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Volatility Clustering of Inflation in Nepal: An ARCH Specification

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Abstract

This paper investigates the volatility clustering of inflation in Nepal using Autoregressive Conditional Heteroscedasticity (ARCH) method developed by Engel (1982). Utilizing 127 quarterly observations of the National Urban Consumer Price Index (CPI) ranging from 1975:QI-2006:IVQ, clustering of inflation is found in ARCH(2) specification. Therefore, it is revealed that inflation in Nepal is volatile which leads to the prevalence of inflation uncertainty and hence an emergence of unanticipated inflation.

Background

Reducing variability of inflation and controlling inflation mean are the two major challenges for the policymakers as well as economic agents. High inflation accompanied with excessive variability lead to uncertainty in economic decision makings and hence is undesirable for the sustained economic growth. Nevertheless, clustering of variability is recognized as the stylized property present in most macroeconomic and financial time series (Rama, 2005). It signifies periods in which it shows wide swings for an extended time period followed by the periods of relative calm. Volatility clustering exhibits phases of relative tranquility followed by the period of high volatility (Enders, 2004). Specific news and exogenous economic events can last for sometime resulting to large positive and negative observations clustering each other (Franses, 1998). The differences of variances that result to volatility clustering from period to period arise from structural changes as well as policy shifts in an economy (Ramanathan, 2002).

If the variance of the errors term is not a function of an independent variable but instead varies over time in a way that depends on how large the errors were in the past, then there is an evidence of a "clumping" of large and small errors. In modeling such a behavior of time series, one is likely to find periods of high volatility (i.e., larger errors) followed by the periods of low volatility (i.e., smaller errors). This is a phenomenon of heteroscedasticity presented in time series in which the variance of the regression error depends on the volatility of the errors in the recent past leading to clustering of volatility (Pindyck and Rubinfeld, 1998). A variable having variable and non-reverting variance is called heteroskedastic

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variable as against a constant variance in homoskedastic variable.

Recent analyses of inflation, exchange rates and market returns have found abundant evidences of clustering of large and small disturbances which suggest a form of heteroscedasticity of variance in which the variance of the disturbance depending on size of the preceding disturbances (Green, 2003). The understanding of volatility clustering is important to the investors, decision makers, policy makers, importers, exporters as well as the traders in foreign exchange market. For some decision makers, inflation itself may not be that much bad, but its variability is bad because it makes financial planning difficult (Gujarati, 2004). An investment decision is vulnerable due to high volatility of inflation.

The study of volatility clustering in inflation is important because it gives an understanding about the identification of variability in inflation and hence making decision to the economic agents. Further, it helps to know the effectiveness of specific policies of the government as well as monetary authority. A worldwide experience shows that fiscal policy is pertained to the objective of economic growth whereas monetary policy to the stability objective (inflation and balance of payment stability). An optimal policy-mix in coordination with the government and the monetary authorities is preferred especially in the developing economies. Therefore, the identification of volatility clustering of inflation is important to signal out appropriate policy-mix for the government and monetary authorities.

Review of Literature

One of the important assumptions of the Classical Linear Regression Model (CLRM) is that the variance of each disturbance term u_i, which is conditional on the chosen values of the explanatory variable, is some constant number equal to σ^2, that is, constant variance (Madala, 2002). This is the assumption of homoscedasticity or equal variance of a variable (Gujarati, 2004). If heteroscedasticity presents, the expected value of error term u_i is equal to variable variance, that is, $E(u_i^2) = \sigma_i^2$. Many macroeconomic and financial time series characterize not only varying means but also variable variances. The latter implies exhibiting phases of relative tranquility followed by period of high volatility (Enders, 2004).

If the mean, variance and autocovariance (at various lags) of a time series remain the same, no matter at what point we measure them, the time series is said to be stationary or time-invariant series (Pindyck and Rubinfeld, 1998)[1]. Such a series is characterized by mean reversion and fluctuating around the mean with constant amplitude (Cuthbertson, Hall and Taylor, 1995). However, a nonstationary time series has varying mean, variance and autocovariance. The latter time series may have either time-varying mean or a time-varying variance or both. Heteroscedasticity of a variable falls under the category of variance non-stationary time series but not the time-varying mean.

Ordinary Least Square (OLS) estimation places more weights on the observations with

[1] Let Y_t be a stochastic time series (i.e. the observations are considered as particular realization of the process). Their mean $E(Y_t)=\mu$, variance $Var(Y_t)=E(Y_t-\pi)^2=\sigma^2$ and covariance $\gamma_k= E[(Y_t-\mu)(Y_{t+k}-\mu)]$ are time invariant.

large error variances than on those with small error variances in case the observations showing heteroscedastic pattern. The regression line is drawn on the basis of minimization of the total sum-of-squared residuals, and this can best be accomplished by guaranteeing a very good fit in the large-variance portion of the data. Therefore, though OLS parameters estimators are unbiased and consistent, they are not efficient, that is, the variances of the estimated parameters are not the minimum variances (Nachane, 2006).

Engle (1982) developed a widely used model of heteroscedastic variance, popularly known as Autoregressive Conditional Heteroscedasticity (ARCH) model, to identify the presence of heteroscedastic conditional variance. The measurement of volatility clustering (clustering of variance conditional on time) is modeled as the ARCH phenomenon. The term "Autoregressive (AR)" in the model signifies the error variance at time *t* depending on previous squared error terms or Markov Autoregressive scheme in p^{th} order. If the heteroscedastic variance at time *t* is conditional on those in previous periods, it is said to be "Conditional Heteroscedasticity (CH)" of variance.

The rational expectations hypothesis argues that the expected or conditional mean and variance are two important statistics that are thought to be superior to unconditional mean and variance. While forecasting time series, rational agents use the conditional rather than the unconditional distribution of the series because such distributions do not waste useful information (Lucas, 1976). For instance, asset holders are interested in the volatility returns over the holding period, not over some historical period. This is a forward-looking view of risk associated with holding a particular asset (Enders, 2004). A portfolio manager or asset holders are interested to know risk (measured by variance) which is conditional over the holding period.

The ARCH model is used to find the autocorrelation of data series in the variance σ^2 at time *t* with its values lagged one or more periods[2]. A common feature of model seems to be the "Switching" of the market between periods of high and low activity with long duration of period (Rama, 2005). An analysis of autocorrelation in time series has been given the name of ARCH and GARCH (Gujarati, 2004). If the error variance is related to the squared error term in the previous term, variances are modeled under ARCH criterion. If the error variance is related to squared error variance terms several periods past, variances are modeled under Generalized Autoregressive Conditional Heteroscedasticity (GARCH) criterion. Engle (1982) suggested the ARCH model as an alternative to the standard time series treatments (Green, 2003). Engle (1982, 1983) and Cragg (1982) found evidence that for some kinds of data, the disturbance variances in time-series models were less stable than usually assumed. If data show variance nonstationary, there is no easy way to correcting this condition other than through an ARCH (DeLurgio, 1998).

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[2] Since σ^2 is not directly observable, it can be derived by calculating estimated variance residual var($\hat{u}_t$) applying O LS method to the regression as: $Y_t = \alpha_0 + \alpha_1 X_t + \alpha_2 X_t ... \alpha_k X_{kt} + u_t$. Under the assumption that $u_t = N[0(\alpha_o + \alpha_1 u_{t-1}^2)]$ that is, u_t is normally distributed with zero mean and $\text{var}(u_t) = \sigma_t^2 = (\alpha_o + \alpha_1 u_{t-1}^2)$ that, the variance follows an ARCH(1) process. The Estimable equation for ARCH effect is: $\hat{u}_t^2 = \hat{\alpha}_o + \hat{\alpha}_1 \hat{u}_{t-1}^2 + \hat{\alpha}_2 \hat{u}_{t-2}^2 ... + \hat{\alpha}_p \hat{u}_{t-p}^2$ where, if there is no autocorrelation in the error variance, we have null hypothesis $H_0: \alpha_1 = \alpha_2 = ... + \alpha_p = 0$ in which case var $(u_t) = \alpha_0$, and it is not found the ARCH effect.

A time series $\{y_t\}$ will be heteroscedastic itself it there is conditional heteroskedasticity in error term $\{\varepsilon_t\}$. Thus ARCH model is able to capture periods of tranquility and volatility in the $\{y_t\}$ series. If the variance of $\{\varepsilon_t\}$ sequence is not constant, the sustained movements in the variance are estimated using Autoregressive Moving Average (ARMA) model (Enders, 2004)[3]. If the conditional variance follows a first-order autoregressive process denoted by AR(1), then the conditional variance of ε_t is dependent on the realized value of ε_{t-1}^2 (Box and Jenkins, 1970). If the realized value of is ε_{t-1}^2 large, the conditional variance in 't' will be large as well. The coefficients are restricted to $\gamma_0 > 0$ and $0<\lambda_1<1$.[4]

The extension of the ARCH(1) model is a more general model of ARCH (q) process with several lags as: $\hat{\varepsilon}_t^2 = \gamma_0 + \lambda_1\hat{\varepsilon}_{t-1}^2 + \lambda_2\hat{\varepsilon}_{t-2}^2 + ... + \lambda_q\hat{\varepsilon}_{t-q}^2 + v_t$. This is an estimable ARCH model.

Engle's (1982) paper considered the residuals of a simple model of the wage/price spiral for the U.K. over the 1958:II-1977:II period. He specified inflation equation as: $\pi_t = \psi_0 + \psi_1\pi_{t-1} + \psi_1\pi_{t-4} + \psi_1\pi_{t-5} + \psi_1 r_{t-1} + \varepsilon_t$, that is, current inflation is determined by lagged inflation rates of π_{t-1}, π_{t-4}, and $\pi_{\tau-5}$ and the previous period's real wage r_{t+1}. In testing for ARCH errors, an ARCH(4) error is found significant with an specification as: $h_t = \gamma_0 + \gamma_1(\psi_1\varepsilon_{t-1}^2 + \psi_2\varepsilon_{t-2}^2 + \psi_3\varepsilon_{t-3}^2 + \psi_4\varepsilon_{t-4}^2)$. The point estimate of γ_1=0.955 indicates an extreme amount of persistence. He found inflation rate is a convergent process. Using the calculated values of the $\{h_t\}$ sequence, Engle found that the standard deviation of inflation forecasts more than doubled as the economy moved from the "Predictable sixties into the chaotic seventies".

Engle's original work (his conditional variance model is an AR process) was extended by Bollerslev (1986) incorporating a technique that allows the conditional variance to be an ARMA process. The generalized ARCH (p,q) model is called GARCH (P,q).[5] This leads to the generalized autoregressive conditional heteroscedasticity (GARCH) model. The reason behind extending the AR process is to resolve the estimation problem in a distributed lag model consisting large number of parameters. Many of these lagged values of ε_t^2 can be replaced by one or two lagged values of variance (the GARCH term). The benefit of GARCH (p,q) is that a high-order ARCH model may have a more parsimonious GARCH representation that is much easier to identify and estimate.

Using quarterly data over the 1948:II to 1983:IV quarters, Bollerslev (1986) calculated the inflation rate as the logarithmic change in the U.S. GNP deflator. Bollerslev estimated

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3 Let $\{\hat{\varepsilon}_t\}$ be the estimated residuals from the model $y_t = \lambda_0 + \lambda_1 y_{t-1} + \varepsilon_t$ so that the conditional variance of y_{t+1} is $y_{t+1}|y_t) = E_t[y_{t+1} - \lambda_0 - \lambda_1 y_t)^2]$ or var $y_{t+1}|y_t) = E_t[\varepsilon_{t+1})^2$ where $E_t[\varepsilon_{t+1})^2$ is equal to constant σ^2 .

4 In order to ensure that the conditional variance is never negative and to ensure the stability of the process, it is necessary $_{y0} > 0$ andλ_1 is$0 < \lambda_1 > 1$.

5 The general GARCH (p,q) model is : $h_t = \lambda_o \sum_{i=1}^{q} \lambda_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \gamma_i h_{t-i}$ It is written in terms of polynomials in the lag operator as:$\sigma_t^2 = \alpha_0 + D(L)\sigma_t^2 + A(L)\varepsilon_t^2$. Thus, the conditional variance of ε_t is the ARMA (p,q) process. GARCH (p,q) allows for both AR and MA components in the heteros cedastic variance. If p=0 and q=1, the first-order ARCH model is simply GARCH (0,1) model. Hence, if all values of γ_i equal zero, the GARCH (p,q) model is equivalent to an ARCH (q) model.

four-order autoregressive model similar to the model specified by Engle. The ACF and PACF did not exhibit any significant coefficients at the 5 percent level in Bollerslev's model. However, in terms of error variance, Bollerslev's model is quite different from that of Engle. Variance h_t is assumed constant in Engle's model whereas in Bollerslev's model it is assumed geometrically declining weighted average over the last eight quarters[6].

Using quarterly data from 1960:I to 1984:II, Engle, Lilien, and Robins (1987) analyzed volatility of stock market returns using ARCH-M model. They extended the basic ARCH framework to allow the mean of a sequence depending on its own conditional variance. This class of model is called the ARCH in mean (ARCH-M) model, particularly suited to the study of asset markets. They took the excess yield on six-month treasury bills for the analysis[7]. They found marked volatility during post-1979 period. To test for the presence of ARCH errors, the squared residuals were regressed on weighted average of past squared residuals[8]. The LM test for the restrictions $\alpha_1 = 1$ yields a value of $TR^2=10.1$, which has a χ^2 distribution with one degree of freedom is 6.635; hence, showing strong evidence of hetreoskedasticity.

Bollerslev and Ghysels (1996) analyzed the exchange rate volatility for the Deutchmark/ Pound using maximum likelihood estimate of the GARCH(1,1) model and concluded that there is evidence of GARCH effects in the residuals[9]. They used 1974 data on the daily percentage nominal returns for the Deutchmark/Pound exchange rate. Regression of the squares of these residuals on a constant and ten lagged squared produced an R^2 of 0.025. With T=1964, the χ^2 statistic is found to be 49.60, a value larger than the table value of 18.31 concluding an evidence of GARCH effects in these residuals.

Summing up, ARCH model has proven to be useful in studying the wage/price spiral Engles (1982). ARCH model is useful in studying the volatility of inflation Bollerslev (1986) Coulson and Robins (1985). Engle, Hendry, and Trumbull, (1985) used ARCH model to study term structure of interest rates. Moreover, an analysis of volatility of stock market returns was made by Engle, Lilien, and Robins (1987) using same model. Attempts were made to model the behavior of foreign exchange markets by Domowitz and Hakkio (1985) and Bollerslev and Ghysels (1996) using ARCH model. Holt and Aradhyula (1990) applied GARCH model with the theoretical framework that rational expectations are assumed

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6 The inflation rate predictions of the two models should be similar, but the confidence intervals surrounding the forecasts will differ. Engle's ARMA model yields a confidence interval that expands during periods of inflation volatility and contracts in relatively tranquil periods. He estimated following GARCH(1,1) model: $h_t = \gamma_o + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 h_{t-1}$

7 $y_t = (1+R_t)^2 - (1+r_{t+1})(1+r_t)$ which is approximately equal to $y_t = 2R_t - r_{t+1} - r_t)$, where, y_t stands for excess yield, r_t denote the quarterly yield on three-month treasury bill held from t to $(t+1)$, and R_t denotes the quarterly yield on a six-month treasury bill.

8 $h_t = \alpha_0 + \alpha_1 \sum_{i=1}^{q} \lambda_i \varepsilon_{t-i}^2$

9 They used GARCH (1,1) model as; $y_t = \pi + \varepsilon_t$, $E[\varepsilon_t I \varepsilon_{t-1}]=0$, $Var[\varepsilon_t I \varepsilon_{t-1}] = \sigma_t^2 = \alpha_0 + \alpha \varepsilon_{t-1}^2 + \delta \sigma_{t-1}^2$ The least squares residuals for this model are simply $\varepsilon_t = y_t - \bar{y}$.

to prevail in the agricultural sector, which is in contrast to the cobweb model. Connolly and Stivers (2005) found that volatility clustering tends to be stronger when there is more uncertainty and disperse beliefs about the market's information signal. Keeping these findings in view, this study attempts to examine volatility clustering of inflation in Nepal and specify ARCH order. Prior to utilizing CPI series for ARCH specification, unit root test is adopted to examine stationarity of the series.

Methodology

This paper attempts a uni-variate analysis. Among the various alternative price variables available in Nepal, Consumer Price Index (CPI) has been used. Quarterly time series of CPI ranging from 1975 to 2006 consisting of 127 observations are taken for the analysis.

In order to test whether there is variance non-stationary in level form data, unit root test of log of CPI is made using Augmented Dickey Fuller (ADF) test with testable equation as $\ddot{A}Y_t=\beta 1+\beta_2 t+\delta Y_{t-1}+\alpha \ddot{A}Y_{t-1}+\varepsilon_t$ (Dickey and Fuller, 1979). If the computed absolute value of the tau statistic $/\tau/$ given by ADF statistic exceeds the table MacKinnon critical $/\tau/$ values, we reject null hypothesis $\delta = 0$ of unit root or accepting alternative hypothesis of time series as stationary.

The volatility of CPI series will be derived on the basis of regression of CPI on intercept as $Y_t=\beta_1+u_t$. The intercept will give mean inflation over the sample period. The residual derived from the given regression equation is achieved $Y_t=\beta_1+u_t$. The coefficient of variation of the inflation series gives single value to measure variation/volatility of the series. In order to model volatility under ARCH framework, residual series is squared and modeled for volatility. ARCH effect is tested under the null hypothesis that there is no ARCH effect, that is $H_0 : \alpha_1 = \alpha_2 = ... = \alpha_p = 0$ against there is ARCH effect, that is, $H_0 : \alpha_1 = \alpha_2 = ... = \alpha_p \neq 0$ using the model: $\hat{u}_t^2 = \alpha + \hat{u}_{t-1}^2 + \hat{u}_{t-2}^2 ... \hat{u}_{t-p}^2 + v_i$. The normality test of the OIS residual is made using Jarque-Bera (JB) test of normality, that is, $JB=n\left[\frac{S^2}{6}+\frac{(K-3)^2}{24}\right]$ where, n=sample size, S= skewness coefficient, and K=kurtosis coefficient. It is a test of the joint hypothesis that S and K are 0 and 3 respectively. In that case the value of the JB statistic is expected to be 0 to confirm normality.

Results of the Analysis

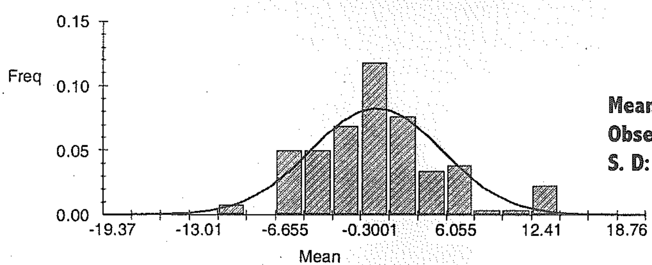
Examining volatility clustering of inflation in Nepal using ARCH model as an objective of this paper, 127 observations of overall consumer price index series have been utilized for the same. The period of analysis ranges from the first quarter of 1975 to the third quarter of 2006. A reasonably large number of the sample observations used for the analysis is thought to be representative of population parameter. The empirical test of ARCH effect of inflation series validates whether inflation in Nepal is highly volatile or not so that economic agents experience uncertainty in economic decision-making. Is inflation volatility clustering creating the problem of uncertainty in the economic activities? In order to find the valid answer of this issue, the ARCH model is applied to examine the volatility clustering of inflation in Nepal.

The analysis starts with graphical depiction of heteroscedasticity (unequal spread) of variance of inflation series for the overall sample as well as two sample periods breaking the overall sample from the year 1990. Variance analysis of CPI follows with test of stationary of level and first difference of CPI to identify mean and variance stationary of the time series in the subsequent section. If first difference of CPI series is found to be variance non-stationary, then it is utilized for ARCH specification in subsequent section followed by conclusion of the study.

A) Variance Measurement of CPI

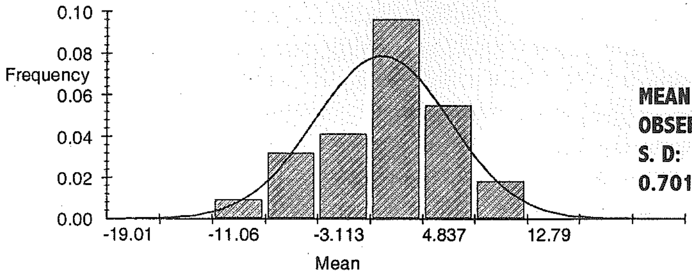
The coefficient of variance is one statistical tool to measure variability of data. Hetroscadasticity may occur as a result of the presence of outliers in the data, skewness in the distribution, incorrect data transformation and functional and misspecification of model. When there is variability in data series, it is called volatility in that series. Using the estimated residuals from the regression of inflation on intercept using 124 observations (four observations are redundant from total observations because the study uses percentage change of quarterly CPI series), inflation is not found to be symmetrically distributed as shown in Diagram 1.

Diagram 1 Histogram of Residuals and the Normal Density (Sample: 1975-2006)



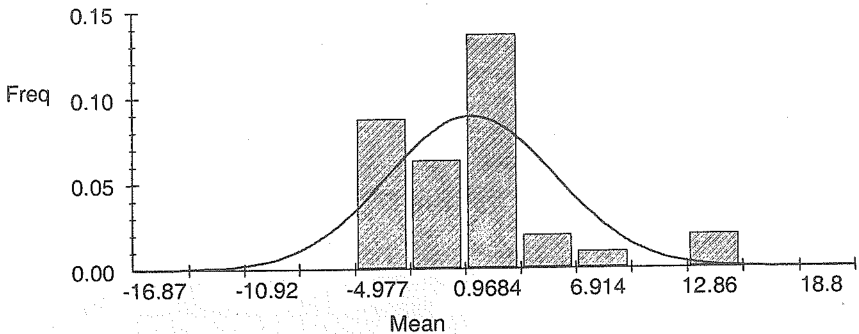
Mean: 8.4709 Jarque-Bera: 8.4105
Observations: 124
S. D: 8.4308 Probability: 0.0149

Diagram 2 Histogram of Residuals and the Normal Density (Sample: 1976-1990)



MEAN: 9.5694 JARQUE-BERA: 0.7101
OBSERVATIONS: 55
S. D: 5.0775 PROBABILITY: 0.7011

Diagram 3 Histogram of Residuals and the Normal Density
(Sample: 1991-2006)



Mean: 7.5946 Jarque-Bera: 41.6345
Observations: 69
S. D: 4.4784 Probability:0.00000

An application of the Jarque-Bera (JB) test also supports the finding that the errors are not normally distributed. The finding of JB statistic of 8.4105 with the probability of obtaining such a statistic under the normality assumption is merely 1 percent rejects the hypothesis that the errors are normally distributed. Similarly, the distribution of the residuals for the two periods after breaking the whole sample period from the year 1990, where the former period characterizing pre-liberalization and the latter post-liberalization, the distribution found to be more symmetrical during pre-liberalization than that of the post-liberalization as shown in the Diagram 2 and 3 respectively. It is because the probability of JB statistic getting symmetrical distribution is equal to zero implying high variability during the latter period. What it is revealed from the above examination is that there is a presence of variability in the distribution of inflation in Nepal.

B) Test of Stationarity

Stationarity test of time series is used to examine whether the mean of the series is stationary or not. The rationale for testing stationarity of CPI series in ARCH model in this paper is that a mean stationary data series will be examined for variance stationarity using ARCH model. As shown in Diagram 4, the trend of log of CPI is upward moving representing variable mean, that is, CPI in its level form is non-stationary or random walk or it has unit root problem. The relationship between the variables using non-stationary data may show spurious result and be against CLRM assumption (Granger and Newbold, 1974). Unit root test gives quantitative test of stationarity in data series. In view of the non-stationary characteristics of most of the macroeconomic time series in their level form, a test result of stationarity on CPI series is presented in Table 1.

Diagram 4: Log of CPI, 1975:QI - 2006: QIII (Quarterly)

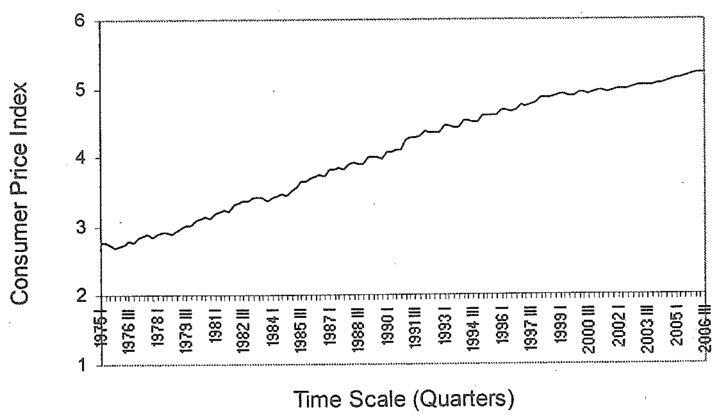


Table: 1 - Unit Root of log of CPI (1975:Q1-2006QIII)

Specification Equation.	Variables	Constant β_1	Trend β_2	One period lag of dep. Variables[1] α_i	ADF Statistics "δ"	MacKinnon Critical Value 1%	5%	10
(1)	Ln CPI[2]	No	No	No	5.6945	-2.5820	-1.9425	-1.6170
(2)	Ln CPI[3]	Yes	No	No	-0.9259	-3.4831	-2.8844	-2.5788
(3)	Ln CPI[4]	Yes	Yes	No	-1.3736	-4.0331	-3.4458	-3.1476
4th	Ln CPI[5]	Yes	Yes	Yes	-0.9005	-4.0337	-3.4461	-3.1477
5th	Δ Ln CPI[6]	Yes	No	No	-13.3935	-3.4835	-2.8845	-2.5729
6th	Δ Ln CPI	Yes	Yes	No	-13.4261	-4.0337	-3.4461	-3.1477

Notes for Table 1

1. In a finite lag model, only one period lag has been considered here because it solves the problem of serial correlation.
2. Model with absence of constant, trend and one period lag of dependent variable ('no', 'no', 'no') is called RWM without drift parameter. If null hypothesis is rejected in the case of RWM model without drift (i.e. $\beta_1=0$, $\beta_2=0$, $\beta_3=1$) it signifies that Y_t is a stationary time series with zero mean.
3. Model with presence of constant and absence of trend and one period lag of dependent variable ('yes', 'no' 'no') is called RWM with drift parameter. If the null hypothesis is rejected in the case of RWM model with drift (i.e. ($\beta_1\neq0$, $\beta_2=0$, $\beta_3=1$), then it implies that Y_t is stationary time series with a non-zero mean [$\beta_{1/(1-P)}$].

4. Model with presence of constant and trend but no one period lag of dependent variable ('yes', 'yes' 'no') is RWM with drift and trend parameter. If the null hypothesis is rejected in the case of RWM model with drift around a stochastic trend ($\beta_1 \neq 0$, $\beta_2 \neq 0$, $\beta_3 < 1$), then it implies that Y_t is stationary around a deterministic trend.
5. Model with presence of constant and trend but no one period lag of dependent variable ('yes', 'yes' 'no') is RWM with drift and trend parameter. If the null hypothesis is rejected in the case of RWM model with drift around a stochastic trend ($\beta_1 \neq 0$, $\beta_2 \neq 0$, $\beta_3 < 1$), then it implies that Y_t is stationary around a deterministic trend.
6. For the first difference stationary, unit root is tested on $\Delta y_t = \beta_1 + \delta y_{t-1} + u_t$ where $\Delta \hat{Y}_t$ is Δ of ΔY.

Taking null hypothesis as CPI is non-stationary, that is, $\delta = 0$ and alternative hypothesis as CPI is stationary, that is, δ` "0, null hypotheses are accepted in the specification of equations with RWM with rift, RWM with drift and trend and RWM with drift, trend and one period lag of dependent variable in equation (2), (3) and (4) respectively. The absolute value of MacKinnon critical values for these three equations are greater than the ADF statistic (table value) resulting into the acceptance of null hypothesis that they are non-stationary. Therefore, CPI series shows non-stationarity in its level form. However, RWM without drift parameter as shown in specification of equation (1) is ruled out because the estimated δ has got positive sign.

In the first difference form, macroeconomic variables are generally found to be stationary (Nelson and Plosser 1982). As shown in specification of equation (5) in Table 1, the first difference of CPI series is found to stationary. However, first difference data may not necessarily be variance stationary. Therefore, instead of modeling the level form of CPI series, its first difference is used to examine volatility clustering applying ARCH model. The first difference of log of CPI (logarithm to the power base 2.718281) series shows a considerable clustering of volatility during the initial period of the study to the early nineties as shown in the Diagram 5. The volatility clustering is more visible if we inspect the plotting of the residuals taken from first the difference of log of CPI as shown in Diagram 6.

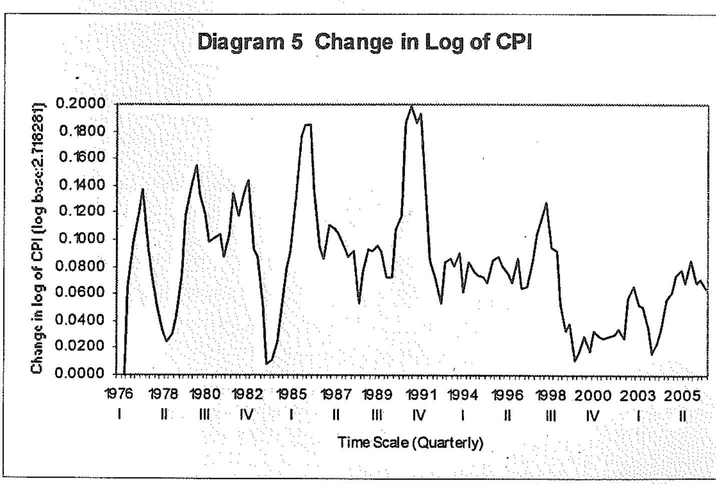
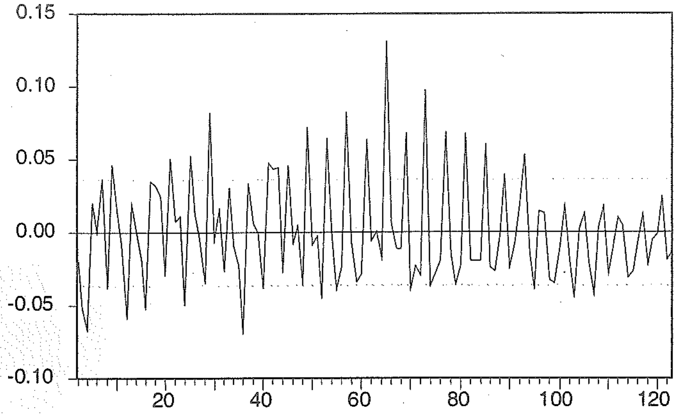


Diagram 6 : Residual of 1st diff. log of CPI

In summing up, log of CPI shows random walk or is non-stationary series. Transforming the level data of CPI into first difference form (relative change or percentage change form), it is found to be stationary. However, first difference data show high volatility as shown in the Diagram 6. The volatility clustering is persistent during late eighties. Considering the possibility of volatility clustering in inflation series, ARCH effect is examined to find volatility clustering of inflation in Nepal.



C) Modelling Volatility Clustering of Inflation

Most of the time, first difference of macroeconomic variables are found to be mean stationary. However, such variables may exhibit variance non-stationary implying volatility clustering. The volatility clustering in time series is modeled as ARCH effect (Gujarati, 2004). As explained above, the squared residual term is considered to be a measure of volatility; the residuals will be obtained by running the regression of changes in the log of CPI on intercept, i.e. $\pi_t = \beta_0 + u_t$, and the resultant residual series is utilized in modeling ARCH effect as follows:

$$D\ln(CPI)_t = 0.080667 \ldots\ldots\ldots \quad (1)$$

(20.25432) R^2=0.01 DW=0.265768 Akaike =-3.39 Schwarz=3.37

In the above equation, a regression has been run between changes in log of CPI as dependent variable and constant as an independent variable. The coefficient is statistically significant at 1 percent level. The coefficient of equation (1) shows that over the long-run, inflation increased by almost 8 percent. The estimated residual taking from the equation and squaring it yields the error variance. The statistical significance of ARCH coefficients is tested with the regression coefficients of current error variance to the error variance of various lags. The ARCH effect is tested under the null hypothesis that there is no ARCH effect, that is $H_0 : \alpha_1 = \alpha_2 = \ldots = \alpha_p = 0$, against the ARCH effect, that is $H_1 : \alpha_1 = \alpha_2 = \ldots = \alpha_p \neq 0$

$$\hat{u}_t^2 = 0.00071 + 0.95059\, \hat{u}_{t-1}^2 - 0.357098\, \hat{u}_{t-2}^2 \text{-------} \ (2)$$

(3.46687) (11.16312) (-4.459979) R^2=0.56 DW=2.00 Akaike=-9.72 Schwarz=-9.64

If we introduce only two lagged variance terms, as shown in equation (2), the null hypothesis of there is no ARCH(2) effect is rejected. All the coefficients are statistically significant at 1 percent level. The values of AIC and SIC are found to be minimum for two lags. The computed χ^2statistic of 69.44 ($nR^2=124(0.56)$ is found to be greater than the table value of 9.21 at 1 percent significant level implying the rejection of null hypothesis. The coefficient of second term of the right hand side of the equation can be interpreted as one unit increase in last quartrer's squared residual will have an effect on this quarter's squared residual by 0.95 units. Therefore, last period's variance has the significant impact on current variance resulting to the clustering of variance (volatility). However, the change in the sign of third term of the equation signifies lack of persistence of such clustering. Therefore, volatility clustering is found in the inflation series of Nepal.

Conclusion

This study found an evidence of volatility clustering of inflation in Nepal using ARCH model. Utilizing 127 quarterly observations (1975:QI-2006:IVQ) of the percentage change in CPI as the inflation variable, clustering of inflation is found in the ARCH(2) specification. The clustering is evident during the late eighties. During these years, Nepalese economy realized a considerable shift in the policy regime. The volatility clustering of inflation, however, is not found to be persistent for an extended period. Therefore, the result of this study reveals an inflation uncertainty prevalent in Nepal and hence an emergence of an unanticipated inflation in the economy. In view of this, Nepal Rastra Bank, the central bank of Nepal, while designing and implementing monetary policy to achieve stability objective should prone to be less discretionary, so that, it may tame the volatility clustering of inflation under rational expectation ground.

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