terms have a symmetric effect on the volatility. In other words, good and bad news have the same effect on the volatility in this model. In practice this assumption is frequently violated, in particular by stock returns, in that the volatility increases more after bad news than after good news which is called Leverage Effect (Black, 1976). From an empirical point of view the volatility reacts asymmetrically to the sign of the shocks and therefore a number of parameterized extensions of the standard GARCH model have been suggested.

The most important and widely used one is the Exponential GARCH (EGARCH) model developed by Nelson (1991). While estimating EGARCH models no restrictions of non-negativity need to be imposed since the volatility of the EGARCH model is measured by the conditional variance as an explicit multiplicative function of lagged innovations. In this study, the EGARCH model has been used to measure the volatility of daily NEPSE index with an aim of estimating best model for forecasting future index values.

Since the residual squared have not become random after estimation of ARIMA model, it is desirable to perform the ARCH test before processing for EGARCH model estimation. From the result of ARCH test it has been found the ARCH effect is present in the data series of NEPSE index. This is confirmed by the probability values of F-statistics and Chi-Square statistics which reject the null hypothesis of no ARCH effect at 5 per cent level of significance. The result is presented in the following table.

Table 5: Heteroskedasticity (ARCH) test of the residuals squared

Statistics		Probability	
F Statistic	6.8274	Prob. F(10,380)	0.0000
Observed R-squared	59.5509	Prob. Chi-Square (10)	0.0000

Once the ARCH effect is confirmed, EGARCH (1, 1) model has been estimated by maximum likelihood method. The first estimate of the model shows that the predictor MA (1) is not significant at 5 per cent level of significance. This is indicated by the probability value of corresponding coefficient.

As the predictor MA (1) is found to be insignificant the model may not able to yield better forecast. Thus, it is desirable to estimate another model without the predictor MA (1) which may produce the better results. Accordingly, the second model has been estimated which shows all the predictors are significant at 5 per cent level of significance. This means the model has been able to incorporate all the positive and negative shocks which create the volatility in the NEPSE index. Similarly, the model seems to be better as indicated by the adjusted R square as well as, AIC and SIC. The result is presented below.

Table-6: Results of EGARCH Model Estimation

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.586834	1.136658	2.275824	0.0229
AR(1)	0.990011	0.003935	251.5673	0.0000
SAR(5)	-0.956371	0.016078	-59.48207	0.0000
SAR(10)	-0.897873	0.017888	-50.19331	0.0000
MA(7)	0.038373	0.014360	2.672147	0.0075
MA(15)	-0.916668	0.014861	-61.68431	0.0000
Variance Equation				
C(7)	0.006315	0.071854	0.087882	0.9300
C(8)	0.162648	0.071846	2.263820	0.0236
C(9)	0.075904	0.037002	2.051376	0.0402
C(10)	0.963149	0.022394	43.00896	0.0000
GED PARAMETER	0.916565	0.079258	11.56435	0.0000
R-squared	0.860940	Mean dependent var	4.524256	
Adjusted R-squared	0.859130	S.D. dependent var	16.75706	
S.E. of regression	6.289377	Akaike info criterion	6.070559	
Sum squared resid	15189.61	Schwarz criterion	6.182424	
Log likelihood	-1172.759	Hannan-Quinn criter.	6.114903	
Durbin-Watson stat	1.516605			

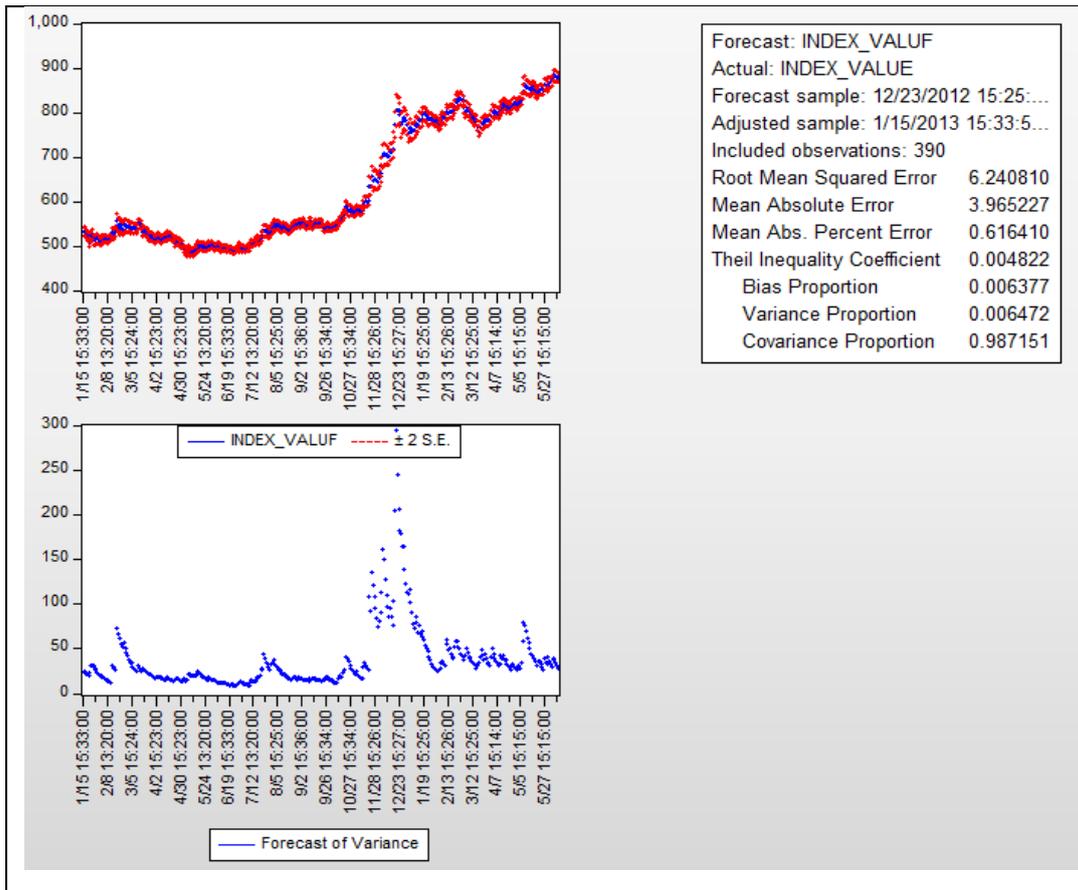
Now before selecting the model for forecasting it is required to confirm whether the residuals have become random. For this ARCH-LM test of residuals needs to be performed. The result of ARCH-LM test shows that the residuals of series have become completely random/white noise which was confirmed as the null hypothesis of no serial correlation has been accepted. Thus the model has been selected for forecasting the daily NEPSE Index. The results are given in the following table.

Table-7: Serial Correlation (ARCH-LM) test

Statistics		Probability	
F Statistic	0.7319	Prob. F(10,380)	0.6943
Observed R-squared	7.3912	Prob. Chi-Square (10)	0.6881

The result of ARCH-LM test confirmed that the selected EGARCH model has been able to capture all sources of volatility (positive and negative shocks) that cause fluctuations in the NEPSE index. Therefore, the model can be used to forecast daily NEPSE index. Accordingly, a within the sample (static) forecasting has been performed to check the reliability of the model. Results of the forecast show the Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) are minimal. Thus it is concluded that the selected EGARCH model would fit best for out of the sample (dynamic) forecasting as well. The result of the static forecast of the NEPSE index is given below.

Static Forecasting of NEPSE through EGARCH Model



IV. FINDINGS AND CONCLUSIONS

Based on the above empirical analysis it has been found that NEPSE index comprises all the components of time series such as Autoregressive (AR) component, Moving Average (MA) component and Seasonal component. Thus a univariate ARIMA model with seasonality i.e. SARIMA is found to be the best model for forecasting future value of daily NEPSE index based on the past behaviour of the same. In the meantime, the volatility of the NEPSE index, which is resulted from both positive and negative shocks, can be captured with the help of Exponential GARCH (EGRACH) model. Thus, EGARCH model found to be best suited for forecasting volatility of the NEPSE index.

Now it is concluded that the daily NEPSE index has all Autoregressive, Cyclical (moving average) and Seasonal components which can be captured and forecasted with the help of SARIMA and EGARCH models. Similarly, AR (1), MA (1), SAR (5), SAR (10), SMA (7) and SMA (15) could be the best predictors for forecasting daily NEPSE index by univariate regression models like ARIMA and GARCH.

The identified models would be applicable and useful for investors, stock analysts and policy makers in forecasting the daily NEPSE index and making policy reforms in the same. More specifically to the investors and analysts, this paper has given clear indication that the daily NEPSE index would be affected by its previous values as well as the random errors in the past. This means both the observed and random factors in the past would affect the future value NEPSE index. Another implication is that the impact of both observed and random factors would be repeated every five days (since Nepali stock market operates 5 days a week) and the process lasts up to the second week.

The major take away of this study is that to be successful in trading of the stocks listed under NEPSE on daily basis all the three components; Autoregressive, Moving Average and Seasonal effect with the identified predictors and respective sign; have to be taken considered. However, price of individual company may not follow exactly the same process as followed by NEPSE index.

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