CHAPTER FOUR

MODELING OF FORECASTING INFLATION IN NEPAL

4.1Introduction

Inflation is a burning economic problem in the developing countries like Nepal that brings adverse effects on the macroeconomic variables like loss of purchasing power of domestic currency, unfavorable balance of payment (BOP) situation, decrease in national output, increase level of unemployment, increase in immoral activities such as theft, murdering, black marketing etc. inflation will have great social and economic costs like poverty, high income inequality and other chaos in social and economic lives. Due to these reasons, the central monetary authority of every economy has the common goal of price stability.

Inflation forecasting plays vital role in the monetary policy perspectives. A number of research studies have been carried out regarding inflation forecasting. Present researches suggest that inflation's predictors like monetary measures, output gap and others have become less sensitive for inflation determination and now inflations are claimed to be more unpredictable. Univariate models tend to show a better forecasting capacity than those based on various inflation theories, such as the Phillips curve. Traditionally, in industrialized countries the Phillips curve has played a predominant role in inflation forecasting, and according to Stock and Watson (1999), Atkenson and Ohanian (2001) and Canova, (2002), it would seem to perform better in terms of forecasting error than other alternative models. In recent years there have been indications, in the United States in particular, that the Phillips curve became unstable as from the eighties, and that perhaps for this reason, its forecasting ability has weakened, in general being overcome by univariate models.

Isakova (2007) opines that central bank should have the full information regarding the economic performance of the country. The central banks should acquire the knowledge on the behavior and interrelationships between and among the macroeconomic indicators to develop effective monetary policies. More the central banks are aware about the macroeconomic indicators; more effective the monetary policies are formulated. The inflation forecasts are most inevitable to formulate the monetary policy in such a way as to stabilize macroeconomic variables like price, output, employment, rate of interest, foreign exchange etc. thus, it is the duty of monetary economists to provide maximum information regarding the inflationary processes in the economy to assist central bank to formulate the suitable monetary policies for economic stability.

Although inflation forecasting is necessary for the economy, it is very difficult job in developing countries like Nepal due to the reasons that economic activities are highly unstable and volatile. Besides, the data on macroeconomic indicators are so reliable due to some reasons like measurement error, imperfect method of measurement, lack of record keeping of the related data etc.

A number of empirical studies are available in the economic literatures regarding the determinants of inflation in developing countries that show inflation is a country-specific phenomenon, and the determinants of inflation differ from country to country. The effectiveness of monetary policy of a country, therefore, depends on the ability of economists to develop a suitable and reliable model that could contribute in acquiring knowledge on the existing economic events forecast for future. So far as the forecasting of inflation is concerned, the central bank will be able to formulate the monetary targets, goals and policies to make the economy walk in the right track maintaining the economic stability.

The central role of inflation expectations has long been recognized in both macroeconomic theory and stabilization policy analysis. Wage bargaining, price setting, asset allocation and investment, all depend on inflationary expectation on one way or another. While inflation expectations received scrupulous attention in market economies over a long period of time, interest for the topic in the former socialist economies arose only with liberalization attempts at the beginning of transition. Given the lack of experience with open inflation on the part of economic agents in majority of transition economies, the literature on the formation of expectations in these economies is still rather trivial. (Nikolic, 2003).

Long-term nominal commitments such as labor contracts, mortgages and other debt, and price stickiness are widespread features of modern economies. In such a world, forecasting how the general price level will evolve over the life of a commitment is an essential part of private sector decision-making. The existence of long-term nominal obligations is also among the primary reasons economists generally believe that monetary policy is not neutral, at least over moderate horizons. While macroeconomists continue to debate whether these non-neutralities give rise to beneficially exploitable trade-offs for monetary policymakers, the recent New Keynesian formulation of optimal policy has raised the prominence of inflation forecasting in policymaking (Woodford (2003). Central banks aim to keep inflation stable, and perhaps also to keep output near an efficient level. With these objectives, the New Keynesian model makes explicit that optimal policy will depend on optimal forecasts (Svensson, 2005), and further that policy will be most effective when it is well understood by the general public. These results helped bolster a transparency revolution in central banking. A centerpiece of this revolution has been the practice of central banks announcing forecasts of inflation and other key variables.

4.2 ARMA/ARIMA Modeling for Forecasting

The dependence of one variable on other/s is very common in time series observations. To model this time series dependence, we start with univariate ARMA models. To motivate the model, basically we can track two lines of thinking. First, for a series X_t, we can model that the level of its current observations depends on the level of its lagged observations. For example, if we observe a high inflation realization this quarter, we would expect that the inflation in the next few quarters will be high as well. This way of thinking can be represented by an AR model. The AR (1) (autoregressive of order one) can be written as:

$$X_t = \psi X_{t-1} + \varepsilon_t \quad (4.1)$$

Where$\varepsilon_t \sim iid(0, {\sigma_t}^2)$ and we keep this assumption through this analysis. Similarly, $AR(p)$ (autoregressive of order ρ) can be written as:

$$X_t = \psi_1 X_{t-1} + \psi_2 X_{t-2} + \cdots + \psi_\rho X_{t-\rho} + \varepsilon_t \quad (4.2)$$

Alternatively, we can model that the observations of a random variable at time t are not only affected by the shock at time t, but also the shocks that have taken place before time t. For example, if we observe a negative shock to the economy, say, a catastrophic earthquake, then we would expect that this negative effect affects the economy not only for the time it takes place, but also for the near future. This kind of thinking can be represented by an MA model. The $MA(1)$ (moving average of order one) and $MA(q)$ [moving average of order (q)] can be written as:

$$X_t = \varepsilon_t + \theta\varepsilon_{t-1} \tag{4.3}$$

And

$$X_t = \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q} \tag{4.4}$$

If we combine these two models [model (4.2) and model (4.4)], we get a general $ARMA(p,q)$ model,

$$X_t = \psi_1 X_{t-1} + \psi_2 X_{t-2} + \cdots + \psi_\rho X_{t-\rho} + \varepsilon_t + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q} \tag{4.5}$$

Economic time series are usually non-stationary that contain unit root. These non-stationary time series are said to be integrated. Hence, the differencing of integrated series is necessary to obtain the stationary series. A time series is said to be integrated of order one as its first difference is stationary and denoted by $I(0)$. In the same manner, if a time series becomes stationary after second differencing, it can said to be $I(2)$, and its second difference is stationary and can be expressed as $I(0)$. In general, if a time series is $I(d)$ after differencing it d times, the series becomes an $I(0)$.

Therefore, if we have to difference a time series d times to make it stationary and apply the $ARMA\,(p,q)$ model to it, then our model converts into $ARIMA(p,d,q)$. Thus, we have the Autoregressive Integrated Moving Average $ARIMA$ with p autoregressive terms, d number of times needed to get difference series and q number of moving average terms.

4.3 ARMA/ARIMA Structure: The Box-Jenkins Approach

The box-Jenkins approach popularized by Box and Jenkins (1970)[17] is one of the most widely used methodologies for the analysis of time series data. It is popular because of its generality; it can handle any series with or without seasonal elements, and it has well-documented computer program.

The basic steps in Box-Jenkins approach are:

[17] Box and Jenkins (1970). Time Series Analysis. First Edition.

- Differencing the series to achieve stationarity. The stationary series can be achieved by differencing by studying the graph of correlogram and unit root tests.
- Estimation of tentative $ARMA$ model by inspecting the correlogram of difference series.
- Having chosen a particular $ARMA$ modeling, and having estimated parameters, it is necessary to examine whether the selected model fits the data reasonably well. If the selected $ARMA$ model is not efficient, we should develop another $ARMA$ model by the same procedures.

4.4 Stability Test of ARMA/ARIMA Modeling

4.4.1 Durbin-Watson Test

The Durbin Watson test is a famous method for testing the serial correlation problem. The serial correlation is a serious problem contained in regression where the residuals are serially correlated. Due the presence of serial correlation, the predicted value of dependent variable in the regression is highly questioned that the estimated value has no reliability. It is a statistic on the basis of which the reliability of estimated coefficient of independent variable that affects dependent variable can be assessed. The D-W statistic can be computed using the following formula.

$$d = \frac{\sum_{t=2}^{n} (\varepsilon_t - \varepsilon_{t-1})^2}{\sum_{t=1}^{n} \varepsilon_t^2}$$

Where, d represents Durbin-Watson (D-W) statistic, ε_t the observed error term or $\left(Y_t - \hat{Y}_t\right) = Y_t - a - bX_t$. The value of d always lies between zero and four. If value of d is zero, then there exists perfect positive correlation among the residuals, and there occurs perfect negative correlation when d is equal to 4. If the error terms are uncorrelated, the expected value of d is equal to 2. There occurs positive first order serial correlation if value of d is further below 2, and as value of d is further above 2 there exists negative serial correlation among the residuals. However, D-W test alone is inconclusive to detect the serial correlation.

The critical values of d for a given level of significance can be tabulated as the pairs of lower d and upper d (d_L& d_U). As the value of d falls between $d_L and\ d_U$, the D-W test becomes inconclusive.

H_0:$\rho = 0$ (No serial correlation)

H_1:$\rho > 0$ (Positive serial correlation)

If $d < d_L$, reject H_0, while if $d < d_U$, do not reject H_0

However, the critical test limits for negative serial correlation are (4 - d_L) and (4- d_U).

H_0:$\rho = 0$ (no serial correlation)
H_1: $\rho < 0$ (negative serial correlation)
If d < (4 - d_U), do not reject H_o, if (d > 4 - d_L), reject H_o.

4.4.2 Residual Diagnostics

4.4.2.1 Correlogram-Q-Statistics for Autocorrelation

Residual Diagnostics/Correlogram-Q-statistics is another test for autocorrelation or serial correlation based on residuals of estimated ARMA model. For this, we run correlogram of Residual Square, together with the Ljung-Box Q-statistics for high-order serial correlation. If there is no serial correlation in the residuals, the autocorrelations and partial autocorrelations at all lags should be nearly zero, and all Q-statistics should be insignificant with large p-values.

4.4.2.2 Normality Test: Jarque-Bera Statistic

In order to find whether or not the residuals of regression equation are normally distributed, we apply Jarque-Bera statistic with the null hypothesis that residuals are normally distributed. With the help of estimated Jarque-Bera statistic corresponding to its probability, we can make the decision that residuals are normally distributed or not normally distributed. If the probability value of Jarque-Bera statistic is above 5 % (0.05), the residuals are claimed to be normally distributed and there will not be serial correlation problem, that is, residuals are not serially correlated and the estimated ARMA model represents the goodness of fit. Contrary to this, if probability of Jarque-Bera statistic is less than 0.05 the residuals are not normally distributed and estimated ARMA does not represent the goodness of fit, there is strong evidence of serial correlation. However, Jarue-Bera test alone is not the sufficient tool for testing normality and serial correlation.

4.4.2.3 Lagrange Multiplier (LM) Test

The D-W test assumes that the regressors are nonstochastic, that is, their values are fixed in repeated sampling. But the assumption of regressors as nonstochastic may not always be true. If the regressors are not nonstochastic, then D-W will not be valid either in finite, or small samples or in large samples. The assumption of D-W test is very difficult to maintain in time series econometric models. (Gujrati, 2009, pp 482). Thus, in case of time series econometric models with large samples the Breusch-Godfrey Lagrange Multiplier (B-G LM) test.

Breusch (1978) and Godfrey (1978) have developed a test of autocorrelation for time series econometric model with nonstochastic regressors, the lagged values of regressand; higher-order autoregressive schemes; and simple or higher-order moving averages of white noise error terms ε_t.

Consider the model with two regressors with reference to a ρ^{th}order autoregressive scheme,

$$Y_t = \beta_1 + \beta_2 X_{1t} + \beta_3 X_{2t} + \varepsilon_t \qquad (4.6)$$

Assume that the error term ε_t follows the ρ^{th} order autoregressive, AR(ρ) scheme as follows:

$$\varepsilon_t = \rho_1 \varepsilon_{t-1} + \rho_2 \varepsilon_{t-2} + \cdots + \rho_\rho \varepsilon_{t-\rho} + u_t \qquad (4.7)$$

The null hypothesis H_0 to be tested is given by:

$$H_0: \rho_1 = \rho_2 = \cdots = \rho_{\rho=0} \qquad (4.8)$$

If H_0 is not rejected, there will not be serial correlation of any order. The B-G LM test follows following steps.

(1) Estimate equation (4.6) using OLS regression.

(2) Find the residuals $\hat{\varepsilon}_t$ and regress $\hat{\varepsilon}_t$ on the X_t. But if the model consists more than one X_t variable and including them also obtain $\varepsilon_{t-1,}\varepsilon_{t-2} \ldots \varepsilon_{t-p}$

Thus, we will have the following regression model:

$$\hat{\varepsilon}_t = \alpha_1 + \alpha_2 X_t + \hat{\rho}_1 \hat{\varepsilon}_{t-1} + \hat{\rho}_2 \hat{\varepsilon}_{t-2} + \cdots + \hat{\rho}_\rho \hat{\varepsilon}_{t-\rho} + u_t \qquad (4.7)$$

Obtain R^2 from equation (4.7).

If the sample size is large, B-G LM model gives as:

$$(n-\rho)R^2 \sim \chi_\rho{}^2 \tag{4.8}$$

Now, in B-G LM model, we can define a $\chi_\rho{}^2$ variable with h degrees of freedom as:

$$\frac{SSR_R - SSR_U}{\hat{\sigma}_R^2} \sim \chi_\rho{}^2 h \tag{4.9}$$

Where h is degree of freedom, equal to order of autoregression $(h=\rho)$. SSR is the sum of squares residuals for the restricted and unrestricted equations and $\hat{\sigma}_R^2$, the estimated variance of the restricted equation. Now, equation (4.9) can be extended as:

$$\frac{SSR_R - SSR_U}{\hat{\sigma}_R^2} = \frac{SST - SSR}{SST/N} = NR^2 = T \times R^2 \tag{4.10}$$

After finding the value of $T \times R^2$, it should be compared with the relevant critical value for χ^2 where the degree of freedom, h is the order of the autoregressive scheme. The null hypothesis of the B-G LM test is: Ho: 'no autocorrelation, will be rejected if $T \times R^2 > \chi^2 h$ critical value.

4.5 ARCH and GARCH Estimation for Forecasting

The autoregressive conditionally heteroscedastic (ARCH) process introduced by Engle (1982) is taken as one of the well known and most often used modeling, which can be applied for the highly volatile economic and financial time series with non-constant variance (heteroscedastic). The RCH model has been generalized by different authors like Bollerslev (1986), Gourieroux (1997) and so on. (Berkes, Horvath and kokoszka, 2003)

The ARCH modeling process was introduced by Engle (1982), which states that time series have the conditional variance over time. The ARCH modeling with heteroscedasticity is proven useful in different economic phenomena. For example, Engle (1982, 1983) and Engle and Kraft (1983) have built the ARCH modeling for the inflation rate. Coulson and Robins (1985) concluded that the estimated inflation volatility is related to some key macroeconomic variables. (Bollerslev, 1986).

The traditional time series models assume that conditional variance remains constant. But in reality, most of the economic and financial series frequently exhibit the non-constant conditional variance. Nortey, et.al.(2014) argue that heteroscedasticity affects the accuracy of forecasts confidence limits. So it is requisite to construct suitable model of time series for forecasting. Since the economic and financial time series are highly volatile with non-constant variance (heteroscedastic), the ARCH model and its variants like GARCH and EGARCH models have been developed for modeling such volatile time series with non-constant variance for forecasting.

However, the present study is concerned with the modeling of inflation for forecasting using ARCH and GARCH, where the conditional error variance is taken as the function of the past realization of the time series. Economists argue that inflation for the periods are usually followed by further periods' inflation, which means periods of high inflation are followed by further periods' inflation and vice-versa.

4.5.1 Developing ARCH/GARCH Model

While developing an ARCH model, it is necessary to examine three conditions. First is the conditional mean equation; second the conditional variance; and third error distribution, each of which can be mentioned below.

The GARCH(1, 1) Model

Let us commence with the simplest $GARCH\ (1,1)$ model,

$$Y_t = X_t'\theta + \varepsilon_t \tag{4.11}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{4.12}$$

The mean equation given in (4.11) can be written as a function of exogenous variables with an error term. The σ_t^2 in equation (4.12) is the one-period ahead forecast variance based on past information; it is called the conditional variance. The conditional variance equation specified in (4.12) is a function of three terms, a constant term ω, the ARCH term (${\varepsilon^2}_{t-1}$) and the GARCH term (${\sigma^2}_{t-1}$).

GARCH (1, 1) model consists of a first-order autoregressive GARCH term in and a first-order moving average ARCH term. The ARCH model is a special case of a GARCH model where there will not be the lagged forecast variances in the conditional variance equation.

This type of specification can be found in financial market. In financial market, a trader's forecast of current period's variance is generated by a weighted average of long term average, the forecasted variance from last period (GARCH term), and information about volatility observed in the past period (ARCH term). If the return from asset becomes large, the trader can increase the estimate of the variance for the next period. This trend occurs not only in financial market but also in economic sphere like inflation, where larger inflation in current time is likely to be followed by further large inflation in future.

Based on the above logic, if the lagged variance is recursively substituted on the right hand side of equation (4.12), we may arrive at the current conditional variance as a weighted average of all the lagged squared residuals given by equation (4.13).

$$\sigma_t^2 = \frac{\omega}{1-\beta}\alpha\sum_{j=1}^{\infty}\beta_{j-1}\,\varepsilon_{t-j}^2 \tag{4.13}$$

Equation (4.13) can be presented as:

$$\sigma_t^2 = \omega + (\alpha+\beta)^2\varepsilon_{t-1}^2 + v_t - \beta v_{t-1} \tag{4.14}$$

Where, $v_t = \varepsilon_t^2 + \sigma_t^2$

Equation (4.14) implies that the squared errors follow the heteroscedastic ARMA (1,1) process. The term $(\alpha+\beta)$ in equation (4.14) represents the autoregressive root that governs volatility shocks.

The GARCH (q, p)Model

Higher order GARCH models, denoted GARCH (q, p), can be estimated by choosing either q or p greater than 1 where q is the order of the autoregressive GARCH terms and p is the order of the moving average ARCH terms. The representation of the hence, the modeling of GARCH (q, p) can be written as:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q}\beta_j\,\sigma_{t-j}^2 + \sum_{i=1}^{p}\alpha_i\sigma_{t-i}^2 \tag{4.15}$$

4.6 Stability of the ARCH-GARCH Model

Goodness of fit of the ARCH-GARCH model is based on residuals and is more specifically on the standardized residuals (Talke, 2003). The residuals are assumed to be independently and identically distributed following either a normal or standardized t-distribution (Tsay, 2002) or (Gourieroux, 2001). Plots of the residuals such as the histogram, the normal probability plot and the time plot of the residuals can be used.

If the model fits the data well the histogram of the residuals should be approximately symmetric. The normal probability plot should be a straight line while the time plot should exhibit random variation. The ACF and the PACF of the standardized residuals are used for checking the adequacy of the conditional variance model. The Engle's test and the Ljung Box Q-test are used to check the validity of the ARCH effects in the data. Having established that our model fits the data well, we can now use the fitted model to compute forecasts.

4.6.1 Model selection Criteria

The selection of suitable model from the given time series is a serious challenge in statistical and econometric modeling. There are different criteria for selecting the suitable model. If the selected model is suitable, it represents the goodness of fit and bears the property of stability of the model. The most common model selection criteria are AIC and BIC, on the basis of which the researchers can develop the reliable model. If fitted model suitable, the forecasting is more reliable.

4.6.1.1 The Akaike Information Criterion

The Akaike information criterion (AIC) was developed by Professor Hirotugu Akaike in 1971 and introduced in 1973 as an extension to the maximum likelihood principle for the selection of suitable model. "Akaike (1973) defined the most well-known criterion as AIC = - $\ln L + p$, where L is the likelihood for an estimated model with p parameters". (Hjorth,1994). The estimated model is claimed to be suitable if the value of AIC is minimum for the particular lag. We employ different lags in the proposed model and go on observing the AIC value on a trial and error basis. The fitted model with minimum AIC can be taken as the suitable model.

4.6.1.2 The Schwartz Criterion

The Schwartz Criterion also called Bayesian information criterion (BIC) is related to the Bayes factor and is useful for model comparison in its own right. The BIC of a model is defined as:

$$\frac{SC}{BIC} = -\,2ln(likelihood) + (k + klnN)$$

Where k denotes the number of parameters and N denotes the number of observations or equivalently, the sample size. BIC penalizes more complex models (those with many parameters) relative to simpler models. This definition permits multiple models to be compared at once; the model with the highest posterior probability is the one that minimizes BIC.

A desirable model is one that minimizes the AIC or the BIC. The other criteria are the R2 associated with the model which is the proportion of variability in a data set that is accounted for by the statistical model (Salkind, 2007). However, as Harvey (1991) indicated that the coefficient of determination (R^2) has a limitation in that, a model which can pick out the trend reasonably well will have R^2 close to unit. In general a model selected by two different criteria mentioned above may differ and thus it should be emphasized that the selection of an ARCH-GARCH model depends on the selection criteria used (Talke, 2003).

4.6.2 Lagrange Multiplier Test for ARCH Effects

The Lagrange Multiplier (LM) test examines whether there is any ARCH effect up to order q in the residuals with null hypothesis of no ARCH effect up to order q in the residuals of estimated GARCH model. The ARCH LM test can be used to identify whether the standardized residuals exhibit further ARCH. If the variance equation is correctly modeled, there cannot be the ARCH effect in the standardized residuals.

The squared series a_t^2 is used to check for conditional heteroscedasticity, where $a_t = r - \mu$ is the residual of the ARMA model. For checking heteroscedasticity, the Lagrange multiplier test is used. This test is equivalent to usual F statistics test. The null hypothesis is: H_0: $\alpha_1 = \alpha_2 = \cdots = \alpha_m = 0$

4.7 Graphical Plot of $LnCPI_t$ and $dLnCPI_t$

The raw data sets associated with inflation ($LnCPI_t$) is plotted in Figure-4.1. From the plot of line graph of $LnCPI_t$, it is observed that the data sets are varying with respect to time that seems to be non-stationary. The non-stationary data sets produce spurious regression results unless they are converted into stationary form. So it is necessary to convert the data sets into stationary with first difference. The line graph of $LnCPI_t$ in first difference is presented in Figure-4.2.

Figure-4.1: Line Graph of $LnCPI_t$ in Level Form

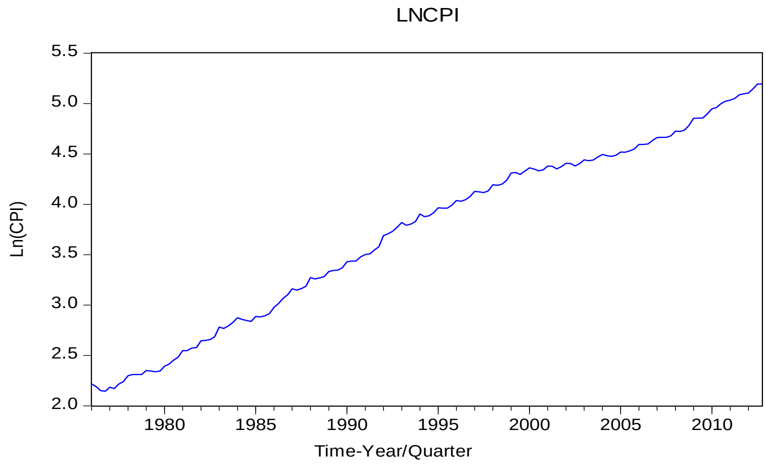
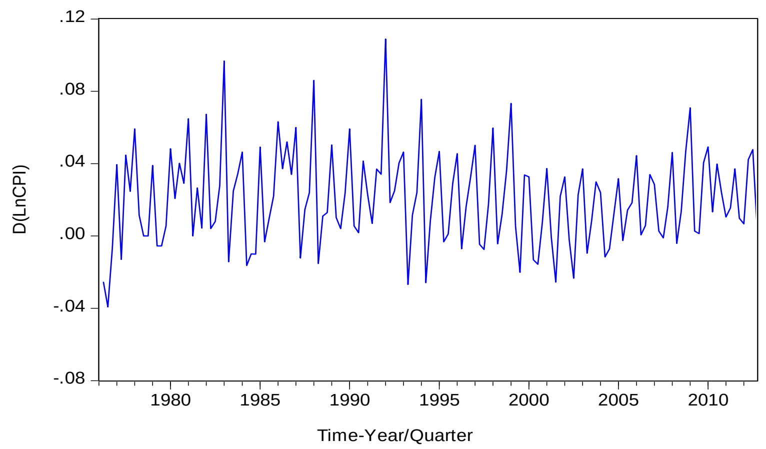


Figure-4.2: Line Graph of $LnCPI_t$ in First Difference



The plot of $LnCPI_t$ in its first difference is not found to be varying with time. The ups and downs of the data sets are the indication of stationarity.

ADF unit root test is the very important econometric technique to examine the stationarity of the data sets. ADF test statistic has to be rejected in order to have stationary process because null hypothesis of Augmented Dickey Fuller test assumes the presence of unit root in time series data. After taking differences and logarithms, the ADF statistics increased significantly and the probability of accepting null hypothesis becomes zero at 1% critical level. Therefore, we rejected the null hypothesis which implied that there was no unit root and the series are stationary.

From Table-4.1, it is observed that the null hypothesis of "$LnCPI_t$ has unit root" cannot be rejected even at 10 % level of significance as reported by t-statistic of ADF unit root test. However, the null hypothesis "$dLnCPI_t$ has unit root" is rejected at 5 % level of significance. Therefore, it can be concluded that $LnCPI_t$ is non-stationary at level form and is stationary at first difference. The first difference of $LnCPI_t$ represents the inflation rate. So, we use the first difference of $LnCPI_t$ as a dependent variable in OLS regression of forecasting inflation.

Table- 4.1: ADF Unit Root Test of $LnCPI_t$

Variable	ADF test statistic	Prob value	Lag length	Test Critical Values 1%	5%	10%
$LnCPI_t$	-1.0482	0.7347	8	-3.4778	-2.8822	-2.5779
$dLnCPI_t$	-3.2268	0.0205	7	-3.4778	-2.8822	-2.5779

4.8 Modeling of ARMA

In order to develop $ARMA(q,p)$ modeling it is necessary to examine suitable AR and MA terms of the stationary variable, $LnCPI_t$. For this, we can have tentative ideas for $ARMA$ with the help of correlogram. Table-4.2 presents the correlogram of $LnCPI_t$

Table-4.2: Correlogram of $LnCPI_t$

```
. ac dlncpi, lags(15) level(99.9)

. corrgram dlncpi, lags(20)

                                          -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1       -0.0226  -0.0227  .07635  0.7823
2       -0.2207  -0.2242  7.4369  0.0243
3       -0.0826  -0.1133  8.4743  0.0372
4        0.5891   0.5697  61.626  0.0000
5       -0.1814  -0.2898  66.701  0.0000
6       -0.3082  -0.1659  81.459  0.0000
7       -0.1538  -0.1346  85.158  0.0000
8        0.5812   0.3554  138.39  0.0000
9       -0.1254  -0.0503  140.89  0.0000
10      -0.2181   0.0554  148.49  0.0000
11      -0.0666   0.0247  149.21  0.0000
12       0.5566   0.1108  199.47  0.0000
13      -0.1046   0.0160  201.26  0.0000
14      -0.2517  -0.0764  211.69  0.0000
15      -0.1321  -0.0917  214.59  0.0000
16       0.5162   0.1464  259.13  0.0000
17      -0.1797  -0.1081  264.57  0.0000
18      -0.2515   0.0509  275.31  0.0000
19      -0.1213  -0.1130  277.83  0.0000
20       0.5640   0.2843  332.68  0.0000
```

From Table-4.3, it is observed that ACFs are statistically different from zero at lags 2,4,5,6,8,10 &12 but PACFs are statistically different from zero at lags 2,4,5,6 and 8. Based on PACF, we can model $LnCPI_t$ with its $AR(2,4,5,6,8)$ and including $MA(1)$ term as:

$$dLnCPI_t = c + \varphi_1 dLnCPI_{t-2} + \varphi_2 dLnCPI_{t-4} + \varphi_3 dLnCPI_{t-5} + \varphi_4 dLnCPI_{t-6} + \varphi_5 dLnCPI_{t-8} + \theta_1 \varepsilon_{t-1} \quad (4.16)$$

The OLS results in accordance with model (4.16) are presented through Table-4.3.

Table-4.3: Results from ARMA Modeling with AR (2,4,5,6,8) & MA(1)

Dependent Variable: $dLnCPI_t$

Variable	Coefficient	Std. Error	t-Statistic	Prob.
$Constant$	$\alpha_1 =$ 0.0105	0.0034	3.0832	0.0025
$dLNCPI_{t-2}$	$\varphi_1 =$ 0.0362	0.0801	0.4519	0.6521
$dLNCPI_{t-4}$	$\varphi_2 =$ 0.3831	0.0766	4.9961	0.0000
$dLNCPI_{t-5}$	$\varphi_3 =$ -0.1209	0.0608	-1.9875	0.0489
$dLNCPI_{t-6}$	$\varphi_4 =$ -0.1510	0.0776	-1.9439	0.0540
$dLNCPI_{t-8}$	$\varphi_5 =$ 0.3563	0.0767	4.6449	0.0000
ε_{t-1}	$\theta_1 =$ 0.1716	0.0891	1.9240	0.0565

R^2 =0.5393, $\bar{R}^2$ =0.5184, S.E. of regression=0.0178, D-W stat=2.0127

From Table-4.4, it is observed that the coefficients of AR at lag 4,5 and 8 are significant at 5 % level, where as the coefficients of AR (6) and MA(1) are significant at 10 % level. However, the coefficient of AR (2) is not significant even at 10 % level.

Although the coefficient of AR (2) is not significant, the D-W statistic is 2.01$\sim$2. This implies that the residuals of $ARMA$ model (4.1) are not correlated. This $ARMA$ model (4.1) is free from serial correlation. Due to this fact, there is goodness of fit of the $ARMA$ model. Therefore, $ARMA$ model (4.16) can be taken as the suitable model of inflation forecasts during the study period in the economy of Nepal.

However, ARMA model (4.16) is still not efficient model due to the reason that the coefficient of $AR(2)$ is not significant. The $AR(2)$ term being meaningless in the $ARMA$ model, this needs omission from $ARMA$ model (4.16). But the decision of omitting the $AR(2)$ term from $ARMA$ model (4.16) or not depends on redundant test.

Under Redundant test, the null hypothesis is that the regression of $dLnCPI_t$ on its AR and MA terms has the redundant variable $dLnCPI_{t-2}$. When the redundant test is applied to the regression model, the null hypothesis is not rejected as reported by t-statistic, F-statistic and Log Likelihood Ratio in Table-4.4, and it can be concluded that $dLnCPI_{t-2}$ term is redundant that can be withdrawn from the regression model (4.16).

Table-4.4: Redundant Test

Redundant Variables: $dLNCPI_{t-2}$

Test-statistic	Value	Degree of Freedom	Probability
t-statistic	0.455551	132	0.6495
F-statistic	0.207527	(1, 132)	0.6495
Likelihood ratio	0.218361	1	0.6403

When the regressor $dLnCPI_{t-2}$ is dropped from ARMA equation (4.16), our new ARMA equation becomes:

$$dLnCPI_t = \alpha + \varphi_1 dLnCPI_{t-4} + \varphi_2 dLnCPI_{t-5} + \varphi_3 dLnCPI_{t-6} + \varphi_4 dLnCPI_{t-8} + \theta_1 \varepsilon_{t-1} \quad (4.17)$$

The results from regression in accordance with equation (4.17) are presented through Table-4.5.

Table-4.5: Results from ARMA Modeling with AR (4,5,6,8) & MA(1)

Dependent Variable: $dLnCPI_t$

Variable	Coefficient	Std. Error	t-Statistic	Prob.
$Constant$	α_1 = 0.0110	0.0032	3.4002	0.0009
$dLNCPI_{t-4}$	φ_1 =.-0.1234	0.0597	-2.1632	0.0323
$dLNCPI_{t-5}$	φ_2 = -0.1291	0.0752	4.6574	0.0000
$dLNCPI_{t-6}$	φ_3 = 0.3502	0.0763	5.0187	0.0000
$dLNCPI_{t-8}$	φ_4 =0.1676	0.0879	1.9064	0.0587
ε_{t-1}	θ_1= -0.3833	0.0032	3.4002	0.0009

R^2 =0.5386, $\bar{R}^2$ =0.5212, S.E. of Regression=0.0177, D-W stat=2.0005

Table-4.5 shows the results of ARMA model after dropping AR (2) term from ARMA model (4.16). The coefficients of all ARMA terms are found to be statistically significant at 5 % and 10 % level. The value of $\bar{R}^2$ is improved in equation (4.17) as compared to equation (4.16). The D-W statistic is also found to be improved, which is 2, which means the residuals are free from serial correlation. The ARMA model represents the goodness of fit to the data.

Therefore, after redundant test our ARMA model (4.16) converts as:

$$dLnCPI_t = 0.011 - 0.1234\, dLnCPI_{t-4} - 0.1291\, dLnCPI_{t-5} + 0.3502\, dLnCPI_{t-6} + 0.1676\, dLnCPI_{t-8} - 0.3833\, \varepsilon_{t-1} \quad (4.18)$$

4.8.1 Residuals Diagnostic Tests

For the efficiency of ARMA model (4.17) or (4.18), further some tests are necessary to perform as residuals diagnostic tests.

4.8.1.1 Correlogram of Squared Residuals

For the stability of ARMA model (4.18), we test the serial correlation with the help of correlogram of square residuals. The correlogram of squared residuals of ARMA model (4.18) has been presented through Table-4.6.

Table-4.6: Correlogram of Squared Residuals of ARMA Equation (4.18)

Lag	AC	PAC	Q-Stat	Prob	Lag	AC	PAC	Q-Stat	Prob
1	-0.025	-0.025	0.0900	-	9	-0.018	-0.025	1.9100	0.984
2	0.038	0.037	0.2973	0.586	10	-0.023	-0.021	1.9924	0.992
3	-0.052	-0.050	0.6870	0.709	11	0.029	0.024	2.1250	0.995
4	0.038	0.034	0.8921	0.827	12	-0.071	-0.078	2.9050	0.992
5	0.049	0.054	1.2402	0.871	13	0.073	0.068	3.7422	0.988
6	0.014	0.011	1.2693	0.938	14	0.048	0.060	4.0972	0.990
7	0.063	0.064	1.8547	0.933	15	-0.004	-0.014	4.0997	0.995
8	-0.007	-0.001	1.8631	0.967	16	0.102	0.115	5.7596	0.984

The ACFs and PACFs of correlogram of the squared residual are nearly zero at all lags and the Q-statistics at all lags are not significant with large p-values. This indicates that there is no evidence of rejecting the null hypothesis of no serial correlation. This implies that the residuals of the fitted ARMA model (4.18) are not correlated with their own lagged values. Hence, there is strong evidence of goodness of fit of the ARMA model (4.17) or (4.18).

4.8.1.2 Breusch-Godfrey LM Test for Serial Correlation

The results of Breusch-Godfrey Lagrange Multiplier test for serial correlation have been presented through Table-4.7.

Table-4.7: Breusch-Godfrey Serial Correlation LM Test

Summary	Statistics	Degree of Freedom	Probability
F-statistic	0.261774	F(1,132)	0.6098
$T \times R^2$	0.274932	χ^2 (1)	0.6000

As reported by F-statistic and $T \times R^2$ value and their corresponding probabilities of B-G LM test of Table-4.7, the null hypothesis of no autocorrelation cannot be rejected. The B-G LM test implies that residuals are not serially correlated. Due to the non-presence of serial correlation, the ARMA model of equation (4.17) is considered as the consistent model for forecasting of inflation in Nepalese economy.

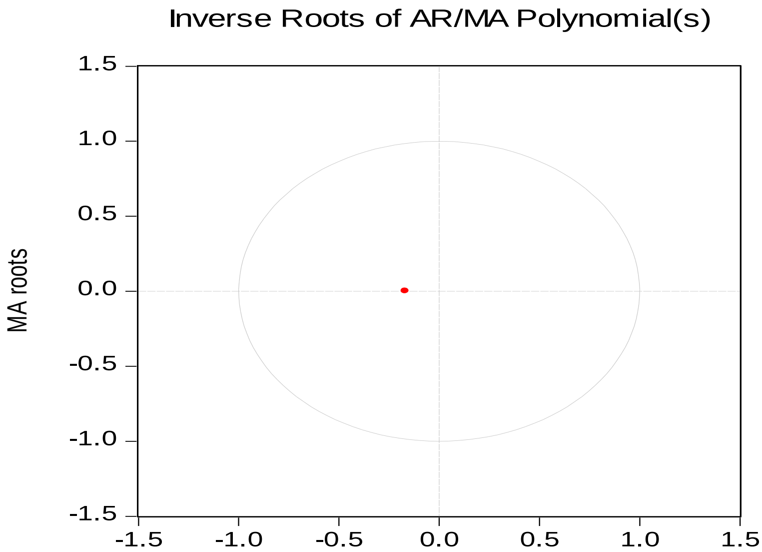
4.8.2 Inverse Roots of ARMA Polynomials

The inverse root of ARMA polynomials is another test for consistency of ARMA model. The modulus of the root represents the consistency of the model. If modulus is less than 1, the fitted ARMA model is claimed to be the model of best of fit. In Table-4.8, the modulus is 0.167 < 1 representing the invertible ARMA model.

Table-4.8: Inverse Roots of ARMA Polynomial

MA Root(s)	Modulus
-0.167624	0.167624

Figure-4.3: Inverse Roots of ARMA Polynomials



The graph view plots the roots in the complex plane where the horizontal axis is the real part and the vertical axis is the imaginary part of each root. If the estimated ARMA process is (covariance) stationary, then all AR roots should lie inside the unit circle. If the estimated ARMA process is invertible, then all MA roots should lie inside the unit circle. Table-4.8 view displays all roots in order of decreasing modulus (square root of the sum of squares of the real and imaginary parts).

For imaginary roots (which come in conjugate pairs), we also display the cycle corresponding to that root. The cycle is computed as: $\frac{2\pi}{\alpha}$, where ,. $\alpha = \tan(\frac{i}{r})$, and i and r are the imaginary and real parts of the root, respectively

4.8.3 ARMA Frequency Spectrum

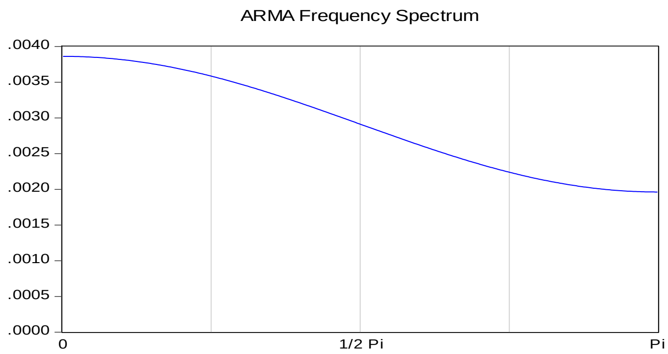
The ARMA frequency spectrum of an ARMA equation represents the range of the estimated ARMA terms in the frequency domain irrespective of time domain. In time domain we examine the autocorrelation functions of the time series, where as in frequency domain we can observe cyclical characteristics of the fitted ARMA model.

The spectrum of an ARMA process can be written as a function of its frequency, λ, where λ is measured in radians, and thus takes values from $-\pi\ to\ \pi$. If a series has strong AR components, the shape of the frequency spectrum will contain peaks at points of high cyclical frequencies. If spectrum density is decreasing, the power is concentrated on low frequency, corresponding to gradual long-range fluctuations.

Contrary to this, if spectrum density is increasing, the power is concentrated on high frequency, which reflects the fact that such a process tends to oscillate.

In Figure-4.4, frequency spectrum tends to fall; meaning the power of frequency spectrum is concentrated on low frequency. This implies that there is a gradual long-range fluctuation of inflation in the economy of Nepal.

Figure-4.4: Graph of Frequency Spectrum of ARMA model (4.13)



4.9 Estimation of ARCH/GARCH Models

4.9.1 GARCH (1,1) Model and Its Stability

Under GARCH modeling, first we have fit GARCH (1,1) model and observed the ARCH effects on it. Table-4.9 presents the results from GARCH (1,1) model using backcast values for the initial variances and computing Bollerslev-Wooldridge standard errors .

The ARCH estimation with 'Variance Equation' contains the coefficients, standard errors,Z-statistics and P-values for the coefficients of the variance equation. The coefficient of ε_t^2 (-1)^2 is the ARCH parameter α and coefficient of GARCH (-1) is the GARCH parameter, β. In the results, the sum $\alpha + \beta < 1$, indicating that volatility shocks of inflation are not persistent. The value of α is significant at less than 1% level as reported by Z-statistic, but the value of β is not significant even at 10 % level.

Table-4.9: Results from GARCH (1,1)

Method: ML - ARCH (Marquardt) - Normal distribution

Bollerslev-Wooldridge robust standard errors & Covariance

Presample variance: backcast (λ = 0.7)

GARCH = $c + \alpha \times \varepsilon^2{}_t(-1)^2 + \beta \times$GARCH(-1)

Variable	Coefficient	Std. Error	Z-statistic	Prob.
$Constant$	c = 0.0006	0.0003	1.9165	0.0553
$\varepsilon_t^2(-1)^2$	α = -0.0843	0.0196	-4.2933	0.0000
$GARCH(-1)$	β = 0.4767	0.3375	1.4124	0.1578

Our next step is to examine the ARCH effect of the estimated GARCH (1,1) model. If serial correlation is present in the fitted model, we can conclude that ARCH effect is prevalent in the estimated GARCH model. Histogram Jarque-Bera test, correlogram test and ARCH LM test are carried out to examine the ARCH effect. Table-4.10 shows the correlogram of squared residuals of estimated GARCH model.

The values of ACFs and PACFs in Table-4.10 do not tend to zero and the Q-statistics are significant at lags above 3 with low/zero probability values. Since the Q-statistics are significant as reported by the corresponding probability values, the null hypothesis of no autocorrelation cannot be rejected. It means there is the presence of autocorrelation in the residuals of GARCH (1,1). This indicates that there is ARCH effect in the estimated GARCH (1,1) model.

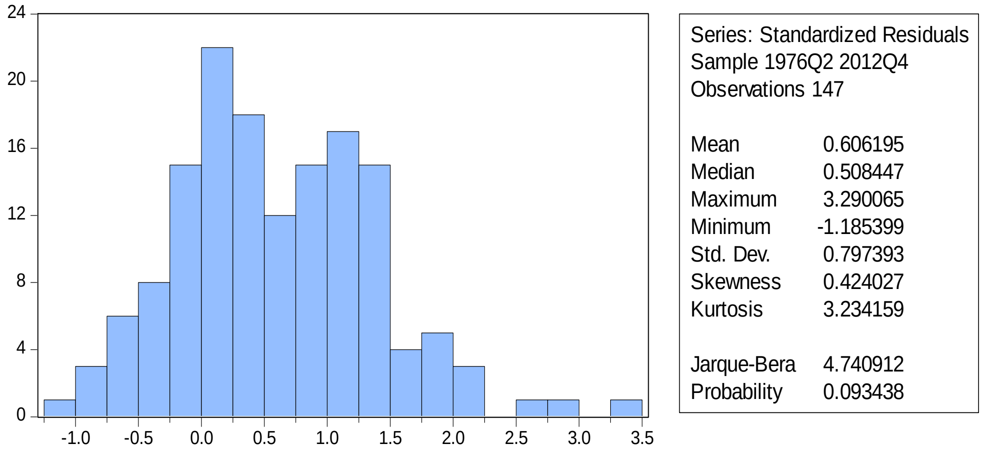
Table -4.10: Correlogram of Squared Residuals of GARCH (1,1) Model

Lag	AC	PAC	Q-Stat	Prob	Lag	AC	PAC	Q-Stat	Prob
1	-0.033	-0.033	0.1609	0.688	7	-0.126	-0.104	37.404	0.000
2	-0.109	-0.110	1.9436	0.378	8	0.478	0.361	73.467	0.000
3	-0.073	-0.081	2.7445	0.433	9	-0.131	-0.115	76.189	0.000
4	0.416	0.406	29.270	0.000	10	-0.135	-0.042	79.081	0.000
5	-0.129	-0.150	31.854	0.000	11	-0.109	-0.049	81.009	0.000
6	-0.141	-0.086	34.933	0.000	12	0.326	0.038	98.212	0.000

After testing ARCH effect by correlogram technique, the next step is to examine the Histogram-normality test of the standardized residuals. Figure- 4.5 shows the Histogram (left panel) and descriptive statistics (right panel). The coefficient of

Kurtosis is 3.23 > 3, which represents leptokurtic, strong indication of non-normality in the distribution of standardized residuals. This non-normality distribution implies that there is ARCH effect in the fitted GARCH (1,1) model. Thus, it can be concluded that the estimated GARCH (1,1) model lacks the stability condition.

Figure-4.5: Histogram-Normality Test of Standardized Residuals of GARCH (1,1)



Since GARCH (1,1) model lacks consistency, it is necessary to change the order of GARCH model and test the consistency. After checking thoroughly, the GARCH (1,2) model is found to be stable model of forecasting inflation in Nepalese economy.

4.9.2 GARCH (1,2) Model

The results from GARCH (1,2) are presented through Table-4.11. From Table-4.11 it is observed that the coefficient of ARCH(1) is significant at less than 1 % level. Likewise, the coefficients of GARCH (1) and GARCH (2) are also strongly significant at less than 1 % level. The sum of ARCH and GARCH coefficient is $\alpha + \beta_1 + \beta_2 = -0.68 < 1$, which implies that volatility shocks in inflation are not persistent.

Table-4.11: Results from GARCH (1,2) Model

Bollerslev-Wooldridge robust standard errors & covariance

Presample variance: backcast (parameter = 0.7)

GARCH = c + $\alpha \times \varepsilon_t^2$ (-1) + $\beta_1 \times$ GARCH(-1) + $\beta_2 \times$ GARCH(-2)

Variable	Coefficient	Std. Error	Z-statistic	Prob.
C (constant)	c = 0.0018	0.0002	8.3807	0.0000
ε_t^2 (-1)	α =-0.1369	0.0315	-4.3387	0.0000
$GARCH(-1)$	β_1 = 0.4075	0.0246	16.5287	0.0000
GARCH(-2)	β_2 = -0.9583	0.0300	-31.8391	0.0000

The next step is to examine the stability condition of estimated GARCH (1,2) model. First we examine the Histogram-Normality test of the residuals of GARCH (1,2). Figure-4.6 shows the Histogram and related descriptive statistics of normality test of residuals of GARCH (1,2).

Coefficient of Kurtosis is 3.02~ 3. The Jarque-Bera statistic is 0.013, which is not significant. Very low value of Jarque-Bera statistic and Kurtosis coefficient (=3) indicate that the residuals of GARCH (1,2) are normally distributed. The Histogram-Normality test supports the stability of GARCH (1,2) model because there is no ARCH effect.

Another important test for the stability of GARCH model is GARCH LM test. Table-4.12 presents the results from GARCH LM test.

Figure-4.6: Histogram-Normality Test of Residuals of GARCH (1,2)

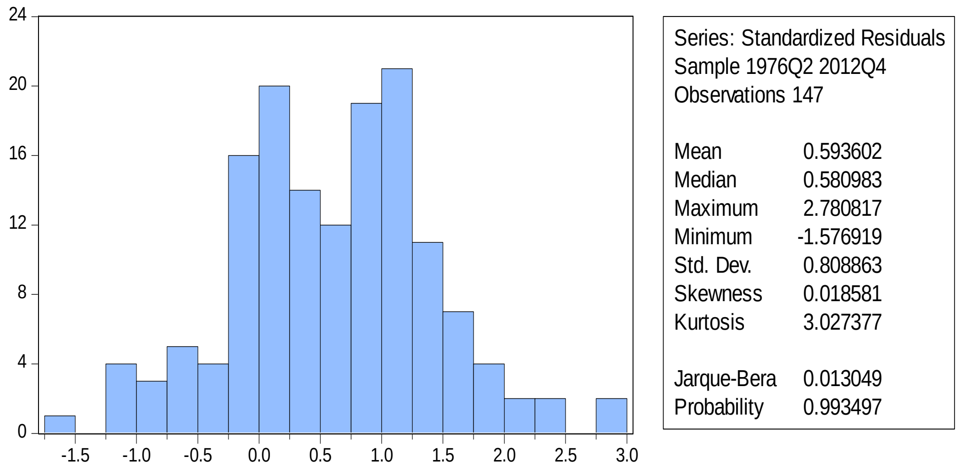


Table-4.12: GARCH LM Test

(Heterossedasticity Test: ARCH)

Summary	Statistics	Degree of Freedom	Probability
F-statistic	0.1142	F(1,144)	0.7358
$T \times R^2$	0.1157	χ^2 (1)	0.7337

Test Equation

Dependent Variable: $weighted\ \varepsilon^2{}_t$

Variable	Coefficient	Std. Error	t-Statistic	Prob.
$Constant\ (C)$	0.9769	0.1400	6.9752	0.0000
$weighted\ \varepsilon^2{}_t$(-1)	0.0282	0.0834	0.3380	0.7358

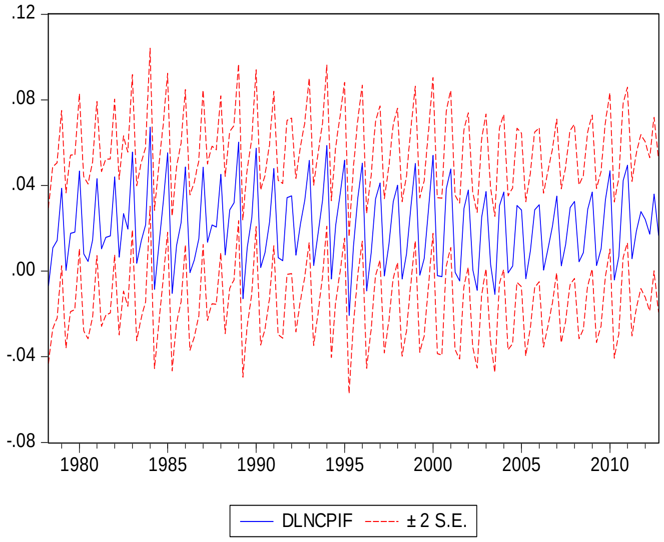
The null hypothesis of no ARCH up to order q cannot be rejected as reported by probability of F-statistic and Chi-Square statistic shown by upper part of Table-4.12. The absence of ARCH effect is associated with stability of GARCH model.

Thus, Histogram-Normality test and GARCH LM test are good indications that our estimated GARCH (1, 2) is a stable and consistent model for forecasting inflation for the economy of Nepal.

4.10 Forecasting Inflation by ARMA and ARCH Process

The most important use of ARMA models is to forecast future values of the sequence of a dependent variable. Since our objective is to examine the formation of inflation expectation based on its own history, it is necessary to test the performance of our ARMA in accordance with model (4.17). This is done by applying static forecasting, or one step ahead forecasts, and presented in the Fig. 4.7.

Figure-4.7: Static Forecast of ARMA{(4,5,6,8),1} Model With the Structural Break



Forecast: DLNCPIF
Actual: DLNCPI
Forecast sample: 1976Q1 2012Q4
Adjusted sample: 1978Q2 2012Q4
Included observations: 139

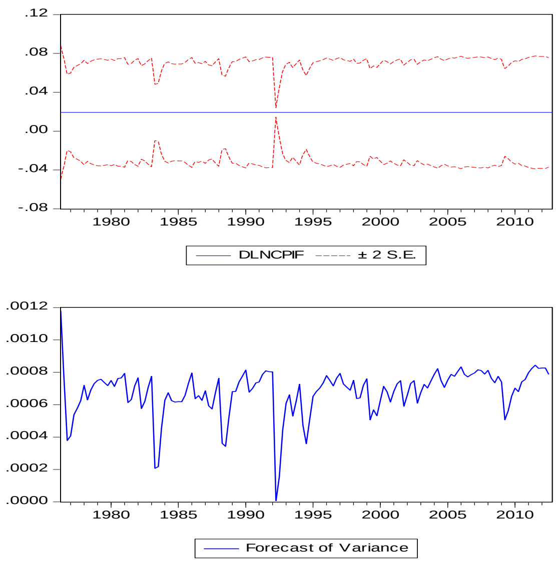
Root Mean Squared Error	0.017632
Mean Absolute Error	0.013432
Mean Abs. Percent Error	123.1786
Theil Inequality Coefficient	0.288289
Bias Proportion	0.000000
Variance Proportion	0.145032
Covariance Proportion	0.854968

The first two forecast error statistics depend on the scale of the dependent variable. These can be used as a relative measure to compare forecasts for the inflation series across different models; the smaller the error, the better the forecasting ability of that model according to that criterion. Theil (1961) inequality coefficient always lies between zero and one. The estimated ARMA model does not indicate a perfect fit as indicated by Theil inequality coefficient, which is 0.28 representing the moderate degree of fit of the model. The mean squared forecast error can be decomposed as: the bias proportion, which tells us how far the mean of the forecast is from the mean of the actual series; the variance proportion, which tells us how far the variation of the forecast is from the variation of the actual series; and the covariance proportion, which measures the remaining unsystematic forecasting errors. Note that the bias, variance, and covariance proportions add up to one. In our model, the sum of these three coefficients is equal to unity. (Quantitative Micro Software, LLC: 2009, Eviews 7: user's Guide II)

In our model, the bias proportion is extremely small, indicating that the mean of the forecasts does a decent job of tracking the mean of the dependent variable. In other words, since the extent to which average values of simulated and actual series deviate from each other is negligible, there is no indication of systematic error in the model. Furthermore, somewhat larger, but still very small, the variance proportions indicates that most of the bias is concentrated on the covariance proportions. Hence, our one-step ahead forecast of ARMA{(4,5,6,8),1} model of inflation seem to perform reasonably well.

We have also applied one-step ahead forecast on the estimated GARCH (I,2) model described **In *Section 4.14.2***. The procedure includes computing static forecast of the mean, its forecast standard error, and the conditional variance. The upper part of the Fig. 4.8 shows the forecast of the dependent variable from the mean equation together with the two standard deviation bands. The lower part of the graph is the forecast of the conditional variance.

Figure-4.8: One-Step Ahead Forecasts on GARCH (1,2)



Forecast: DLNCPIF	
Actual: DLNCPI	
Forecast sample: 1976Q1 2012Q4	
Adjusted sample: 1976Q2 2012Q4	
Included observations: 147	
Root Mean Squared Error	0.026272
Mean Absolute Error	0.021354
Mean Abs. Percent Error	238.7373
Theil Inequality Coefficient	0.501565
Bias Proportion	0.001599
Variance Proportion	NA
Covariance Proportion	NA

As compared GARCH (1,2) to ARMA{(4,5,6,8),1}, it is found to be unreasonably fit whose Theil Inequality Coefficient is 0.5 (very high). For the reasonably fit of the model, the sum of bias proportion, variance proportion and covariance proportion must be one, but here the coefficients of variance proportion and covariance proportion are not available. Therefore, nothing can be interpreted from forecast results of GARCH (1,2) model and it is not comparable to ARMA{(4,5,6,8),1} model. So, further comparison between ARMA and GARCH models is not necessary. Thus, ARMA {(4,5,6,8),1} is far better efficient for forecasting inflation for the economy of Nepal.

4.11 Conclusion of Chapter Four

The following are the conclusions of Chapter Four.

- The Consumers' Price Index in logarithmic form $LnCPI_t$ is found to be non-stationary at level but it is stationary at its first difference.
- ARMA{(2,4,5,6,8),1}model for $dLnCPI_t$ is found to be efficient as indicated by D-W statistic. However, the coefficient of AR(2) term is not statistically significant. As a result, this model still lacks the robustness.
- AR(2) term of the ARMA model needs omission as reported by redundant test.
- After dropping $dLnCPI_{t-2}$ from ARMA model, the new estimated ARMA{(4,5,6,8),1} is found to be efficient due to the non-presence of serial correlation problem. Additionally, this model is found to be efficient as modulus of inverse roots lies inside unit circle.
- *The inflation of Nepal during the study period is found to be long-range fluctuating as reported by Frequency Spectrum of estimated* $ARMA\{(4,5,6,8),1\}$ *model.*
- The GARCH(1,1) model for inflation forecasting is not found to be stable due to the presence of ARCH effect as reported by Correlogram of Squared Residuals and Histogram Normality (J-B) test.
- GARCH(1,2) model of forecasting inflation is found to be efficient model as the residuals are not autocorrelated.
- ARMA{(4,5,6,8),1} model is found to be more efficient than GARCH(1,2) model for forecasting inflation in Nepal. It is because the Theil inequality coefficient under ARMA{(4,5,6,8),1} is smaller (0.28) than that of GARCH(1.2) model with Theil inequality coefficient 0.5.

Thus, ARMA{(4,5,6,8),1} model is recommended for forecasting of inflation in the economy of Nepal.