INFLATION AND INFLATION UNCERTAINTY IN NEPAL

A

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Letter of Recommendation

The thesis entitled **INFLATION AND INFLATION UNCERTAINTY IN NEPAL** has been prepared by Dharmendra Timilsina under my supervision. I hereby recommend this thesis for examination by the thesis committee as a partial fulfillment of the prerequisites for the degree of Masters of Arts in Economics.

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Approval Letter

The thesis entitled **INFLATION AND INFLATION UNCERTAINTY IN NEPAL** has been prepared by Dharmendra Timilsina has been accepted as a partial fulfillment of the requirement for the degree of Master of Arts in Economics.

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Table of Contents

Lists of Figures

Lists of Tables

Abbreviations

AIC	Akaike Information Criterion
ARCH	Autoregressive Conditional Heterosedasticity
ARFIMA	Autoregressive Fractionally Integrated Moving Average
ARIMA	Autoregressive Integrated Moving Average
BIC	Bayesian Information Criterion
CPI	Consumer Price Index
GARCH	Generalized Autoregressive Conditional Heterosedasticity
HQ	Hannan-Quinn Information Crietrion
IRF	Impulse Response Function
GIRF	Generalized Impulse Response Function
IT	Inflation Targeting
SDM	Spatial Durbin Model
SNP	Semi-nonparametric

CHAPTER-I

INTRODUCTION

1.1 Introduction

Inflation means substantial and continual rise in the general price level over a period of time (Marwick, 1945). However, there is no universally acceptable definition of inflation. Inflation is a process that raises price levels (Hart, 1957). According to Keynes, if the money supply increases beyond the full employment, output ceases to rise and price rise in proportion with the money supply and this is known as inflation. The rise in the price level during the period of below full employment level is known as bottleneck inflation or semi-inflation. In the words of Friedman, inflation is always and everywhere a monetary phenomenon and can be produced by a more rapid increase in the quantity of money than output.

The uncertainty about future levels of inflation has been one of the major costs of inflation, as it hampers the decision making of economic agents. The relationship between inflation and inflation uncertainty is important for policymakers because if systematic inflation has any real effects, governments can influence economic performance through monetary policy (Berument, Yalcin & Yildirim, 2012). The relationship between inflation uncertainty, inflation, output growth uncertainty and output growth is always interesting and controversial for economists (Bhar & Mallik, 2010).

Inflation uncertainty is now accepted as an important economic variable. The reasons of its variation are not well understood. Uncertainty about future levels of inflation may adversely affect the saving and investment decisions of economic units due to the value of future nominal payments to be unknown. Inflation uncertainty, as the either cause or outcome of the inflation negatively affects economic variable like consumption, investment and growth. Thus, the association between inflation and inflation uncertainty has received considerable attention in economic literature.

Friedman (1977) states an increase in inflation may persuade a fickle policy response by the monetary authority and, therefore, lead to more uncertainty about the future rate of inflation and inflation uncertainty has a negative effect on output. Cukierman and Meltzer (1986) suggest the possibility that inflation uncertainty could cause higher inflation as the central bank takes advantage of an uncertain environment to produce inflation surprises to stimulate the economy. This relation may further encourage a central bank’s inflationary bias, leading to lower long-run economic growth.

Inflation has become major concern in Nepal. Money supply, lack of adequate infrastructure, budget deficit, Indian Inflation, remittance income etc. are major determinants for Inflation in Nepal. Controlling inflation is complicated task in Nepal, which heavily dependent with India on the imported goods for the daily consumption and materials for other development activities.

1.2 Statement of Problem

Inflation is a major problem in case of Nepal. Various studies have been conducted to analyze the cause, impacts and remedial measures of inflation in Nepal. There is a significant positive relationship between inflation and inflation expectations in Nepal and it is desirable for the policymakers to consider inflation expectations while formulating monetary policy to anchor inflationary expectations of the economic agents (Koirala, 2008). Rise in food price likely to increase the poverty in Nepal. Thus, policymakers should consider the food inflation to mitigate the impact of food price hike on the poor section of the population (Shrestha and Chaudhary, 2012). In addition to supply smoothing policies to control inflation in Nepal, consistent and credible policies that are not exposed to change over time may reduce the gap of actual inflation from its targets and hence trigger inflation into desired level (Koirala, 2013). Budget deficits, Indian prices, broad money supply, exchange rate and real GDP are the major determinants of inflation in Nepal (Paudyal, 2014).

Thus, it can be concluded that various studies has been carried out to find out the causes, impacts and remedial measures of inflation in Nepal. There may be possibility that inflation uncertainty could cause higher inflation in Nepal as explained by Cukierman and Meltzer (1986). This study will find out the causality between inflation and inflation uncertainty in Nepal. As well as this study has provided further scope for study of impacts of inflation uncertainty on output, investment, saving, employment, consumption etc. in the context of Nepal. The study tries to answer the following research questions:

a) What is the data generating process of inflation and inflation uncertainty in the context of Nepal?
b) Can we calculate inflation uncertainty in the context of Nepal?
c) If there is causality between inflation and inflation uncertainty in the context of Nepal?

1.3 Objectives of the Study

The objectives of the study are given below:

i. To analyze temporal properties of Nepalese inflation and inflation uncertainty.
ii. To calculate inflation uncertainty in the context of Nepal.
iii. To study the causality between inflation and inflation uncertainty in the context of Nepal.

1.4 Significance of the Study

This study will start discussion about inflation uncertainty and its nature in Nepal. It may provide hints for policymaker to include inflation uncertainty into consideration while forming monetary policy. As well as, this study has provided further scope for study of inflation uncertainty and its impacts on macroeconomic variable like: investment, output etc.

1.5 Limitations of the Study

This study is based on univariate and bivariate monthly data series of inflation. Even though multivariate is more appropriate but the data limitation open the opportunity to research in univariate model. The multivariate model can trace the transmission under the cost of forecasting capability but univarite can be appropriate and robust on forecasting but the obvious cost is it cannot tell the detailed transmission. This limitation of study opens the floor to propel ahead in advanced research directions. This study will provide scope for further study of inflation uncertainty by analyzing bivariate and multivariate data in Nepal.

1.6 Organization of Study

The present study is organized in such way that the stated objectives can easily be fulfilled. The structure of the study will try to analyze the study in a systematic way. The study report has presented the systematic presentation and finding of the study. The study report is designed in five chapters which are as follows:

Chapter I deal with introduction of the main topic of the study. It includes introduction, statement of the problem, objectives of the study, significance of the study, limitations of the study and organization of the study and other introductory framework.

Chapter II assures readers that they are familiar with important research that has been carried out in similar areas. This chapter includes conceptual review and review of relegated studies. It includes the conceptual review of the related books, journals, articles published, research works as well as thesis.

Chapter III covers the research methodology employed in the study. This chapter further attempts to explain the nature and sources of data and data collection techniques. This purpose of this chapter is to provide information about various econometric models, which is used for the analysis of the presented data. This chapter includes research design, data collection, methods and analysis and research variables.

Chapter IV is the major part of the whole study in which all collected relevant data are analyzed and interpreted the help of different econometric tools and graphical presentation. In this chapter there is explanation of major findings of study. Data processing, data analysis and interpretation are given in this chapter.

Chapter V presents summary and conclusions of the study. It also focuses on the major findings along with other empirical evidences. Recommendations for further research are also offered. The references are incorporated at the end of the study.

CHAPTER-II

REVIEW OF LITERATURE

2.1 Global Context

Friedman (1977) explained the potential effects of increased inflation on inflation uncertainty in that it can reduce output growth. He argued that a rise in inflation leads to more uncertainty about the future rate of inflation. When there is higher inflation rate, individuals become uncertain about future monetary policy. They postpone their decision regarding savings and investment. Accordingly, the real value of future nominal payments is unknown and it may adversely affects on the efficiency of resource allocation and even on the level of real activities.

Cukierman and Meltzer (1986) explained that an increase in uncertainty about money growth and inflation will raise the optimal average inflation rate because it provides an incentive for the monetary authority to create an inflation surprise in order to stimulate output growth. Thus, they concluded that higher inflation uncertainty leads to more inflation.

Kim (1993) broadened the standard unobserved-component time series model to incorporate Hamilton's Markov-switching heteroscedasticity. He provided an alternative to the unobserved-component model with autoregressive conditional heteroscedasticity, as developed by Harvey, Ruiz, and Sentana and by Evans and Wachtel. He applied a generalized version of the model to analyze the association between inflation and its uncertainty. He assumed that inflation consists of a stochastic trend (random-walk) component and a stationary autoregressive component. By incorporating regime shifts in both mean and variance structures, he explained the interaction of mean and variance over long and short horizons. His empirical findings showed that inflation is costly because higher inflation is associated with higher long-run uncertainty.

Clavijo (1994) examined two aspects of Colombian chronic but moderate inflation experience during the period 1970-1990. They adopted an ARIMAX((p,d,q)) estimation procedure for the whole-sale price index (WPI), where "X" represents the deterministic components of the right hand side variables (Box and Jenkins, 1976) to test the impact of relative price changes on Colombian inflation. In this case, the "X" components are given by the rate of inflation registered in fuels and electric power. The opinion is that the portions of the general inflation not explained by the ARIMA constitute "surprises", which, ceteris paribus, could be accounted for by changes in relative prices of energy-related goods. Concerning price variability in Colombia, they found that uncertainty did not impetus inflation, as happened in some developed economies.

Holland (1995) stated that as inflation uncertainty rises due to increasing inflation, the monetary authority responds by contracting money supply growth in order to eliminate inflation uncertainty and the associated negative output effects.

Baillie, Chung, and Tieslau (1996) conceived the application of long-memory processes to depicting inflation of ten countries. They applied a new procedure to find approximate maximum likelihood estimates of an ARFIMA-GARCH process; which is fractionally integrated I(d) with a superimposed stationary ARMA component in its conditional mean. As well as, this long memory process is permitted to have GARCH type conditional heteroscedasticity. On analyzing monthly Post-World War-I CPI inflation for ten different countries, they obtained strong evidence of long memory with mean reverting behavior for all countries except Japan, which appears stationary. For three high inflation economies, they demonstrated that the mean and volatility of inflation interact in a way that is uniform with the Friedman hypothesis.

Davis and Kanago (1998) employed a data set of twenty years and forty-four countries to analyze the association between the level and uncertainty of inflation. They found strong evidence of the relationship between average inflation and average uncertainty across countries but they found little evidence in their data for a within country relationship. Very few of the countries in their sample exhibit an association between lagged inflation and future uncertainty.

Grier and Perry (1998) employed the GARCH models to measure the monthly inflation uncertainty in the G-7 countries by taking twenty years data. They further analyzed the association between inflation and inflation uncertainty in the G7 countries using Granger-causality tests. They find amazing evidence that increased inflation raises inflation uncertainty even over a very short horizon, supporting the theoretical predictions made by Friedman and Ball. Their result found mixed evidence on the effect of inflation uncertainty on average inflation. Japan and France showed the association anticipated by Cukierman and Meltzer that increased uncertainty is associated with higher inflation. The US and Germany (and the UK, though less strongly) showed the opposite pattern; increased inflation uncertainty leads to lower average inflation.

Aarstol (1999) employed three models that predict the association between the variability of relative price changes (RPV) and aspects of inflation such as expected inflation, unexpected inflation, and inflation uncertainty. These are, respectively, the menu-costs model, the Lucas-Barro signal-extraction model, and the Hercowitz-Cukierman extension of the Lucas-Barro model that allows for different price elasticities of supply across markets. His result implied that rejection of the hypothesis that any one of the models entirely explained the association between inflation and RPV and also implied rejection of the hypothesis that the three models together jointly explained the relationship.

Ouellette and Paquet (1999) developed a measure of the cost of inflation uncertainty where a risk premium can be interpreted as the amount of real consumption that a representative agent is willing to forgo in order to be guaranteed a perfectly anticipated path of inflation. This premium are calculated based on the estimation of a utility function that takes into account portfolio adjustment costs with respect to money balances and bonds, subject to a budget constraint that includes the after-tax returns on savings. With Canadian and U.S. data, they showed that economic agents' preferences are such that the uncertainty of unexpected inflation was not big enough to induce a large premium.

Grier and Perry (2000) adopted GARCH-M methods and examined the effects of real and nominal uncertainty on average inflation and output growth taking forty eight years data of United States. They concluded with evidence that higher inflation uncertainty or higher output growth uncertainty does not raise the average inflation rate. They also recognized that there is no support for the idea that more risky output growth is associated with a higher average real growth rate. Using variety of models and sample periods, they exhibited that inflation uncertainty significantly lowers real output growth.

Fountas (2001) provided strong evidence in favor of the hypothesis that inflationary periods are associated with high inflation uncertainty by employing long series of UK inflation data. Their result supports the Friedman hypothesis and has important inference for the inflation–output relationship provided that more inflation uncertainty leads to lower output.

Nas and Perry (2001) analyzed the association between inflation, inflation uncertainty, and real output growth taking thirty seven years data of Turkey. Beginning with Friedman (1977), many macroeconomists have advised that there should be a positive relationship between inflation and inflation uncertainty, since monetary policy becomes more erratic and unpredictable during periods of high inflation. Friedman and others suggested that greater inflation uncertainty will adversely affect real economic activity, because inflation uncertainty reduces the information content of prices, distorts relative prices, and therefore lowers economic efficiency. They employed a bivariate GARCH-M system to simultaneously estimate inflation, inflation uncertainty, and output growth to test the potential relationships between inflation, inflation uncertainty, and real output growth. Their findings indicated strong statistical support that inflation significantly raises inflation uncertainty and that inflation uncertainty significantly lowers real output growth over the sample period.

Seyfired and Ewing (2001) examined whether the inflation uncertainty impacted in the G-7 countries over the last two decades. They indicated that inflation uncertainty had a significant short-run effect upon the unemployment rate in Canada, France, Italy, and the US while no effect was found for Germany, Japan, or the UK. They also found that there is no long-run trade-off between inflation uncertainty and unemployment.

Grier et al (2004) examined the impacts of growth volatility and inflation volatility on average rates of output growth and inflation for Post-War US data. Their findings suggested that increased growth uncertainty is associated with significantly lower average growth, while higher inflation uncertainty is significantly negatively correlated with lower output growth and lower average inflation. Both inflation and growth display evidence of significant asymmetric response to positive and negative shocks of equal magnitude.

Kontonikas (2004) studied the relationship between inflation–uncertainty and the impacts of inflation targeting using British data over the period 1972–2002. He proxied uncertainty by using the estimated conditional volatility from symmetric, asymmetric and component GARCH-M models of inflation. He founds a positive relationship between past inflation and current uncertainty. He controlled the indirect effect of lower average inflation throughout the last decade of inflation targeting and found that the adoption of an explicit target eliminates inflation persistence and reduces long-run uncertainty. He also suggested that monetary authorities of implicit targeting countries should consider the extra benefits associated with formal targets.

Conrad and Karanasos (2005) applied parametric models of long memory in both the conditional mean and the conditional variance of inflation and monthly data in the USA, Japan and the UK for the period 1962–2001 to analyze the relationship between inflation and inflation-uncertainty. By using ARFIMA-GARCH model they concluded that inflation significantly raises inflation-uncertainty as anticipated by Friedman. Increased nominal uncertainty influences inflation in Japan and the UK but not in the same manner. The findings from Japan indorse the Cukierman–Meltzer hypothesis. In the UK uncertainty surrounding the future inflation seems to have a mixed effect on inflation.

Daal, Naka, and Sanchez (2005) examined the association between inflation and inflation uncertainty for developed as well as emerging countries by applying the asymmetric power GARCH model. They observed that positive inflationary shocks influence strongly on inflation uncertainty for mainly Latin American countries. They also observed that inflation Granger causes inflation uncertainty for most countries but the proof for causality of the opposite direction is mixed. Their results strongly support the Friedman–Ball hypothesis for developed as well as emerging countries.

Lahiri and Liu (2006) analyzed the determinants of inflation forecast uncertainty using a panel of density forecasts from the Survey of Professionals Forecasters (SPF). Employing a dynamic heterogeneous panel data model, they found that the persistence in forecast uncertainty is much less than what the aggregate time series data would suggest. As well as, they also showed the strong link between past forecast errors and current forecast uncertainty, as often noted in the ARCH literature, is largely lost in a multi-period context with varying forecast horizons. They proposed a novel way of estimating 'news' and its variance using the Kullback-Leibler information, and showed that the latter is an important determinant of forecast uncertainty. They also suggested a strong relationship of forecast uncertainty with level of inflation, but not with forecaster discord or with the volatility of a number of other macroeconomic indicators.

R. Grier and Grier (2006) estimated an augmented multivariate GARCH-M model of inflation and output growth for Mexico at business cycle frequencies. The main findings are: (1) inflation uncertainty has a negative and significant effect on growth; (2) once the effect of inflation uncertainty is accounted for, lagged inflation does not have a direct negative effect on output growth; (3) However as predicted by Friedman and Ball, higher average inflation raises inflation uncertainty, and the overall net effect of average inflation on output growth in Mexico is negative. That is, average inflation is harmful to Mexican growth due to its impact on inflation uncertainty. (4) The Mexican Presidential election cycle significantly raises inflation uncertainty both during the year of the election and the year following the election which has correspondingly negative effects on output growth.

Thornton (2006) found a positive and significant relationship between the level and variability of monthly inflation in India in the period 1957-2005 by applying a GARCH model, with Granger causation running from inflation to uncertainty about future inflation, as hypothesized by Friedman. He concluded that inflation uncertainty has negative output effects and suggested central bank to focus on price stability as one of the main objective of monetary policy.

Fountas and Karanasos (2007) employed univariate GARCH models of inflation and output growth and monthly data for the G7 covering the 1957-2000 periods to test for the causal effect of real and nominal macroeconomic uncertainty on inflation and output growth, and the effect of inflation on inflation uncertainty. Their empirical findings supported a number of important conclusions. First, inflation is a positive determinant of uncertainty about inflation. Second, output growth uncertainty is a positive determinant of the output growth rate. Third, there is not the uniform evidence regarding the impact of inflation uncertainty on inflation and output growth. Hence, uncertainty about the inflation rate is not necessarily detrimental to economic growth. Finally, there is not much evidence supporting the hypothesis that output uncertainty raises inflation.

Thornton (2007) applied standard Generalized Autoregressive Conditional Heteroskedastic (q,v) to construct a measure of monthly inflation uncertainty in 12 emerging market economies, and the relationship between inflation and inflation uncertainty is examined using Granger causality tests. Their findings suggested that higher inflation rates increased inflation uncertainty in all the economies, providing strong support for the Friedman hypothesis. The evidence on the effect of inflation uncertainty on average monthly inflation is more mixed, with increased inflation uncertainty leading to lower average inflation in Colombia, Israel, Mexico, and Turkey, consistent with the Holland hypothesis, but to higher average inflation in Hungary, Indonesia, and Korea, consistent with the hypothesis of Cukierman and Meltzer.

Abidin and Fisunoglu (2008) analyzed the Friedman and the Cukierman and Meltzer hypothesis for the Jordanian, Philippine and Turkish economy. They employed a parametric model of long memory in the conditional mean of inflation and a generalized autoregressive conditional heteroskedasticity (GARCH) model to examine inflation uncertainty and to measure the association between inflation and inflation uncertainty. The study is based on the rate of the change of the monthly seasonally adjusted consumer price index (CPI) from Feb. 1987 to Nov. 2003. The empirical results of this paper supported the Friedman hypothesis; however, they did not support the Cukierman–Meltzer hypothesis fully.

Payne (2008) extended the literature on the relationship between inflation and inflation uncertainty by examining three Caribbean countries: the Bahamas, Barbados, and Jamaica. ARMA-GARCH models are used to estimate inflation uncertainty along with Granger-causality tests to infer the relationship between inflation and inflation uncertainty. His findings showed that both the Bahamas and Jamaica exhibit a high degree of volatility persistence in response to inflationary shocks, while Barbados has a much lower persistence measure. Granger-causality tests indicated that an increase in inflation has been a positive impact on inflation uncertainty for each country. However, an increase in inflation uncertainty yields a decrease in inflation in the case of Jamaica. In summary, the results for the Bahamas and Barbados supported the Friedman-Ball hypothesis, whereas the results for Jamaica supported Holland’s stabilization-motive hypothesis. Future research on inflation and inflation uncertainty can be extended to incorporate possible regime shifts associated with fiscal and monetary policy.

Berument, Yalcin, and Yildirim (2009) investigated the impact of inflation uncertainty innovations on inflation over time by taking the monthly United States data for the time period 1976–2006. In order to analyze the impact of inflation uncertainty innovation on inflation, a Stochastic Volatility in Mean model (SVM) has been employed. SVM models are generally used to capture the innovation to inflation uncertainty, which cannot be achieved in the framework of popular deterministic ARCH type of models. Empirical evidence provided here suggests that innovations in inflation volatility increases inflation persistently.

Miles and Vijverberg (2009) examined the changes in the level, persistence, and uncertainty of U.S. inflation by employing GARCH estimation and concluded that there is negative impact of inflation uncertainty on output. As well as, by analyzing both the standard Consumer Price Index (CPI) and the CPI minus energy, they found that volatile energy costs contribute to the higher inflation uncertainty in the United States in the current decade.

Bhar and Mallik (2010) analyzed the impacts of inflation uncertainty and growth uncertainty on inflation and output growth in the United States by applying a multivariate EGARCH-M. Their study showed that inflation uncertainty has a positive and significant effect on the level of inflation and a negative and significant effect on the output growth. They found that output uncertainty has no significant effect on output growth or inflation but the oil price also had a positive and significant effect on inflation. These results are robust and had been confirmed by use of an Impulse Response Function (IRF). These findings have important implications for inflation-targeting (IT) monetary policy and for the purpose of stabilization policy in general.

Thornton (2010) employed unit root tests and suggested that inflation in Argentina for the period 1810–2005 is a stationary series when account is taken of structural breaks that coincide with bouts of hyperinflation. A GARCH (1,1) model of annual inflation suggested a positive short-run relation between the mean and variance of inflation, supporting Friedman's hypothesis that high inflation is associated with more variable inflation.

Brunner and Hess (2011) examined Friedman's inflation-uncertainty hypothesis empoying SDM's of conditional moments. SDM framework nests ARCH, GARCH, and the Rx portion of Gallant and Tauchen's (1990) SNPRx model that have been widely used for the study of inflation-uncertainty hypothesis. They observed that higher levels of inflation are less predictable, which is contrast to the outcomes of Engle (1983), Bollerslev (1986), and Cosimano and Jansen (1988). As well as, these models clearly specified, as evidenced by their ability to pass a battery of diagnostic tests taken to detect serial correlation and heteroscedasticity.

Mallik and Chowdhury (2011) determined the relationship between inflation, inflation uncertainty, growth and growth uncertainty for Australia. Multivariate EGARCH models have been used to estimate the relationship between inflation, inflation uncertainty, growth and growth uncertainty for Australia. Using quarterly data in multivariate EGARCH models, this study concluded that both inflation uncertainty and output uncertainty have negative and significant impacts on output growth. They also found that, while inflation uncertainty has a positive and significant effect on inflation, output uncertainty has a negative and significant effect on inflation. The study employed a newly constructed oil price dummy as a control variable and found that oil price changes significantly increase inflation uncertainty. The study also found that inflation uncertainty and the inflation level have both declined since the adoption of a formal inflation-targeting monetary policy in Australia.

Berument, Yalcin, and Yildirim (2012) investigated the direct relationship between inflation and inflation uncertainty by employing a dynamic method for the monthly country–region–place United States data for the time period 1976–2007. While the bulk of previous studies has employed GARCH models in investigating the association between inflation and inflation uncertainty, in this study Stochastic Volatility in Mean models are used to capture the shocks to inflation uncertainty within a dynamic framework. These models allowed researchers to assess the dynamic effects of innovations in inflation as well as inflation volatility on inflation and inflation volatility over time, by incorporating the unobserved volatility as an explanatory variable in the mean (inflation) equation. Their empirical findings suggested that innovations in inflation volatility increases inflation. This evidence is robust across various definitions of inflation and different sub-periods.

Bhar and Mallik (2012) examined the association between inflation, growth, inflation uncertainty and growth uncertainty using multivariate EGARCH modeling for Australia. Using quarterly data they found that inflation uncertainty have negative and significant impacts on inflation and output growth at least after the inflation targeting. They also concluded that output uncertainty has negative and significant impact on inflation. They applied a newly constructed oil price dummy variable as a control variable and concluded that oil price changes notably increase the inflation uncertainty. These results are robust and the Generalized Impulse Response Functions (GIRF) confirmed the conclusions. These findings are significant for inflation targeting (IT) monetary policy, and for the purpose of stabilization policy in general.

Castillo, Humala, and Tuesta (2012) analyzed the link between inflation and inflation uncertainty is evaluated using Peruvian data, in a context of changing monetary policies because of regime shifts The employed a Markov regime-switching heteroskedasticity model that includes unobserved components. The model showed how periods of high (low) inflation accompany periods of high (low) short- and long-run uncertainty in inflation. The results of the model also illustrated how, during the recent period of price stability in Peru, both permanent and transitory shocks in inflation show a decrease in volatility. Finally, a time-varying measure of inflation uncertainty is derived from the estimates, giving additional evidence on the positive link between the level of inflation and its uncertainty.

Hartmann and Herwartz (2012) tested for causality between inflation and its associated uncertainty by means of both in-sample and out- of-sample modeling. Their findings indicated that the impact of inflation on inflation uncertainty is more pronounced than the reverse causal effect.

Karahan (2012) analyzed the relationship between inflation and inflation uncertainty in Turkey from 2002 to 2011 using two-step procedure. At first step, ARMA-GARCH model of monthly inflation data is estimated and the conditional variance from these estimates is indicated as the monthly inflation uncertainty series. Then, the Granger causality tests between primarily inflation and generated inflation uncertainty series are performed. Empirical results of their study provided strong evidence in favor of the Friedman-Ball hypothesis that inflationary period result in high inflation uncertainty in Turkish case. These results presented significant implications for the relationship between inflation and inflation uncertainly in developing countries as much as monetary policy adopted Inflation Targeting in Turkey.

Hartmann and Roestel (2013) provided cross country robust evidence on interdependencies among inflation, output growth and respective uncertainties for the current era of low inflation policies. They attributed the extant empirical disagreement on these relations to the fact those long sampling periods and single economies are typically considered for analysis. In their study, VARX-MGARCH-M models are estimated for 34 developed and emerging economies and the time period of 1990–2010. They studied average (Granger) causal effects by aggregating parameter estimates over economies. The cross sectional variation of estimates serves as a means to assess the robustness of empirical findings. Over the entire cross section, they found that both inflation and inflation uncertainty significantly reduce output growth. Economies with low inflation rates are particularly at risk to incur output losses from increasing inflation. They also find spillover effects among uncertainty variables, where the causal impact, if present, seems to point from the uncertainty in output to inflation uncertainty.

Jones and Olson (2013) employed a new uncertainty index from Baker et al. (2012) and evaluated the time-varying correlation between macroeconomic uncertainty, inflation, and output. Estimation results from a multivariate DCC-GARCH model revealed that the sign of the correlation between macroeconomic uncertainty and inflation changed from negative to positive during the late 1990s, whereas the correlation between uncertainty and output is consistently negative.

Neanidis and Savva (2013) analyzed the causal effects of real and nominal macroeconomic uncertainty on inflation and output growth by considering whether these effects are cycle phase specific. They employed a bivariate Smooth Transition EGARCH-M model for the G-7 countries during 1957–2009 and found strong nonlinearities. First, uncertainty regarding the output growth rate is related with a higher average growth rate mostly in a low-growth regime, supporting the theory of ‘‘creative destruction’’. Second, higher inflation uncertainty diminishes growth rates, mainly at a high-inflation regime. Finally, real uncertainty has mixed effects on average inflation, while the effect of nominal uncertainty is typically positive, especially so during inflationary periods. Their findings suggested that these relationships are sufficiently complex to require treatment with nonlinear models.

Chowdhury (2014) applied maximum likelihood estimates from the GARCH model and revealed strong support for the presence of a positive relationship between the level of inflation and its uncertainty. He also indicated a feedback between inflation and uncertainty by employing Granger causality.

Daniela, Mihail-Ioan, and Sorina (2014) employed monthly inflation data spanning from 1996 to 2012 we test the influence between inflation uncertainty [IU] and inflation, the inflation is modeled using the GARCH family models: GARCH, asymmetric GARCH and GARCH in Mean with different distribution, checking for any structural break in the series using the Zivot-Andrews test and PELT algorithm, the structural breaks in mean and variance are captured using dummy variables in the GARCH models, we identify the best models using the informational criterion (Akaike, Schwarz, Log-likelihood). The inflation uncertainty proxy is the conditional volatility from the GARCH family models and the influence between inflation uncertainty and inflation is tested using Granger causality.

Buth, Kakinaka, and Miyamoto (2015) analyzed the association between inflation and inflation uncertainty in Cambodia, Lao PDR, and Vietnam. Inflation uncertainty is estimated as the conditional variance in a family of generalized autoregressive heteroskedasticity (GARCH) models. They found that inflation causes inflation uncertainty in these countries, which supports the argument of Friedman (1977). Moreover, they demonstrated that inflation uncertainty causes inflation only in Lao PDR, which implies that Cukierman and Meltzer's (1986) argument can be supported in Lao PDR.

2.2 Context of Nepal

Shrestha (2006) mentioned that conventional measures of price by consumer price index cannot separate the supply shock effect on the price movement with which monetary policy has no any relationship. He concluded that for the accountability and credibility of the monetary policy, there should be a measurement of core inflation, omitting distortionary effects of supply shocks.

Koirala (2008) stated that there is a significant positive relationship between inflation and inflation expectations in Nepal by employing Adaptive Expectation Hypothesis (AEH). Using 33 annual observations of actual inflation from 1973 to 2006, he concluded that one percent increase in inflation expectations has 0.83 percent impact on contemporaneous inflation. The forecast-ability of inflation expectations on current inflation is higher than that of the expected inflation proxied by one-period lagged inflation. The forecast-ability of the model has been analyzed on the basis of minimum Root Mean Squared Error (RMSE). He also suggested to consider inflation expectations while formulating monetary policy to anchor inflationary expectations of the economic agents.

Shrestha and Chaudhary (2012) examined the impact of food price hike on poverty in Nepal by taking cross-sectional sample household consumption data of Nepal Living Standard Survey III. The findings of his study suggested that a 10 percent rise in food prices is likely to increase overall poverty in Nepal by 4 percentage points. He also considered the impact at the regional level and suggested some policy options to consider the food inflation and to rationalize the impact of food price hike on the poor section of the population.

Koirala (2013) examined the stability of time-varying parameters of the random walk model of inflation in Nepal. By taking monthly time series of inflation ranging from August, 1997 to July, 2012, he applied the Kalman Filter technique for the estimation of coefficients of random walk model and concluded that non-constant time varying parameters of both the constant and autoregressive of order one AR(1) coefficient of inflation over the long run. He advised that in addition to supply smoothing policies to control inflation in Nepal, consistent and credible policies that are not exposed to change over time may reduce the gap of actual inflation from its targets and hence trigger inflation into desired level.

Paudyal (2014) analyzed the short term and long term impacts of the macroeconomic variables on the inflation in Nepal during 1975-2011. He has taken budget deficits, Indian prices, broad money supply, exchange rate and real GDP as major macroeconomic variables. By employing Wickens-Breusch Single Equation Error Correction model he suggested that all variables taken are significant in long run indicating that these variables are the determinants of inflation in Nepal and budget deficit, money supply and Indian prices cause inflation in the short run.

CHAPTER-III

RESEARCH METHODOLOGY

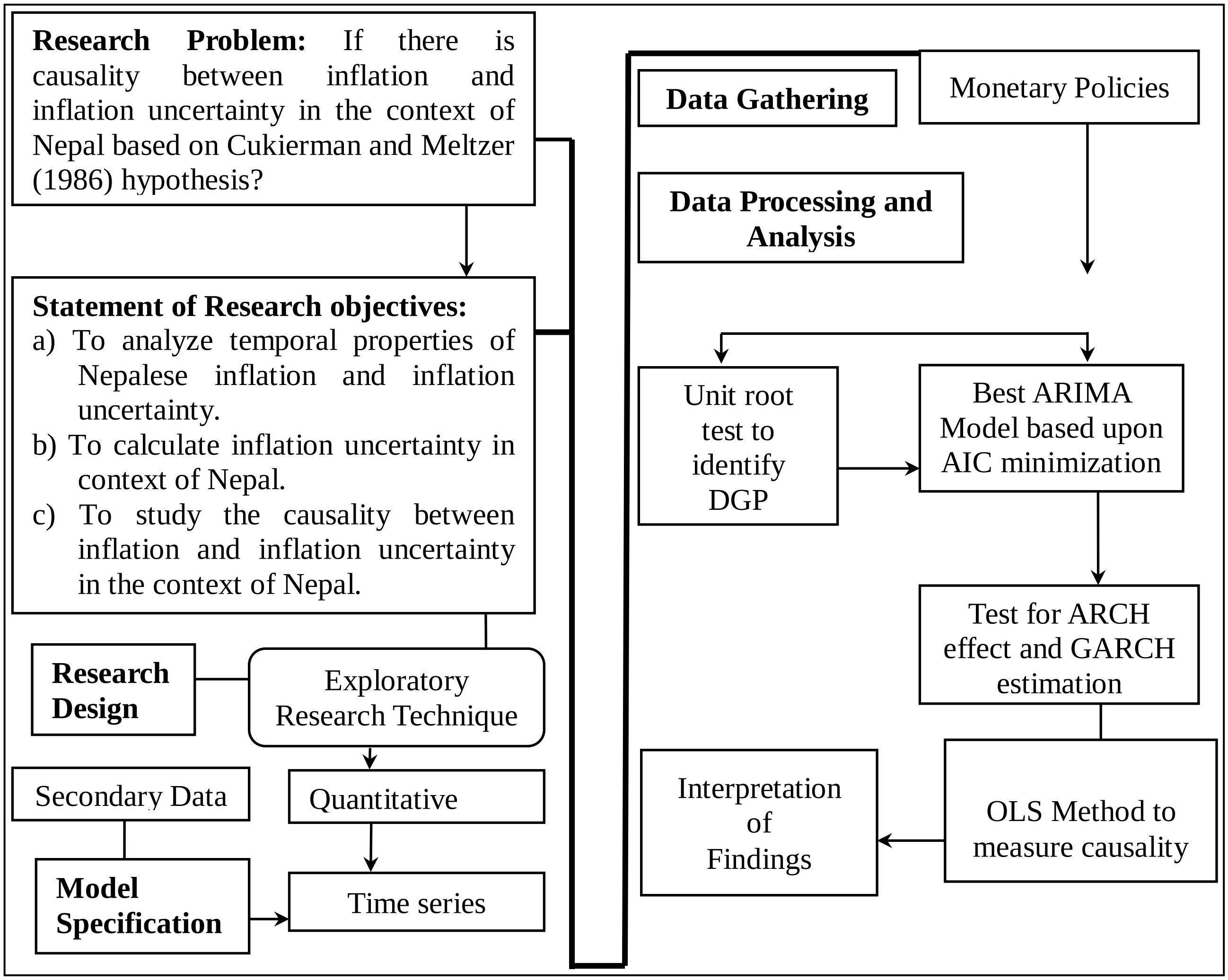
3.1 Introduction

The topic of the study has been selected as "Inflation and Inflation Uncertainty in Nepal." In order to reach and accomplish the objectives of the study, different activities will be carried out. For this purpose, the chapter aims to present and reflect the methods and techniques that are carried out and followed during the study period. The research methodology that is adopted for the present study is mentioned in this chapter which deals with research design, sources of data, data collection, processing and tabulating procedure and methodology.

3.2 Research Design

Decisions regarding what, where, when, how much, by what means concerning an inquiry or a research study constitute a research design. It is a conceptual structure within which research is conducted; it constitutes the blueprint for the collection, measurement and analysis of data. To achieve the objectives of the study, this thesis follows an exploratory research design. For this purpose, econometric tools are applied to find out the causality between inflation and inflation uncertainty in the context of Nepal. The study will be based on secondary data.

Figure 3.1: Research Design



Source: Author

3.2 Sources of Data

This research has considered the monthly time series data of inflation. These are secondary data in nature available from 2002 to 2014 onwards from website of Nepal Rastra Bank. For the purpose of processing and analyzing the data, different econometric tools have been applied.

3.3 Augmented Dickey Fuller Unit Root Test

To fulfill the first objective of research, Augmented Dickey Fuller Unit Root Test is performed in this section. In the time series, new arriving observation is stochastically depending on the previously observed data. Therefore, time series often are non-stationary or have means, variances and covariances that vary over time–due to trends, cycles, random walks or combinations of the three. This dependency makes the inferences spurious. Hence, any time series, if suffer from non-stationary issue, it must be transformed into a stationary process (a random process where all of its statistical properties do not vary with time) to infer.

The test which checks if – time series is stationary or not – is known as a unit root test. To apply unit root test following *AR* equation is taken.

$$\pi_t = \rho_1\pi_{t-1} + \rho_2\pi_{t-2} + ... + \rho_n\pi_{t-n} + \varepsilon_t \qquad \textbf{(1)}$$

where, π_t is the monthly inflation rate and $\pi_{t-1}, \pi_{t-2,} \dots \dots \pi_{t-n}$ are lag values of monthly inflation rate. $\rho_1, \rho_2, \dots \dots . \rho_n$ are parameters to be estimated, and they are assumed to be white noise. Time series data are usually non-stationary. Augmented Dickey-Fuller (ADF) tests the stationary or unit root of the series. The data then were made stationary by differing with necessary orders as per requirement.

3.4 Method to Calculate Inflation Uncertainty

The second objective of the research is to calculate inflation uncertainty in context of Nepal. To fulfill the second objective of the research, ARIMA (p,d,q) and GARCH (P,Q) model are used in this study. ARIMA is forecasting tool. Unlike the regression models, in which Y_t is explained by k regressors $X_1, X_2, X_3, \ldots. X_k$, the ARIMA (p,d,q) model allow Y_t to be explained by past, or lagged values of Y itself and stochastic error terms. In this study ARIMA (p,d,q) model is applied to forecast monthly inflation rate (π_t) by taking past values of π itself and stochastic error terms. But, Box-Ljung test shows that the residuals of ARIMA (p,d,q) are suffered from ARCH effect. Instead of modeling the levels of inflation data, first differences data are used but these first differences also exhibit volatility, suggesting that the variance of time series data of inflation varies over time. Thus, to measure this varying variance, GARCH (P,Q) model is applied in this study. The conditional variance measured by the GARCH (P,Q) is called inflation uncertainty.

3.3 ARIMA Model

ARIMA (autoregressive integrated moving average) models are generalizations of the simple Autoregressive model. ARIMA has 3 parts: the auto regression part (AR), the integration part (I) and the moving average part (MA). AR part of π_t (here, monthly inflation rate) is that the observed value depends linearly on its previous observed values up to a defined maximum lag (denoted p), plus a random error term ε_t. MA part of π_t is that the observed value is a random error term plus some linear combination of previous random error terms up to a defined maximum lag (denoted q). Time series data are usually non stationary and in order to make them stationary, the series has to be differenced. The process of differencing the series is known as an integration part (I) and the order of differencing is denoted as d. Differencing removes the trend or seasonality of the time series data.

Autoregressive Part (AR Part)

AR part of a monthly inflation rate (π_t) is that the observed value linearly depends on previous observed values up to a defined maximum lag (denoted p), plus a random error term ε_t and which can be presented as:

$$\pi_t = \varphi_1\pi_{t-1} + \varphi_2\pi_{t-2} + \ldots\ldots + \varphi_p\pi_{t-p} + \varepsilon_t \qquad \text{(i)}$$

where the parameters φ_t are constants.

Moving Average Part (MA Part)

MA part of a monthly inflation (π_t) is that the observed value is a random error term plus some linear combination of previous random error terms up to a defined maximum lag (denoted q).

$$y_t = \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \ldots\ldots + \theta_q\varepsilon_{t-q} \qquad \text{(ii)}$$

where the parameters θ_t are constants.

The Mixed Model ARMA (p,q)

The mixed model would then be known as ARMA(p, q) model and can be expressed as:

$$\pi_t = \varphi_1\pi_{t-1} + \varphi_2\pi_{t-2} + \ldots\ldots + \varphi_p\pi_{t-p} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \ldots\ldots + \theta_q\varepsilon_{t-q}$$

$$\pi_t - \varphi_1\pi_{t-1} - \varphi_2\pi_{t-2} - \ldots\ldots - \varphi_p\pi_{t-p} = \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \ldots\ldots + \theta_q\varepsilon_{t-q} \qquad \text{(iii)}$$

The Integration Part (I Part)

Time series data are usually non-stationary or they have unit root and in order to make them stationary the series has to be differenced. The process of differencing to make series stationary is known as integration part (I) and the order of differencing is denoted as d. Differencing removes the trend or seasonality from the series, so that it consist only the noise or the irregular component to be modeled. Algebrically, for first difference data, it can be written as:

$$\Delta^1\pi_t = \pi_t - \pi_{t-1} \qquad \text{(iv)}$$

In ARIMA, to make stationary, data are differentiated appropriately, and then AR (to consider the grounds of habit persistence of any time series) and MA process (to consider the grounds of habit persistence of any errors left after the AR process) are applied.

Monthly inflation rate (π_t) is differenced once to make stationary and such stationary series of π_t is R_t. The ARIMA (p,d,q) process of R_t can be written as:

$$R_t = \alpha_0 + \sum_{i=1}^{p} \vartheta_i R_{t-i} + \sum_{j=1}^{q} \nu_j \varepsilon_{t-j} + \varepsilon_t \qquad \text{(v)}$$

3.4 GARCH Model

Now, once the best ARIMA fitted, again the model left with residuals of ARIMA i.e. ε_t. Unconditionally, the error term (ε_t) is a zero mean with white noise process. The conditional distribution of ε_t is normal, $N(0,h_t)$. The residual should be free from autocorrelation and heteroskedasticity. The residual mostly becomes well behaved if the ARIMA model is best fitted.

However, for the high frequency data, the Autoregressive Conditional Heteroskedasticity (ARCH) effect persists because the high volatility are followed by high volatility times and low with low times. Hence second step is to check whether such ARCH effect persist in residual of ARIMA or not. As Box-Ljung test shows ARCH effect persists on ARIMA (p,d,q) then GARCH process has been applied. A GARCH (P,Q) can be modeled with the $N(0,h_t)$ white noised error term (εt).

$$h^2{}_t = \alpha_1 + \sum_{m=1}^{P} \alpha_m \varepsilon^2_{t-m} + \sum_{n=1}^{Q} \beta_n h^2{}_{t-n} + \varepsilon_t \qquad \text{(vi)}$$

where, h^2_t is the conditional variance.

3.5 OLS Method

To fulfill the third objective the study OLS method is applied. The first difference data of monthly rate of inflation is taken for study, as it fails to accept the alternative hypothesis that data consists unit roots. The ARIMA (0,0,1) model is used for the first difference data of inflation as the time series data consists moving average part of error term. The best fit ARIMA (0,0,1), again left with residuals i.e. ε_t. As the residuals of ARIMA (0,0,1) persists ARCH effect, then GARCH (2,2) process is used. Using GARCH (2,2), the uncertainty of rate of change of inflation is calculated. To test causality between change in inflation rate and inflation uncertainty of change in inflation rate, OLS method is used. The equation can be presented as follows:

$$\Delta\pi_t = \beta_1 + \beta_2 h_t + \varepsilon_t \qquad \text{(vii)}$$

Equation (vii) is used to test whether inflation uncertainty causes inflation or not. As well inflation may also cause inflation uncertainty. To test causality the following OLS equation is applied.

$$h_t = \beta_1 + \beta_2 \Delta\pi_t + \varepsilon_t \qquad \text{(viii)}$$

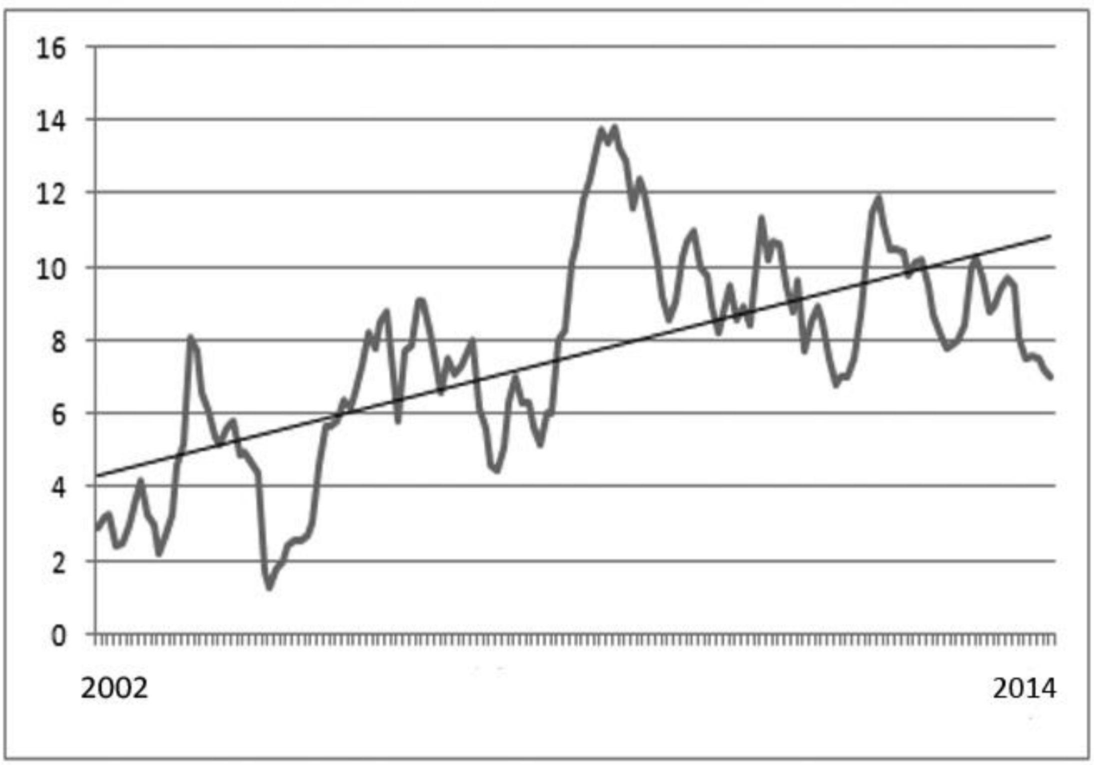
CHAPTER-IV

DATA PRESENTATION AND ANALYSIS

The research question revolves to analyze casual nexus between inflation and inflation uncertainty in Nepal. To analyze above research objectives, this paper considers the monthly inflation rate data from 2002 to 2014. The data were retrieved from the website of Nepal Rastra Bank.

4.1 Descriptive Statistics

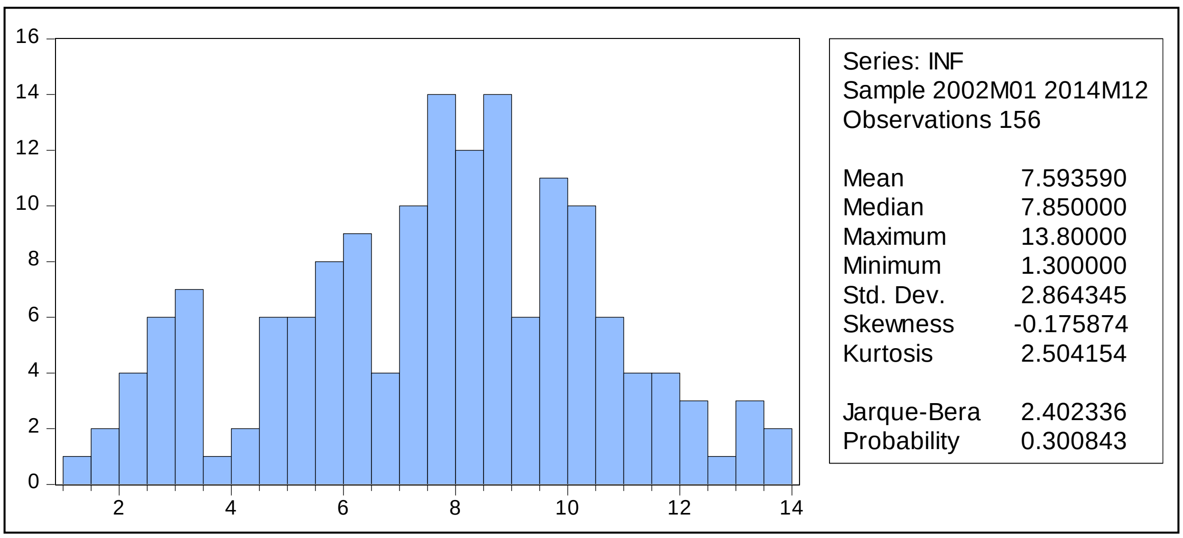
Figure 4.1: Monthly Inflation of Nepal (2002-2014)



Source: www.nrb.org.np

Figure 4.1 shows the monthly inflation of Nepal from 2002 to 2014. The figure shows highly fluctuating nature of inflation during the study period. The inflation rate in 2008/09 soared up to a record high in 17 years. The pressure on food prices continued to rise despite a sharp decline of international commodity prices. The decline in production of winter crops on account of long dry winter, poor distribution and supply channel, transport syndication, crisis, increase in salary and wage rate and carteling created pressure in the overall price level in Nepal. All these factors have posed challenges to the bank to achieve primary objective of maintaining price stability (Monetary Policy, 2009/10)

Figure 4.2: Histogram of Inflation



Source: EViews 9.0

Figure 4.2 shows that the data of inflation are normally distributed with mean 7.59 and standard deviation 2.86. Jarque-Bera 2.40 (0.30) shows that the observations are normally distributed as it fails to reject null hypothesis of normality.

Inflation rate is advanced economies was 1.4% and the inflation in emerging and developing countries was 5.1% in 2014. The inflation of Nepal in 2014 was 8.41%, which shows that the inflation of Nepal is much higher than developed as well as emerging economy (Monetary Policy, 2015/16).

4.2 Augmented Dickey-Fuller Unit Root Test

The time series data generally consist unit roots. The presence of unit root reveals that the series is non stationary, if the mean, variance and auto co-variances of the series keeps changing in different sub sample, then series is said to be contaminated by presence of unit root or non stationary. To identify such presence of unit root ADF unit root is performed in this section.

Table 4.1: ADF Test Statistic

Augmented Dickey-Fuller test statistic							
Variable	**t-Statistic (Prob.*)**						**Sample (2002:2014)**
	Level			**1st Difference**			
	intercept	**trend and intercept**	**none**	**intercept**	**trend and intercept**	**none**	**Decision**
INF	-2.55 (0.11)	-2.83 (0.19)	-0.61 (0.45)	-9.92 (0.00)*	-9.92 (0.00)*	-9.95 (0.00)*	I(1)

*Note: * represents significant in 5% level of significance.*
Source: Author's calculation from Annex-1

Table 4.1 reports the results of the ADF unit root test for the monthly inflation rates for levels and the first difference. The table shows that inflation rates under consideration are non-stationary in their levels and become stationary when they are first differenced.

ADF unit root tests are performed on the variables to identify their order of integration. The test allowed maximum 13 lags, and the optimum lags were automatically selected by minimizing Schwarz Info Criterion (SIC). The test was imposed without permitting an 'intercept and trend' or 'intercept' as exogenous variable/s as they are insignificant.

The Table-4.1 illustrates ADF unit root test. Presence of unit root or failure to reject the null hypothesis (*p*-value > 5% level of significance) indicates that the original data are non-stationary. Monthly inflation rate (INF) is contaminated by presence of unit root (is stationary i.e. *p*-value > 5%). Hence, the order of integration of INF is *I(1)*.

1st Order difference data of monthly inflation rate shows that the data are stationary as it reject the null hypothesis (*p*-value < 5%) indicates that the data are stationary. 1st order difference of INF is stationary (i.e. *p*-value < 5%). Hence the order of integration of INF after 1st order difference is *I(0)*.

4.3 ARIMA (p,d,q) Model

In this study, the best ARIMA (p,d,q) is selected by using Akaike Information Criterion (AIC). The more fitted is the model, the smaller is AIC. To use this criterion to select among alternative model specifications, the model with the smallest AIC value is selected. The following table shows the different models of ARIMA (p,d,q) and their AIC value.

Table 4.2: ARIMA (p,d,q)

ARIMA (p,d,q)	AIC
ARIMA(2,0,2) with non-zero mean	1.00E+20
ARIMA(0,0,0) with non-zero mean	385.6638
ARIMA(1,0,0) with non-zero mean	381.2789
ARIMA(0,0,1) with non-zero mean	381.0945
ARIMA(1,0,1) with non-zero mean	383.256
ARIMA(0,0,2) with non-zero mean	381.8771
ARIMA(1,0,2) with non-zero mean	384.729
ARIMA(0,0,1) with zero mean	379.2117
ARIMA(1,0,1) with zero mean	381.3355
ARIMA(0,0,0) with zero mean	383.8217
ARIMA(0,0,2) with zero mean	379.979
ARIMA(1,0,2) with zero mean	382.8103
Best Model : ARIMA (0,0,1)	**379.2117**

Source: R 3.0.3

Thus, the best model is ARIMA (0,0,1) based upon minimum AIC Criterion. Based upon the ADF, the series just has one period lag moving average part of error term. Series doesn't contain autoregressive part.

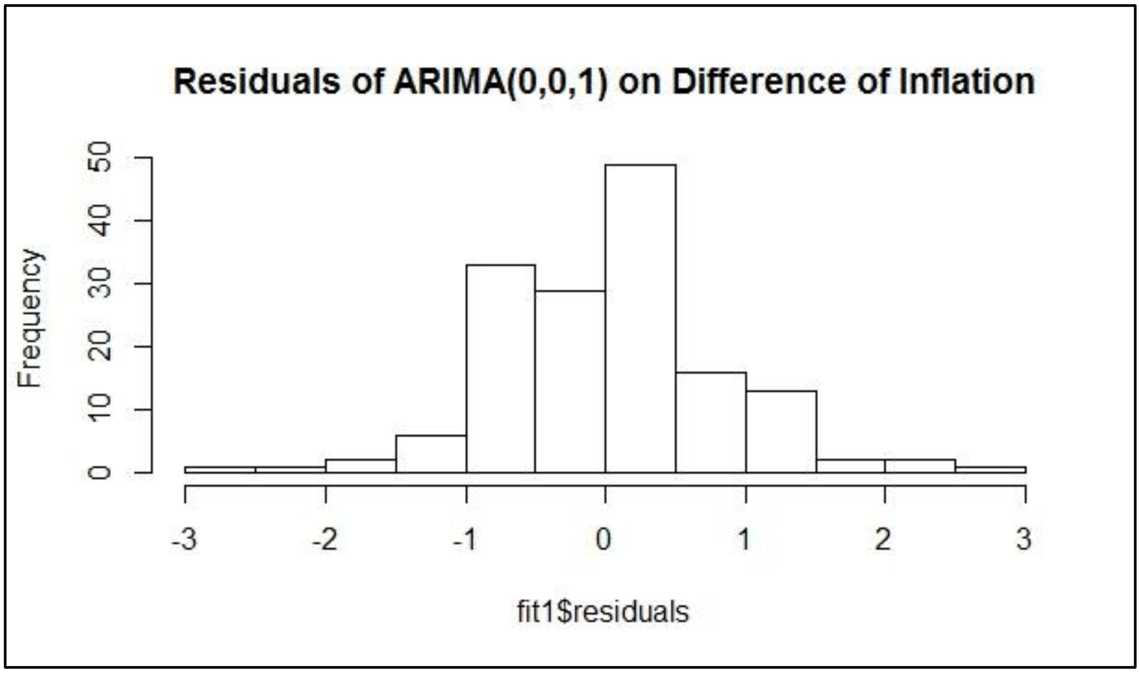
Table 4.3: Summary of ARIMA (0,0,1)

Series: 1st Difference Data of Inflation	
ARIMA(0,0,1) with zero mean	
Coefficients:	
ma1	0.1919
s.e.	0.0722

Source: R 3.0.3

Table 4.3 shows that the monthly inflation rate is explained by one period lagged moving average (ma1) value and its coefficient is 0.1919 and S.E. is given by 0.0722. When we divide coefficient by its S.E., value will be 0.1919/0.0722 = 2.65789, which is simple t-test. So, the coefficient of ma1 is statistically significant as p-value > 5% level of significance (i.e. 2.65789 > 1.96).

Figure 4.3: Residuals of ARIMA (0,0,1) on Difference of Inflation



Source: R 3.0.3

Figure 4.3 shows that residuals of ARIMA (0,0,1) are normally distributed. Box-Ljung Test is applied to test whether there is serial correlation or not in the ARIMA (0,0,1). The summary of Box-Ljung test on residuals of ARIMA (0,0,1) is as follows:

Table 4.4: Box-Ljung test on residuals of ARIMA (0,0,1)

Data: Residuals of ARIMA (0,0,1)		
X-squared	**df**	**p-value**
34.7053	12	0.0005217

Source: R 3.0.3

Table 4.4 shows that the null hypothesis (independence) cannot be accepted and there is serial correlation in the residuals of ARIMA (0,0,1). The result shows that despite the non-stationary components of data has been removed, the model still contains auto regressive components. Thus, Box-Ljung test on squared residuals of ARIMA (0,0,1) is applied to know whether it is suffered from ARCH effect or not.

Table 4.5: Box-Ljung test on squared residuals of ARIMA (0,0,1)

Data: Squared values of residuals of ARIMA (0,0,1)		
X-squared	**df**	**p-value**
22.8778	12	0.02878

Source: R 3.0.3

From Table 4.5 Box-Ljung test shows that the null hypothesis (independence) cannot be accepted and there is serial correlation in the squared residuals of ARIMA (0,0,1). In other words, there is ARCH effect. As, the ARIMA (0,0,1) is suffered from ARCH effect, GARCH (P,Q) model is applied to measure volatility or uncertainty of monthly inflation rate in context of Nepal.

4.4 GARCH (P,Q) Model on Residuals of ARIMA (0,0,1)

In this study, the best GARCH (P,Q) is selected by using Akaike Information Criterion (AIC) as Box-Ljung test on squared residuals of ARIMA (0,0,1) shows that there is ARCH effect. The more fitted is the model, the smaller is AIC. To use this criterion to select among alternative model specifications, the model with the smallest AIC value is selected. Thus, the best model is GARCH (2, 2) based upon minimum AIC Criterion (Annex-6). It shows that the model contains 2 lagged terms of the squared error term and

2 terms of the lagged conditional variance.The parameters of GARCH (2,2) is presented as follows:

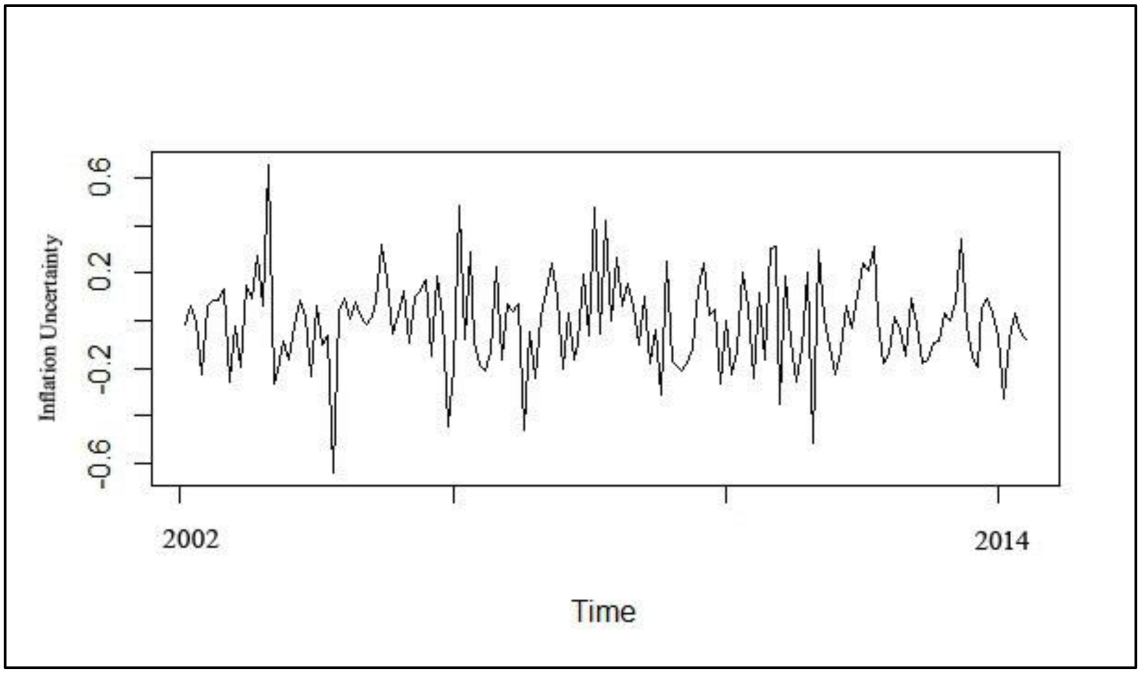
Table 4.6: Optimal Parameters of GARCH (2,2)

	Estimate	Std. Error	t value	Pr(>|t|)
omega	0.489306	0.168311	2.90715	0.003647
alpha1	0.000000	0.064609	0.00000	1.000000
alpha2	0.313791	0.164196	1.91107	0.055995
beta1	0.000000	0.181948	0.00000	1.000000
beta2	0.000000	0.230758	0.00000	1.000000
shape	7.823287	4.811967	1.62580	0.103993

Source: R 3.0.3

Table 4.6 shows that the intercept of model (omega) is 0.489306 and the *p*-value shows that it is statistically significant as it fails to reject the null hypothesis that coefficient is zero. Alpha 2 is 0.313791 and the *p*-value shows that it is statistically insignificant as it fails to reject the alternative hypothesis that coefficient is different than zero. From the parameters of Table 4.6 the inflation uncertainty is calculated. The values of inflation uncertainty is presented in Annex-5 as well as shown on the Figure 4.4.

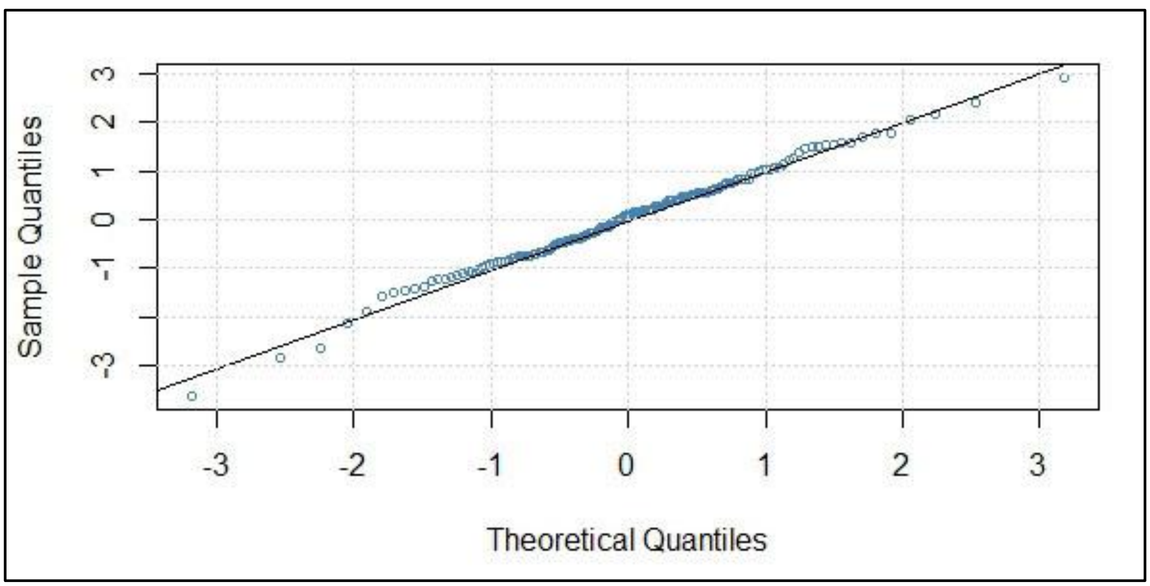
Figure 4.4: Inflation Uncertainty



Source: R 3.0.3 (Annex-5)

Figure 4.4 shows the inflation uncertainty, which is obtained from GARCH (2,2) based on Annex-5.

Figure 4.5: Quantile-Quantile Plots of Residuals



Source: R 3.0.3 (Annex-5)

Figure 4.5 shows that the residuals of GARCH (2,2) are normally distributed as they are nearer to theoretical lines. Weighted Ljung-Box Test is applied to test whether GARCH (2,2) is suffered from serial correlation or not.

Table 4.7: Weighted Ljung-Box Test on Standardized Residuals of GARCH (2,2)

	statistic	**p-value**
Lag[1]	0.02978	0.8630
Lag[2*(p+q)+(p+q)-1][2]	0.51770	0.9599
Lag[4*(p+q)+(p+q)-1][5]	2.45667	0.5788
d.o.f=1		
H0 : No serial correlation		

Source: R 3.0.3

Table 4.7 show that standardized residuals of various lags are fall under null region; it means residuals are independently distributed. Weighted Ljung-Box Test of Squared Residuals of GARCH (2,2) is applied to test whether contains ARCH effects or not.

Table 4.8: Weighted Ljung-Box Test on Standardized Squared Residuals of GARCH (2,2)

	statistic	**p-value**
Lag[1	0.3046	0.5810
Lag[2*(p+q)+(p+q)-1][11]	3.9967	0.7334
Lag[4*(p+q)+(p+q)-1][19]	8.7611	0.5889
d.o.f=4		

Source: R 3.0.3

Table 4.8 further shows that standardized squared residuals of various lags fall under null region; it means squared residuals are independently distributed. Thus, GARCH (2,2) is free from ARCH effect. Thus, causality between inflation and inflation can be find out by using OLS method.

4.5 Causality between Inflation and Inflation Uncertainty

In this section, OLS method is applied to find out the causality between change in inflation rate and uncertainty of change in inflation rate. The uncertainty of change in inflation has been calculated from GARCH (2,2) model. Table 4.9 shows the causality between change in monthly inflation rate and uncertainty of change in inflation rate taking 1st difference of monthly inflation rate data as dependent variable.

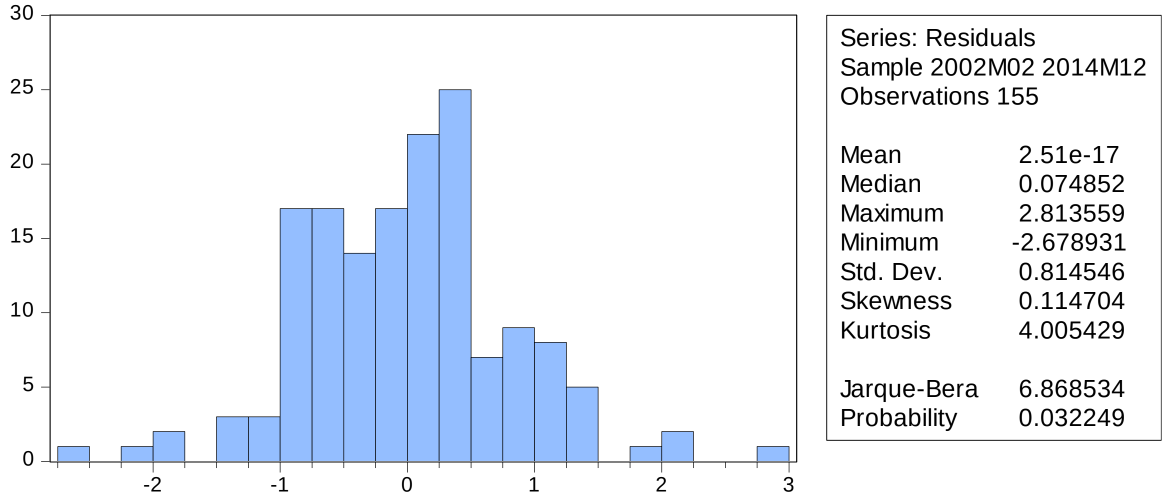
Table 4.9: OLS Method (Inflation Rate as Dependent Variable)

Dependent Variable: 1st Difference Data of Monthly Inflation Rate				
Method: Least Squares				
Sample: 2002M02 2014M12				
Included observations: 155				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
UNC	0.859499	0.340114	2.527089	0.0125
C	0.032605	0.065685	0.496391	0.6203

Source: EViews 9.0

Table 4.9 shows that the *p*-value is less than 5% that means, it falls under alternative region, which means it fail to reject the coefficient is zero that means the coefficient is significant. Thus, it can be said that the change in rate of inflation is explained by uncertainty of change in rate of inflation by 85.95% and rest by other factors in Nepal.

Figure 4.6: Correlogram of Squared Residuals



Source: EViews 9.0

Figure 4.6 shows that the residuals of OLS are normally distributed. For the best fit model, the residuals of the equation should be free from serial correlation. Thus, Breusch-Godfrey Serial Correlation LM Test is applied to test whether residuals are free from serial correlation or not.

Table 4.10: Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.705809	Prob. F(2,151)	0.4953
Obs*R-squared	1.435590	Prob. Chi-Square(2)	0.4878

Source: EViews 9.0

Table 4.10 shows the results of Breuch-Godfrey Serial Correlation LM Test. The result shows that residuals of OLS are fall under null region (i.e. there is no auto correlation); it means residuals are independently distributed. Thus, Breuch-Godfrey Serial Correlation LM Test shows that there is no serial correlation among the residuals of OLS equation. For the best model, there should be equal variance or homoskedasticity. To test this Breusch-Pagan-Godfrey test is applied.

Table 4.11: Heteroskedasticity Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	0.065580	Prob. F(1,153)	0.7982
Obs*R-squared	0.066409	Prob. Chi-Square(1)	0.7966
Scaled explained SS	0.097234	Prob. Chi-Square(1)	0.7552

Source: EViews9.0

Table 4.11 further shows that standardized squared residuals are fall under null region (i.e. the squared residuals are not correlated); it means squared residuals are independently distributed. It means there is no heteroskedasity problem in residuals of OLS.

From the analysis it can be concluded that uncertainty of change in inflation rate affects the change in inflation rate in context of Nepal. There may be possibility that rise in inflation may causes more uncertainty. Thus, here OLS is applied by taking uncertainty of change in inflation rate as dependent variable to measure causality between uncertainty of change in inflation rate and change in inflation rate.

Table 4.12 OLS Method (Uncertainty as Dependent Variable)

Dependent Variable: Uncertainty of Change in Inflation Rate				
Method: Least Squares				
Sample: 2002M02 2014M12				
Included observations: 155				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
DINF	0.046617	0.018447	2.527089	0.0125
C	-0.008393	0.015295	-0.548735	0.5840

Source: EViews9.0

Table 4.12 shows that the coefficient of change in inflation rate is 0.046617 or 4.67% of uncertainty of change in inflation rate is explained by the change in inflation rate in context of Nepal .Thus it can be concluded that there is not a significant effect on uncertainty of change in inflation rate due to change in inflation rate as explained by Friedman (1977).

CHAPTER-V

SUMMARY, CONCLUSION AND RECOMMENDATIONS

This study considered the monthly inflation rate (π_t) from 2002 to 2014. The logic behind the selection of monthly inflation data was to test the causality between inflation and inflation certainty was as explained by Cukierman and Meltzer (1986).

5.1 Summary

The monthly rate of inflation from 2002 to 2014 is taken for this study to found out the causality between inflation and inflation uncertainty in context of Nepal. To identify presence of unit root, ADF Test is performed in this study. ADF test indicated that the initial data are non stationary. Thus, the first difference data are taken for study. ADF test shown that first order difference data are stationary.

The first difference data of rate of inflation is taken for study. The ARIMA (0,0,1) model has been used because the first difference data of inflation consists one period lag moving average of error term. The best fit ARIMA (0,0,1), again left with residuals i.e. ε_t. The Box-Ljung test shows that residuals of ARIMA (0,0,1) persists ARCH effect, then GARCH (2,2) process has been used. Using GARCH (2,2), the uncertainty of change in rate of inflation has been calculated.

OLS method has been used to test causality between change in inflation rate and uncertainty of change in inflation rate. Firstly, OLS is applied taking change in inflation rate as dependent variable and secondly, the OLS is applied taking uncertainty of change in inflation rate as dependent variable. The result shows that change in inflation rate is explained by uncertainty of change in rate of inflation by 85.95% in Nepalese context. But, the study shows that uncertainty of change in rate of inflation is not dependent on the change in inflation in context of Nepal as the coefficient is not significant. Statistical test shows that the coefficient is statistically significant. As well as, the statistical test shows that the residuals and squared residuals of OLS are independent.

5.2 Conclusion and Recommendation

The result of this study shows that change in rate of inflation is explained by uncertainty of change in rate of inflation by 85.95% in Nepal. This study confirmed the Cukierman & Meltzer (1986) that higher inflation uncertainty leads to more inflation. But this study rejected the Friedman (1977) hypothesis that higher inflation lead to higher inflation uncertainty in context of Nepal. The reasons for the inflation uncertainty in Nepal are Indian inflation, international oil prices, weather etc. These are exogenous factors and cannot control by monetary authority. It may provide an incentive for the monetary authority to create an inflation surprise in order to stimulate output growth as explained by Cukierman & Meltzer (1986).

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Annex

Annex-1: Monthly Inflation Rate of Nepal

Year	Month	Inflation	Year	Month	Inflation	Year	Month	Inflation
2002	Jan	2.9	2006	May	9.1	2010	Sep	8.6
2002	Feb	3.2	2006	Jun	9.1	2010	Oct	8.9
2002	Mar	3.3	2006	Jul	8.3	2010	Nov	8.4
2002	Apr	2.4	2006	Aug	7.3	2010	Dec	9.6
2002	May	2.5	2006	Sep	6.6	2011	Jan	11.3
2002	Jun	3	2006	Oct	7.5	2011	Feb	10.2
2002	Jul	3.5	2006	Nov	7.1	2011	Mar	10.7
2002	Aug	4.2	2006	Dec	7.3	2011	Apr	10.6
2002	Sep	3.3	2007	Jan	7.6	2011	May	9.5
2002	Oct	3	2007	Feb	8	2011	Jun	8.8
2002	Nov	2.2	2007	Mar	6.2	2011	Jul	9.6
2002	Dec	2.7	2007	Apr	5.6	2011	Aug	7.7
2003	Jan	3.3	2007	May	4.6	2011	Sep	8.5
2003	Feb	4.6	2007	Jun	4.5	2011	Oct	8.9
2003	Mar	5.2	2007	Jul	5.1	2011	Nov	8.5
2003	Apr	8.1	2007	Aug	6.3	2011	Dec	7.5
2003	May	7.7	2007	Sep	7	2012	Jan	6.8
2003	Jun	6.6	2007	Oct	6.3	2012	Feb	7
2003	Jul	6.1	2007	Nov	6.3	2012	Mar	7
2003	Aug	5.4	2007	Dec	5.7	2012	Apr	7.5
2003	Sep	5.2	2008	Jan	5.2	2012	May	8.7
2003	Oct	5.6	2008	Feb	6	2012	Jun	9.9
2003	Nov	5.8	2008	Mar	6	2012	Jul	11.5
2003	Dec	4.9	2008	Apr	8	2012	Aug	11.9
2004	Jan	5	2008	May	8.3	2012	Sep	11.2
2004	Feb	4.7	2008	Jun	10.1	2012	Oct	10.5
2004	Mar	4.4	2008	Jul	10.6	2012	Nov	10.5
2004	Apr	1.7	2008	Aug	11.8	2012	Dec	10.4
2004	May	1.3	2008	Sep	12.4	2013	Jan	9.8
2004	Jun	1.8	2008	Oct	13.2	2013	Feb	10.1
2004	Jul	2	2008	Nov	13.7	2013	Mar	10.2
2004	Aug	2.4	2008	Dec	13.4	2013	Apr	9.5

2004	Sep	2.6	2009	Jan	13.8	2013	May	8.7
2004	Oct	2.6	2009	Feb	13.2	2013	Jun	8.2
2004	Nov	2.7	2009	Mar	12.9	2013	Jul	7.8
2004	Dec	3.1	2009	Apr	11.6	2013	Aug	7.9
2005	Jan	4.6	2009	May	12.4	2013	Sep	8
2005	Feb	5.7	2009	Jun	12	2013	Oct	8.4
2005	Mar	5.7	2009	Jul	11.1	2013	Nov	10
2005	Apr	5.8	2009	Aug	10.1	2013	Dec	10.3
2005	May	6.4	2009	Sep	9.2	2014	Jan	9.7
2005	Jun	6.2	2009	Oct	8.6	2014	Feb	8.8
2005	Jul	6.6	2009	Nov	9.1	2014	Mar	8.9
2005	Aug	7.3	2009	Dec	10.3	2014	Apr	9.4
2005	Sep	8.2	2010	Jan	10.7	2014	May	9.7
2005	Oct	7.8	2010	Feb	11	2014	Jun	9.5
2005	Nov	8.5	2010	Mar	10	2014	Jul	8.1
2005	Dec	8.8	2010	Apr	9.8	2014	Aug	7.5
2006	Jan	7	2010	May	8.9	2014	Sep	7.6
2006	Feb	5.8	2010	Jun	8.2	2014	Oct	7.5
2006	Mar	7.7	2010	Jul	9	2014	Nov	7.2
2006	Apr	7.9	2010	Aug	9.5	2014	Dec	7

Source: www.nrb.org.np

Annex-2: First Difference Data of Monthly Inflation Rate of Nepal

Period	dinf	Period	dinf	Period	dinf
1	0.3	53	0	105	0.3
2	0.1	54	-0.8	106	-0.5
3	-0.9	55	-1	107	1.2
4	0.1	56	-0.7	108	1.7
5	0.5	57	0.9	109	-1.1
6	0.5	58	-0.4	110	0.5
7	0.7	59	0.2	111	-0.1
8	-0.9	60	0.3	112	-1.1
9	-0.3	61	0.4	113	-0.7
10	-0.8	62	-1.8	114	0.8
11	0.5	63	-0.6	115	-1.9
12	0.6	64	-1	116	0.8
13	1.3	65	-0.1	117	0.4
14	0.6	66	0.6	118	-0.4

15	2.9	67	1.2	119	-1
16	-0.4	68	0.7	120	-0.7
17	-1.1	69	-0.7	121	0.2
18	-0.5	70	0	122	0
19	-0.7	71	-0.6	123	0.5
20	-0.2	72	-0.5	124	1.2
21	0.4	73	0.8	125	1.2
22	0.2	74	0	126	1.6
23	-0.9	75	2	127	0.4
24	0.1	76	0.3	128	-0.7
25	-0.3	77	1.8	129	-0.7
26	-0.3	78	0.5	130	0
27	-2.7	79	1.2	131	-0.1
28	-0.4	80	0.6	132	-0.6
29	0.5	81	0.8	133	0.3
30	0.2	82	0.5	134	0.1
31	0.4	83	-0.3	135	-0.7
32	0.2	84	0.4	136	-0.8
33	0	85	-0.6	137	-0.5
34	0.1	86	-0.3	138	-0.4
35	0.4	87	-1.3	139	0.1
36	1.5	88	0.8	140	0.1
37	1.1	89	-0.4	141	0.4
38	0	90	-0.9	142	1.6
39	0.1	91	-1	143	0.3
40	0.6	92	-0.9	144	-0.6
41	-0.2	93	-0.6	145	-0.9
42	0.4	94	0.5	146	0.1
43	0.7	95	1.2	147	0.5
44	0.9	96	0.4	148	0.3
45	-0.4	97	0.3	149	-0.2
46	0.7	98	-1	150	-1.4
47	0.3	99	-0.2	151	-0.6
48	-1.8	100	-0.9	152	0.1
49	-1.2	101	-0.7	153	-0.1
50	1.9	102	0.8	154	-0.3
51	0.2	103	0.5	155	-0.2
52	1.2	104	-0.9		

Source: R 3.0.3

Annex-3: Augmented Dickey Fuller Test

Null Hypothesis: INF has a unit root				
Exogenous: Constant				
Lag Length: 1 (Automatic - based on SIC, max lag=13)				
			t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic			-2.550303	0.1058
Test critical values:	1% level		-3.473096	
	5% level		-2.880211	
	10% level		-2.576805	
*MacKinnon (1996) one-sided p-values.				

Source: *Eviews 9.0*

Null Hypothesis: INF has a unit root				
Exogenous: Constant, Linear Trend				
Lag Length: 1 (Automatic - based on SIC, max lag=13)				
			t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic			-2.834739	0.1873
Test critical values:	1% level		-4.018748	
	5% level		-3.439267	
	10% level		-3.143999	
*MacKinnon (1996) one-sided p-values.				

Source: *Eviews 9.0*

Null Hypothesis: INF has a unit root				
Exogenous: None				
Lag Length: 1 (Automatic - based on SIC, maxlag=13)				
			t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic			-0.607275	0.4529
Test critical values:	1% level		-2.580065	
	5% level		-1.942910	
	10% level		-1.615334	
*MacKinnon (1996) one-sided p-values.				

Source: *Eviews 9.0*

Null Hypothesis: D(INF) has a unit root				
Exogenous: Constant				
Lag Length: 0 (Automatic - based on SIC, maxlag=13)				
			t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic			-9.919826	0.0000
Test critical values:	1% level		-3.473096	

	5% level		-2.880211	
	10% level		-2.576805	
*MacKinnon (1996) one-sided p-values.				

Source: *Eviews 9.0*

Null Hypothesis: D(INF) has a unit root				
Exogenous: Constant, Linear Trend				
Lag Length: 0 (Automatic - based on SIC, max lag=13)				
			t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic			-9.925663	0.0000
Test critical values:	1% level		-4.018748	
	5% level		-3.439267	
	10% level		-3.143999	
*MacKinnon (1996) one-sided p-values.				

Source: *Eviews 9.0*

Null Hypothesis: D(INF) has a unit root				
Exogenous: None				
Lag Length: 0 (Automatic - based on SIC, max lag = 13)				
			t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic			-9.945819	0.0000
Test critical values:	1% level		-2.580065	
	5% level		-1.942910	
	10% level		-1.615334	
*MacKinnon (1996) one-sided p-values.				

Source: *Eviews 9.0*

Annex-4: Residuals of ARIMA (0,0,1)

Start = 1							
End = 155							
Frequency = 1							
[1]	0.294623837	0.044443966	-0.908501654	0.274342862	0.447351876	0.414150306	0.620521898
[8]	-1.019082135	-0.104431596	-0.779958906	0.649679121	0.475322406	1.208782579	0.368026864
[15]	2.829373282	-0.942974895	-0.919037064	-0.323630888	-0.637893155	-0.077584209	0.414888908
[22]	0.120380155	-0.923101725	0.277149147	-0.353186700	-0.232221205	-2.655435260	0.109595072
[29]	0.478968002	0.108082966	0.379258185	0.127217920	-0.024413935	0.104685191	0.379910240
[36]	1.427092786	0.826131733	-0.158539983	0.130424840	0.574970636	-0.310340556	0.459556345
[43]	0.611808187	0.782590081	-0.550184060	0.805583853	0.145403287	-1.827903824	-0.849213522
[50]	2.062969526	-0.195897095	1.237593910	-0.237502216	-0.754421800	-0.855221614	-0.535877482

[57]	1.002838329	-0.592451113	0.313695172	0.239799883	0.353980863	-1.867931200	-0.241532012
[64]	-0.953648456	0.083011261	0.584069606	1.087913293	0.491222455	-0.794268742	0.152425270
[71]	-0.629251388	-0.379242619	0.872779093	-0.167491911	2.032142773	-0.089981243	1.817267978
[78]	0.151254609	1.170973270	0.375282713	0.727980838	0.360295804	-0.369143078	0.470840926
[85]	-0.690357396	-0.167515984	-1.267852607	1.043309054	-0.600217705	-0.784814369	-0.849389085
[92]	-0.736996782	-0.458565587	0.588001680	1.087158703	0.191367266	0.263275393	-1.050524238
[99]	0.001602345	-0.900307500	-0.527225211	0.901177902	0.327058176	-0.962764563	0.484760700
[106]	-0.593028690	1.313806012	1.447872193	-1.377855968	0.764419405	-0.246696991	-1.052657264
[113]	-0.497988314	0.895567154	-2.071865086	1.197604210	0.170172064	-0.432657112	-0.916970323
[120]	-0.524027509	0.300564243	-0.057680208	0.511069202	1.101922539	0.988533991	1.410293981
[127]	0.129355532	-0.724824157	-0.560901591	0.107640616	-0.120656925	-0.576845162	0.410700289
[134]	0.021183978	-0.704065341	-0.664885341	-0.372404235	-0.328533237	0.163047637	0.068710112
[141]	0.386814088	1.525767893	0.007195347	-0.601380833	-0.784591158	0.250568080	0.451914377
[148]	0.213274730	-0.240928790	-1.353764219	-0.340203956	0.165287323	-0.131719698	-0.274722144
[155]	-0.147279057						

Source: R 3.0.3

Annex-5: Inflation Uncertainty under GARCH (2,2)

1	2	3	4	5	6	7	8
-0.01534	0.059587	-0.00573	-0.22781	0.06255	0.0886	0.082411	0.131401
9	10	11	12	13	14	15	16
-0.26039	-0.02475	-0.19953	0.15087	0.091375	0.271828	0.062636	0.658809
17	18	19	20	21	22	23	24
-0.2669	-0.21328	-0.08346	-0.16182	-0.02441	0.085501	0.011869	-0.23199
25	26	27	28	29	30	31	32
0.063544	-0.10171	-0.06245	-0.64201	0.042164	0.093444	0.009981	0.077331
33	34	35	36	37	38	39	40
0.01381	-0.01862	0.012847	0.07665	0.322846	0.169313	-0.05556	0.021625
41	42	43	44	45	46	47	48
0.122083	-0.09186	0.101528	0.126858	0.168359	-0.15038	0.18671	0.011581
49	50	51	52	53	54	55	56
-0.44576	-0.19454	0.482318	-0.08241	0.28936	-0.08409	-0.18543	-0.20887
57	58	59	60	61	62	63	64
-0.13203	0.229869	-0.16499	0.071384	0.038982	0.07044	-0.45974	-0.04866
65	66	67	68	69	70	71	72
-0.24137	0.018253	0.122885	0.240582	0.09382	-0.20394	0.03312	-0.16576
73	74	75	76	77	78	79	80
-0.09475 81	0.197253 82	-0.0622 83	0.474634 84	-0.05683 85	0.425838 86	0.002285 87	0.269236 88

0.063252	0.159712	0.065515	-0.10218	0.10398	-0.1826	-0.04323	-0.31394
89	90	91	92	93	94	95	96
0.249331	-0.16961	-0.18887	-0.20806	-0.17974	-0.11519	0.13083	0.238694
97	98	99	100	101	102	103	104
0.02299	0.050481	-0.26493	9.02E-05	-0.22919	-0.1272	0.204962	0.054764
105	106	107	108	109	110	111	112
-0.24218	0.113485	-0.1611	0.308055	0.315384	-0.35162	0.187006	-0.08353
113	114	115	116	117	118	119	120
-0.25685	-0.12063	0.203401	-0.51509	0.297125	0.009107	-0.11254	-0.22619
121	122	123	124	125	126	127	128
-0.12791	0.062574	-0.0302	0.110638	0.243492	0.211926	0.314464	0.004987
129	130	131	132	133	134	135	136
-0.18284	-0.13821	0.017503	-0.04325	-0.14762	0.091016	-0.0132	-0.17852
137	138	139	140	141	142	143	144
-0.163	-0.09541	-0.08771	0.029262	0.001471	0.079353	0.345963	-0.02626
145	146	147	148	149	150	151	152
-0.15165	-0.19314	0.054313	0.090557	0.034427	-0.07103	-0.33109	-0.07923
153	154	155					
0.027248	-0.04557	-0.07579					

Source: R 3.0.3

Annex-6: GARCH (P,Q)

	GARCH (P,Q)	AIC
1	(1, 1)	2.4707
2	(1, 2)	2.483544
3	(1, 3)	2.496426
4	(1, 4)	2.509311
5	(1, 5)	2.522191
6	(1, 6)	2.53509
7	(1, 7)	2.547968
8	(1, 8)	2.560827
9	(2, 1)	2.483586
10	**(2, 2)**	**2.458376**
11	(2, 3)	2.470197
12	(2, 4)	2.484526
13	(2, 5)	2.487523
14	(2, 6)	2.500206
15	(2, 7)	2.51457

16	(2, 8)	2.52613
17	(3, 1)	2.496468
18	(3, 2)	2.470197
19	(3, 3)	2.483101
20 21	(3, 4) (3, 5)	2.497429 2.500426
22 23	(3, 6) (3, 7)	2.519222 2.527473
24	(3, 8)	2.539033
25	(4, 1)	2.509351
26	(4, 2)	2.484526
27	(4, 3)	2.497429
28	(4, 4)	2.510333
29	(4, 5)	2.51333
30	(4, 6)	2.532125
31	(4, 7)	2.540376
32	(4, 8)	2.548624
33	(5, 1)	2.52223
34	(5, 2)	2.49696
35	(5, 3)	2.509863
36	(5, 4)	2.522766
37	(5, 5)	2.526233
38	(5, 6)	2.545028
39	(5, 7)	2.55328
40	(5, 8)	2.561527
41	(6, 1)	2.535106
42	(6, 2)	2.510708
43	(6, 3)	2.523612
44	(6, 4)	2.536515
45	(6 5)	2.539025
46	(6 6)	2.551819
47	(6 7)	2.566183
48	(6 8)	2.57443
49	(7 1)	2.547977
50	(7 2)	2.523753
51	(7 3)	2.536657
52	(7 4)	2.549565
53	(7 5)	2.553907

54	(7 6)	2.570626
55	(7 7)	2.579086
56	(7 8)	2.590646
57	(8 1)	2.560846
58	(8 2)	2.529209
59	(8 3)	2.542119
60	(8 4)	2.551887
61	(8, 5)	2.557856
62	(8, 6)	2.570759
63	(8, 7)	2.582719
64	(8, 8)	2.595622
Best Model	**GARCH (2,2)**	**2.458376**

Source: R 3.0.3