Macroeconomic Uncertainties, Inflation and Output growth in India

A thesis submitted to Pondicherry University in partial fulfilment of the requirement for the award of the degree

DOCTOR OF PHILOSOPHY IN ECONOMICS

by

Balaji .B

Under the Guidance of

Prof. M. Ramachandran

DEPARTMENT OF ECONOMICS
School of Management
Pondicherry University
Puducherry- 605 014.

APRIL 2013

Dr. M. Ramachandran
Professor and Head
Department of Economics
School of Management
Pondicherry University
Puducherry- 605014

CERTIFICATE

This is to certify that the thesis titled "**Macroeconomic Uncertainties, Inflation and Output growth in India"** submitted to Pondicherry University in partial fulfillment of the requirements for the award of Doctor of Philosophy in Economics is based on the original research work done by Mr. **Balaji.B** at the Department of Economics, Pondicherry University under my supervision and guidance. The thesis has not formed the basis for the award to the candidate of any degree, diploma, fellowship or other similar title before.

Place : Pondicherry
Date : 08-04-2013

Prof. M. RAMACHANDRAN
(Research Supervisor)

Counter Signed :

Prof. R. PRABHAKARA RAYA
Dean, School of Management
Pondicherry University
Puducherry - 14.

Balaji.B
Ph.D. Research Scholar
Department of Economics
School of Management
Pondicherry University
Puducherry- 605014

DECLARATION

I hereby declare that the thesis titled "**Macroeconomic Uncertainties, Inflation and Output growth in India"** submitted to Pondicherry University for the award of Doctor of Philosophy in Economics is a record of my original research work and no part of this thesis has not formed the basis for the award of any degree, diploma, fellowship or other similar title before.

Place : Pondicherry
Date : 08-04-2013

B. BALAJI

Dedicated to My Beloved Parents

ACKNOWLEDGMENTS

Though only my name appears on the cover of this thesis, a great many people have contributed to this thesis. It is a very difficult task to acknowledge all individuals who have influenced and contributed in different ways. I am very grateful to all, who made this work possible; however, I would like to add a few special words for their concern and care.

My deepest gratitude is to my supervisor, Dr. M. Ramachandran, Professor and Head, Department of Economics, Pondicherry University. I have been tremendously fortunate to have an advisor who gave the freedom to explore the study area on my own and at the same time the guidance to recover when my steps faltered. His kindness, commitment, encouragement and motivation have been invaluable and kept me going ahead for the completion of this work.

My special thanks are due to Dr. S. Raja Sethu Durai, a young dynamic personality who is more like a student himself than a teacher. His energy and clear way of thinking were the driving force for me at all stages of research. I have learned from him how to listen quietly to any naive idea, and then probe it with few precise questions. He is the one who is behind the extremely complicated estimations of this thesis for which I feel very lucky to be associated with a scholarly person like him.

I express my sincere gratitude to Prof. M. Ramadass, who is one of the best teachers whom I have had in my life. His teachings on research methodology and uncompromised research ethics hold me to keep high research standards enforcing strict validations for each and every result.

I thank Prof. D. Sambandhan profusely for his insightful comments and constructive criticisms on my views at different stages of research which have helped to enrich my research ideas. An interaction with him always ended up with a benefit from his intellectual brilliance.

Discussions with many people led to improvements in this thesis. I am very grateful to Dr. Amaresh Samantaraya for his constant support, numerous discussions, stimulating suggestions and practical advice on the research issues strengthening the understanding of the research issue and steer me up in a right path.

I am very pleased to thank Prof. P. Ibrahim and Dr. V. Nirmala, Department of Economics for their personal care, valuable suggestions and encouragement in all my academic accomplishments. I also thank Prof. P. Muthaiyan and Dr. Sankaran for their constant encouragement and support.

My heartfelt thanks are due to Dr. C. Jerome Samraj, for his friendly and scholarly approach. He is the one who sets up high standards to the students and encourages and guides them to meet those standards. I also thank other faculty members of the Department, for their academic help and support.

I extend my profound gratitude to Prof. A M S Ramasamy, Dean of Ramanujam School of Mathematics for his moral support during the entire research as a Doctoral committee member.

I also thank the well-timed assistance in various ways of the supporting staffs of the Department of Economics, especially Mr. C. Balamurugane, Mr. Ramachandran, (Office Managers) Mr. Loganathan and Mr. G. Janakiramane, (Office Assistances).

I am thankful to the staff members of Ananda Ranga Pillai Library, Pondicherry University and Mr. K. Ramanujam and Mr. G. Saravanan from French Institute of Pondicherry for permitting me to use the library for research purpose.

A special remembrance to (Late) Prof. Amannulla, for his kindness, support and camaraderie.

I am very much grateful for the fellowship I received from UGC through Pondicherry University during my research period.

I indebted to Dr. V. Adimoulame, Joint Director, Directorate of Economics & Statistics, Government of Puducherry for his kindness, encouragement, personal care and support during the course of my thesis. In addition, I would also like to thank Dr. Muralidasan, Assistant Registrar, Pondicherry University for his constant advices, friendly nature and support throughout my stay in the campus.

I thank sincerely Mr. R. Satish, Indian Economic Service (IES) officer and Dr. A. Balachandaran, Associate Professor, Tagore Arts College, Pondicherry, for their moral support.

A special group is not mentioned yet, because they deserve their own part. My special words of gratitude to R. Sharl and his family for all their personal and professional help that they have extended to me all the way through. He is the friend who provided me two laptop computers for my research. I would also like to acknowledge the support rendered by K. Balasubramanian, M. Senthil Kumaran, S. Thiyagarajan, D.Balaji, M.Vijayan and S. Raj & family ever since the beginning of my academic career.

I have been fortunate to come across many funny and good friends, without whom life would be bleak. My heartfelt thanks are due to U. Devasenathipathi, K. Durairaj, S. Mariappan, M. Sankaran, C. Vijaya Baskar, A. Tharmalingam, A. Senthamilraja, A. Vadivel, B. Ezhumalai, P. Karmenivannan, R. Rajesh, Suchi Selva, Linkon and Sunil Paul for their wonderful company. I greatly value their friendship and deeply appreciate their belief in me. I have missed out some of the names because the list is endless...thanks to one and all.

I am very much grateful to Mrs. C.U. Tripura Sundari, Mrs. A. Vijaya Lakshmi and Mrs. S. Jackline for the sisterly affection rather than a junior-senior relationship they have shown during this course of work.

Thanks to A. Arul Jason for undertaking the meticulous task of reading and editing my manuscript from day one under his hectic program. A special acknowledgement and thanks goes to Ms. Swathi Sulagna for her friendship and ethical support during the time of depression. Their support and care helped me overcome setbacks and stay focused on my study.

I owe my sincere thanks to my friends, G. Kuppuraman & family and D. Mohan & family for providing me both financial and moral support throughout my educational career. My special thanks go to K. Jaikumar and Sivasankar for the timely help whenever required on the administrative side.

I make a special note of credit to S. Pouviarasan and S. Pougajendy for their moral support, love and care in my all my academic endeavor recent past.

I am really thankful to K.J. Suresh, CCafe, for his support on collecting web resources and printing issues. I am also grateful to Dr.Tamil for his supportive thoughts. I also thank Mrs. Chitra for the adroitness and promptness in executing the fine manuscript.

Most importantly, none of this would have been possible without the love and patience of my family. I am indebted to my father, Mr. R. Bathmanaban and my mother Mrs. B. Mahalakshmi for unflagging care and support throughout my life. Their patience never faded in spite of all the hardships they faced in life. I am ever grateful to their blessings.

I would also like to thank my brothers Mr. R. Sakthiyanarayanan, Mr. R. Sudarsanom, Mr. B. Srinivasan and Mr. B. Lakshiminarayan who have helped me stay sane throughout these difficult years.

I pay my sincere gratitude to V. Pradip Kumar and his parents (late) Venugopal, a dynamic personality, and (late) Jayalakshmi a lovable aunt, without whom I would not have been shaped up this way and might have ended up like an empty vessel in my life.

It's my greatest fortune to have the blessings of my Guru Thiru. Egilane Lebel. His teachings and wisdom show me the true priorities and facts of life. I feel myself blessed for being his disciple.

Above all, I owe all my sincere gratefulness to the Lord Almighty, who always steer me up in the tricks and thins of life. I always believed in Invisible hand, which ensures peace and wisdom in my path.

CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter-1
The Issues, Objectives and Methodology

1.1. Introduction

Price stability has been the prime objective of monetary policy framework all over the world. It is a common belief that low and stable inflation improves the functioning of the markets with effective allocation of resources. Monetary policy that ensures low and stable inflation over time, contributes to long-run economic growth and financial stability (Bernanke, 2011). There are plenty of studies that provide arguments in favour of moderate inflation rates benefiting growth as well as against it. Tobin (1965) argued that an increasing inflation reduces accumulated wealth in the economy that in turn raises current savings, investment, and growth[1]. Besides, there are number of studies that provide theoretical as well as empirical evidence in support of a significant negative impact of inflation on growth as inflation crosses a particular threshold level. Sarel (1996) found that the negative influence of inflation on output growth is significant, only if the average rate of inflation exceeds the threshold value[2].

In contrast, Sidrauski (1967) postulated a neutral effect of inflation on economic growth. Nevertheless, there is no common support for the view that inflation can raise growth[3]. Bruno and Easterly (1998) examined the association and confirmed that there exists a robust non-linear relationship between inflation and growth. Further, Akerlof et al. (1996) propounds that absolute price stability should not be the goal, since zero inflation incurs output loss even in the long run[4]. The negative impact of zero and higher inflation on growth entrusts the authorities to design the policy framework that accommodates positive inflation consistent with potential growth. However, there is no unanimous agreement on price stability being the dominant objective where, Orphanides and Solow (1990) pointed out that,

[1] Useful summaries of the literature on the inflation–growth relationship can be found in Briault (1995), Bruno and Easterly (1996), Haslag (1997), Temple (2000) and Klump (2003).
[2] See Barro (1995), Fisher (1993), Ghosh and Phillips (1998), Sarel (1996) and Khan and Senhadji (2001).
[3] Refer Haslag (1997) for a detailed review on this subject.
[4] They found that zero inflation reduces output growth by 1 to 3 percent. Tobin (1965) and Krugman (1996) hold similar views.

theoretically the direction of the impact of inflation on economic growth is quite ambiguous.

However, in recent times there is a spurt of research which focus not only on the relationship between inflation and growth but also on the relationship with their uncertainties. The issue dates back to Okun (1971), who reported that countries with high rates of inflation would also experience high variable inflation rates. These findings led to number of interesting research questions as whether reduction in macroeconomic uncertainties can have a favourable impact on the real economic growth and inflation. Since the early 1980s, there has been a remarkable development in macroeconomic performance of developed and developing counties with stable inflation and output growth[5]. Cecchetti and Krause (2001) reported a decline in both inflation and output variability in developed and developing countries in the 1990s compared with previous decades and identified a strong case in favour of a relationship between macroeconomic uncertainties with inflation and growth.

1.2. Uncertainties in Macroeconomics

In theoretical and empirical literature, the term macroeconomic uncertainty[6] is classified as nominal uncertainty (inflation volatility) and real uncertainty (output volatility). The relationships between inflation, real output growth and their volatility components have become a special research area in macroeconomics, because of its strong policy relevance and its ability in explaining the dynamics of various vital macroeconomic associations.

An uncertainty in any macroeconomic variables influence the actions taken by policy makers, firms and individuals, resulting in low capital formation in an economy by reducing the rate of investment spending. News on such variables is keenly monitored through time and is quickly reflected in agent's beliefs about

---

[5] Krause (2003) reports that in a cross section of 63 countries; mean inflation has fallen from approximately 83% in the pre-1995 period to approximately 9% in the latter half of the 1990s.

[6] Though volatility (fluctuations in a variable) and uncertainty (unpredictability of fluctuations) are two different notations, it is common practice to use them as a same concept. Hence, in the rest of chapters both terms are used as interchangeably.

future events (Patton, 2008). It is generally accepted that an uncertain economic situation causes economic agents to make decisions that are different from the ones they would make otherwise (Berument et al., 2009). In dynamic macroeconomic analysis, Kydland and Prescott (1982) and Dixit and Pindyck (1994) emphasized the irreversible and lagged effects of macroeconomic uncertainties on the economic decisions of the agents.

1.2.1. Competing Theories on Macroeconomic Uncertainty

Generally, economic theories hypothesize 12 causal relationships between real uncertainty, nominal uncertainty, output growth, and rate of inflation. Some of these hypothesis are lacking empirical support in the existing literature. The present study focus on the five important causal relationship associating the nominal uncertainty and real uncertainty with actual rate of inflation and output growth which are postulated as follows:

a) nominal uncertainty vs. inflation rate
b) nominal uncertainty vs. output growth
c) real uncertainty vs. inflation rate
d) real uncertainty vs. output growth
e) nominal uncertainty vs. real uncertainty

Empirical studies testing these relationships further classified them on the basis of positive effects, negative effects and the direction of causation.

a) Nominal uncertainty vs. inflation rate

Most of the surveys on the relationship between inflation and inflation uncertainty often ends up with a verdict that a rise in level of inflation raises uncertainty about the future inflation. This idea is first observed and postulated by Okun (1971) and Friedman (1977). Using the data for seventeen industrial OECD countries over the period 1951-1968, Okun (1971) reported that countries with high rates of inflation would also experience highly variable inflation rates.

In his Noble lecture, Friedman (1977) outlined an informal argument that increase in inflation will lead to more uncertainty about future rate, which may in turn distort the effectiveness of price mechanism and causes adverse output effects. Hence, higher inflation uncertainty has a negative causal effect on real growth. This statement is taken as two separate research issues as it involves substantial policy relevance. The first part posits the positive relationship with higher inflation and uncertainty about the future inflation. The second part of the statement explains the negative effects of inflation uncertainty on output. Both the hypotheses are well addressed and documented as separate research.

Further, Ball (1992) has provided a formal justification for Friedman's hypothesis in a monetary policy model, which is popularly known as '*Friedman-Ball Hypothesis*'. In his asymmetric game theoretic model, there are two types of policymakers, where one is willing to bear the economic costs of reducing inflation while the other is not interested to accept costs. When inflation is low, public are certain about the fact that both types of policymakers will keep it low, thus uncertainty concerning future inflation will also be low. But, during the high inflationary periods, uncertainty about future inflation escalates due to ambiguities in monetary policy stance. In this situation, public does not know which type of policymaker will be in charge and whether he is willing to reduce inflation or compromise with high inflation rates for the fear of recession. This potentially asymmetric monetary policy response implies a positive relationship between the level of inflation and inflation uncertainty.

On the contrary to *Friedman-Ball* hypothesis, using the well-known Barro–Gordon (1983) model of Fed behaviour, Cukierman and Meltzer (1986) theoretically validate that an increase in uncertainty about money growth and higher inflation uncertainty leads to a rise in optimal average rate of inflation. In their model, the objective function of the monetary policy and the money supply process are assumed as random variables. Though, Fed dislikes inflation but also looks to stimulate the output with surprise inflation. Thus, the economic agents may not able to understand the future inflation and face uncertainty about rate of money supply and monetary policy objective function. Consequently, this uncertainty provides an incentive to the monetary authorities to create an inflation surprise by raising optimal inflation rate in order to stimulate output growth which leads to a positive correlation between uncertainty and optimal average inflation.

Alternatively, in contrast to the positive association between inflation and its uncertainty, Holland (1995) claims that more inflation uncertainty leads to a lower average inflation rate and thus, the effect of inflation uncertainty on inflation is negative. He argues that since price stability is the Central Bank's principle target, as inflation uncertainty rises due to increasing in inflation, the monetary authority may respond by reducing money supply growth in order to reduce inflation uncertainty and the associated negative welfare effects. This negative association between inflation and uncertainly is referred as the '*Stabilizing Fed Hypothesis*'.

Further, Pourgerami and Maskus (1987), has supplied a different argument on the possibility of a negative effect of inflation on its uncertainty. He pointed out that in an accelerating inflation environment, economic agents may invest more resources in forecasting future inflation which would reduce uncertainty about inflation. A more formal model for this effect is presented by Ungar and Zilberfarb (1993), where the effect of inflation on uncertainty depends on the cost of inflation and the cost of gathering information to forecast inflation.

In summary, *Friedman –Ball* hypothesis and *Cukierman - Meltzer* hypothesis suggest a positive relationship between inflation and inflation uncertainty however they differ in the direction of causality. whereas Ungar and Zilberfarb (1993) and Holland (1995), supports a negative relationship. In spite of the difference in the direction of causality, all the theories in this line of research have acknowledged the importance of inflation uncertainty in explaining the real effects of inflation.

b) Nominal uncertainty vs. output growth

On the negative impact of inflation uncertainty on output growth, Friedman (1977) made an informal argument that rising inflation uncertainty reduces the effective allocation of resources and hinders long-term contracting, thus reducing output growth. Cukierman and Meltzer (1986) presented a model in which surprise money shocks by monetary authorities increases inflation uncertainty and in turn affects output growth. Similarly, Pindyck (1991) claimed that inflation uncertainty increases the uncertainty associated with potential returns to investment, thus it adversely affects the output growth[7].

On the contrary, by using a model that allows for symmetric adjustment costs of investment, Abel (1983) showed that inflation uncertainty raises investment and growth. The positive effect of inflation uncertainty on output growth was formally addressed by Dotsey and Sarte (2000) in a cash-in-advance model. The positive real effects of nominal uncertainty is the result of higher precautionary savings and risk aversion during high inflationary regimes which in turn leads to higher investment and results higher growth rates.

c) Real uncertainty vs. inflation rate

The positive effect of real uncertainty on inflation rate has been examined by Devereux (1989) in an extended Barro-Gordon model of endogenous wage indexation. He argued that the more real uncertainty reduces the optimal amount of wage indexation and induces the policymaker to create more inflation surprises in order to obtain *favour*able real effects. This study combines the Taylor (1979) effect with the Cukierman-Meltzer hypothesis. As the Taylor effect suggests a negative association between output variability and inflation variability and the Cukierman-Meltzer hypothesis illustrates a positive effect of inflation variability on average inflation, their combination yields a negative impact of output uncertainty on the rate of inflation. Using Barro and Gordon model, Cukierman and Gerlach (2003) supports the positive causal effect of output uncertainty on the inflation rate and confirmed Devereux's claim.

d) Real uncertainty vs. output growth

Similar to inflation and nominal uncertainty relationship, the effect of real uncertainty on average growth is well researched in the literature. The recent growth theories have shown a significant attention to the mechanism by which output

[7] Huizinga (1993) and Blackburn and Pelloni (2004) holds a similar view.

volatility influences economic growth and the sign and direction of this relationship. However, there is a lack of solid theoretical consensus on the anticipated relationship between these variables and hence economic theory offers three different possibilities, independent, negative or positive relationships between the output growth rate and its volatility

The first possibility is one in which there is no a priori relationship between output fluctuations and growth as asserted by standard business cycle models before 1980s. Caporale and McKiernan (1998) argued that the traditional theories of macroeconomic fluctuations view deviations of output from its trend is independent of the long-run growth rate. Friedman (1968) outlined that, the natural rate of output growth depends on skill, technology and the other real facts and the deviations of output from its natural rate is the consequence of misallocation of resources triggered by the price level misperceptions. This temporary variability in output growth is the consequence of monetary shocks and these deviations does not have any role in determining the natural rate of output growth[8].

The possibility of a positive relationship between output volatility and growth rates is credited to Schumpeter's (1942) idea of '*creative destruction*', where the fluctuations in output is associated with recessions leads to more spending on research and development which in turn geared up the growth rates. In the theory of saving under income uncertainty, Sandmo (1970) outlined a positive relationship between these two variables that the higher uncertainty in income leads to higher savings which in turn generates higher capital accumulation and resulting in higher growth rates. Mirman (1971) come out with a different justification for the positive relationship that higher fluctuations in the growth rate will motivate higher savings rate and therefore to a higher rate of investment. If there is a positive association between the level of investment and growth rate, then increase in investments leads to higher growth.

In contrary to the conventional business cycle theories, Black (1987) argued that the agents face a positive tradeoff between the risk and the return, and they

[8] Phelps (1969), and Lucas (1973), are holding the similar view on this association.

make riskier investments only when the expected rate of returns from the investments are high enough to compensate the risk bounded in those speculations. Thus the risk liking behaviour of the investors would generate more volatility which would eventually signal the higher growth rate. Aghion and Paul (1998), offer a different explanation to the positive link by arguing that, labour will move to more productive sectors than the least productive units, because during recessions, the opportunity cost of labour is low and level of unemployment is high and these transformations in labour force may result in higher growth rates. Blackburn and Galindev (2003) come out with the different argument that the increase in the volatility of output shocks boost the pace of knowledge accumulation and, consequently, affects the growth rates positively.

However, the possibility of inverse relationship between output volatility and growth was attributed to Keynes (1936) who believed that larger swings in growth could make the returns and long run profitability more risky and thus lower the demand for investment, which in turn reduces output growth. This hypothesis pointed out the significance of entrepreneurial expectations on investment and the influence of uncertainty on investment decisions which is detrimental to the long term growth. The studies by Bernanke (1983) and Pindyck (1991) argued that the irreversibility in investments make the re-allocation of capital more expensive and hence fluctuations in growth rates generate uncertainty about the future profitability of investment which in turn lower the investments and growth rates.

Ramey and Ramey (1991) proposed a negative relationship by arguing that if firms must commit to their technology in advance, then volatility may lead to reduction in the output because firms find themselves producing at suboptimal levels ex post. In contrary to Schumpeterian idea of *'creative destruction'*, Stiglitz (1993) come out with a different claim that the cost of output volatility may extensively outweigh the benefits of creative destruction, through its negative effect on the research and development and thus less investment in innovations will result in lower growth rates. At the same time Aghion and Howitt, (2006) argue that a negative relationship between volatility and growth is the result of the presence of irreversibility or diminishing returns to investments, or the imperfections in credit market that constrain investments during recessions.

The different possibilities discussed above is particularly concerned only about the sign and the direction of the relationship running form output fluctuations to output growth. But, there is also a possibility of the reverse causality that may run from output growth to output variability with different signs. The possibility of negative association is due to an increase in output growth results in higher inflation (the short-run Phillips curve effect) and the higher inflation leads to higher inflation uncertainty which distorts the effectiveness of the price (Friedman, 1977) and, hence, causes a negative output effect (Taylor, 1979).

e) Nominal uncertainty vs. real uncertainty

The association between nominal and real uncertainties received much consensus among the monetary authorities. Logue and Sweeney (1981) believed that greater variability in inflation rate leads to great variability in real growth rate. The higher fluctuations in relative prices results unstable producer uncertainty where the producers are find it difficult to distinguish the real changes from the nominal shifts, which in turn decreases the output growth.

In contrast, Taylor (1979) argued that more inflation uncertainty would be accompanied by less output growth uncertainty as a result of the tradeoff between inflation uncertainty and output growth uncertainty (the so-called Taylor curve). A fall in output growth in response of the monetary policy shocks results higher uncertainty about future prices, which consequently reduce the output uncertainty. Cecchetti and Ehrmann (1999) also pointed out that the aggregate supply shocks create a positive trade-off between nominal and real uncertainties. Moreover, Devereux (1989) claim that the real uncertainty can have a positive impact on the nominal uncertainty, where unexpected output shocks contributed to a reduction in the degree of wage indexation and increase the benefits of creating surprise inflation which cause higher nominal uncertainty.

The entire research on exploring the connection between nominal uncertainty and real uncertainty with inflation and output growth is based an informal argument made by Friedman (1977) that inflation may have a negative effect on output growth by increasing inflation uncertainty. In the words of Friedman (1977, p. 466) "*A burst* *of inflation produces strong pressure to counter it. Policy goes from one direction to another, encouraging wide variation in the actual and anticipated rate of inflation...*"

From a policy perspective, this statement is about two coherent relationships. The first relationship posits that rising inflation may induce an erratic policy response by the monetary authority and therefore, lead to more uncertainty in the future rate of inflation. The second part of the relationship contends that as a result of increase in inflation uncertainty, market prices becomes less efficient for coordinating economic activity, thus causing a decline in output growth. These two relationships have been developed as a separate research problem in the field of macroeconomics. But, the empirical evidence on some of these macroeconomic relationships remains scanty or not holding good for all the countries (Neanidisa and Savva, 2010). The validation of these relationships depends on the country's economic environment and the strength of the policy instruments followed by the monetary authorities.

In this backdrop, the present study attempts to verify the validity of the above discussed issues in the Indian context from a developing country perspective. First it examine the relationship individually between (i) nominal uncertainty and inflation; ii) real uncertainty and output growth. Second the combined effects of both nominal and real uncertainty on inflation and output growth are studied.

1.3. Objectives of the Study

The main objectives of the study are as follows:

1) To examine the validity of the relationship between inflation and nominal uncertainty.
2) To examine the nexus between output growth and real uncertainty, and
3) To verify whether these two macroeconomic uncertainties have any spillover effects among themselves and have any other effects on both inflation and output growth.

1.4. Scope and Relevance of the Study

In the Indian context, there is a plethora of studies that focus on inflation-growth nexus[9]. Altogether most of these studies support a negative association between inflation and output growth for India. With reference to macroeconomic uncertainties, except few, there are very limited studies in the Indian context. Thornton (2005) studied the relationship between inflation and inflation uncertainty in India and concludes in *favour* of both Friedman and Cukierman hypothesis. Similarly, Chowdhury (2011) argues that Friedman-Ball and Cukierman-Meltzer hypotheses hold simultaneously in India.

To our knowledge, there is no study that has attempted to examine the spillover effects between uncertainties of inflation and output growth in India. In this background, the present study, aimed at providing a comprehensive evaluation of all possible effects between output growth, inflation and their respective volatilities

1.5. Data and Methodology

1.5.1. Data

The empirical examination of the issues chosen for the present study has been carried using two data series. The Wholesale Price Index (WPI) and Index of Industrial Production (IIP) are used as variables for price level and output growth. The Wholesale Price Index (WPI) data for India is available from the early 1950s on monthly basis, whereas the data on Gross Domestic Product (GDP) is available only on quarterly basis that too from 1996 onwards, prior to which it is available only as annual series. Using annual or quarterly data for GDP, which has only around 50 observations may not be suitable for the sophisticated econometric exercises used in this thesis which are very sensitive to the data points. So, the Index of Industrial Production (IIP) data which is available on monthly basis from early 1980s has been used as a measure for output.

[9]Refer to Rangarajan (1983), Rangarajan and Arif (1990), Bhattacharya and Lodh (1990), Nachane and Lakshmi (2002), Virmani and Kapoor (2002), Singh and Kalirajan (2003) and Virmani (2004).

The inflation-inflation uncertainty relationships was estimated by using monthly WPI data from 1961:06 to 2011:04 and the output-output uncertainty relationships was investigated by employing monthly IIP data from the year 1980:04 to 2011:04. The cross relationship and spillover effects between the real and nominal uncertainties are studied for the time period from 1980:04 to 2011:04. Both the WPI and IIP data are converted to 1993-94 base year prices and seasonally adjusted. Inflation is measured as the logarithmic monthly difference of the wholesale price index as $\pi_t = log\ (WPI_t/WPI_{t-1})*100$ and similarly, output growth is logarithmic monthly difference of industrial production index as $y_t = log\ (IIP_t/IIP_{t-1})*100.$

All the data used in this study are obtained from various issues of Handbook of Statistics on Indian Economy and the other publications of Reserve Bank of India (RBI), Economic Advisor to Ministry of Industry and Commerce, Government of India (www.eaindustry.gov.in) and Central Statistical Organization (CSO).

1.5.2. Methodology

The empirical verification of the above discussed theories necessitates the construction of an appropriate measure for uncertainty. The absence of direct measure of uncertainty enforced the researchers to measure it in different methods. In the earlier studies, moving standard deviation of the series and dispersion in long run survey forecasts are commonly used as measure of uncertainty.

In recent times more scientific and sophisticated measure are developed in the literature. The conditional variance generated from the class of volatility models are used as uncertainty. Generally, there are two popular classes of volatility models available. Firstly, it is the Autoregressive Conditional Heteroscedasticity (ARCH) models developed by Engle (1982) and their extended version proposed by Bollerslev (1986) as a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models, which is based on the conditional volatility of the series. Secondly, the set of models used for measuring volatility are called as latent volatility or Stochastic Volatility (SV) models.

This study follows the methodology of Grier and Perry (1999) and Berument et al. (2009). The uncertainty measure for nominal and real variables are derived using both simple GARCH model and Stochastic Volatility (SV) model. After this measure is obtained, following Granger (1969), the bivariate VAR model was employed to test for causality between the inflation rate and output growth with their respective uncertainties.

Since the data used in this study has covered long time span, the existence of structural breaks is to tested to get a holistic picture of the relationship. This study used multiple structural break procedures proposed by Bai and Perron (1998, 2003) to identify the structural breaks. Once the breaks are identified, causality tests and other tests for different measures of uncertainty are re-estimated for different regimes in order to identify the effects of structural changes in the established relationship[10].

The modified version of bivariate GARCH model with BEKK parameterization proposed by Grier et al. (2004) was used to examine the causal relationship and volatility spillovers between macroeconomic uncertainties, inflation and output growth. This model has an advantage of simultaneously estimating the conditional means with variances and covariances and used to generate the conditional variances of inflation and output growth as a measure uncertainty.

An important distinction between the approach adopted here and the vast majority of previous studies is that the present model takes into account the possible non-diagonality in the covariance structures. The Granger-Causality tests are performed to test the causal effects of the estimated real (output growth) and nominal (inflation) uncertainties on inflation and output growth and their own interactions. The volatility spillovers are identified by expanding the conditional variance of each equation in the bivariate GARCH model.

[10] Here, the terms structural changes, structural breaks and regime switches are used interchangeably.

1.6. Organization of the Study

The thesis consists of five chapters. The present chapter provides an overview of inflation-output tradeoff with discussions about the influences of uncertainties on the policy decisions. In addition, the competing theories on the relationship are dealt in detail. It also highlights the objectives, scope and relevance, data, methodology and the limitations of the study.

Chapter 2 investigates the empirical validity of the relationship between inflation and its uncertainty in Indian context. It discusses the methodological issues in measuring uncertainty and different methods of constructing it. The empirical section of the chapter documents the results of the symmetric and asymmetric GARCH models and the Stochastic Volatility models.

Chapter 3 examines the causal nexus between the output and real uncertainty with select review of existing literature. Similar to previous chapter, the estimations of various types uncertainty measures and the results are provided.

Chapter 4 briefly summarises the literature on the earlier studies of macroeconomic uncertainties, inflation and output growth dynamics. To understand the spillovers between the variables, the results from the bivariate BEKK, and GARCH-M model are presented.

Chapter 5 concludes by summarising the empirical findings with discussion on useful policy implications based on the results. It also provides directions for future research.

1.7. Limitations

1. The analysis incorporated the data on Index of Industrial Production as a proxy for output growth due to non-availability of GDP data at monthly frequencies may limits the empirical validity of findings to some extent.

2. This study ignored the possible influence of other important variables which would have influenced the mean value of inflation and output. The mean equation of both the variables are modeled using Autoregressive (AR)

variables and this is mainly due to the non-availability of other variables for a long time period.

3. The study excluded the possible structural changes in conditional variances and all the estimated sub-sample analysis are based on the structural breaks in the mean values of the output growth and inflation rate.

Chapter 2
INFLATION AND INFLATION UNCERTAINTY

2.1. Introduction

One of the most controversial issues in economic theory is the "welfare cost" associated with the level of inflation. Ever since the contributions of Bailey (1956) and Friedman (1969), there is a long line of investigation on the welfare cost of inflation. It has been a most crucial policy variable in conducting monetary policy due to its commanding influence over the objective of price stability[1]. Mankiw (2006) listed cost of inflation as one of the 'four most important unresolved questions of macroeconomics.' Dotsey and Ireland (1996), pointed out that if price stability is the principal goal of monetary policy, then it necessitates an accurate measurement of the consequences of sustained price inflation. It is argued that welfare cost of inflation is higher when future inflation is unpredictable and also cited as a major source of cost of inflation.

Unanticipated inflation will reduce the level of investment because of its predominant influence on nominal contracts which creates costly real effects and distorts the working efficiency of the price mechanism. It makes the future prices unknown and causes the problem of allocation inefficiencies in the system. As a consequence, the central banks around the world are keen to control the factors that affect the unanticipated future inflation in order to manage the associated welfare cost. It is widely claimed in the literature that the knowledge of welfare cost of inflation closely associates with the link between the level of inflation and its uncertainty[2]. Evans (1991) pointed out that inflation rates impose significant economic costs on society through the channel of unexpected future inflation rates. Moreover, theoretical and empirical monetary models have reported that uncertainty about future inflation is positively related with inflation.

---

[1] See Lucas (2000) for a survey of the literature.

[2] A detailed discussion on Welfare Cost of Inflation and Inflation Uncertainty can be found in Friedman (1977), Jaffee and Kleiman (1977), Fischer and Modigliani (1978), Malkiel (1979), Mullineaux (1980), Levi and Makin (1980), Makin (1982) and Hughes (1982).

A number of different arguments were put forwarded since Okun (1971) made his claim that higher inflation in current period itself is a driving factor for greater uncertainty about the future path of inflation rates[3]. Friedman (1977) in his Noble lecture pointed out that change in inflation may stimulate unpredictable policy responses of monetary authorities, which may lead to more uncertainty about the future inflation. Fischer and Modigliani (1978) supported Friedman's argument by pointing out that an announcement of unrealistic stabilization program in high inflation regimes make future inflation rate more uncertain. Ball (1992), using a game theoretic framework, provides a formal justification to Friedman's insight and his claim on inflation-inflation uncertainty relationship is popularly known as "*Friedman-Ball hypothesis*".

In contrary to Friedman's judgment on the association between inflation and its uncertainty, Cukierman and Meltzer (1986) expounded the reverse linkage. On the premises of Barro-Gordon framework, they reported that higher inflation uncertainty leads to an increase in the optimal inflation rate as it provides an incentive to the policymaker to create an inflation surprise in order to stimulate output growth, and the direction of causality runs from inflation uncertainty to inflation.

However, Holland (1993) draws a different empirical justification for the negative association between inflation and inflation uncertainty based on the stabilization motive of the monetary authority which is known as ''*Stabilizing Fed hypothesis*''. A possible negative effect of inflation on inflation uncertainty was put forwarded by Pourgerami and Maskus (1987), in high inflation regimes, economic agents may spend more in predicting inflation which may reduce the inflation variability and a more formal analysis for this argument is presented in Ungar and Zilberfarb (1993).

Although empirical literature put forward different arguments in addressing this issue, it fails to establish a concrete association between inflation and inflation

[3] Gordon (1971) claimed this evidence to be "far from universal" due to its bias on the choice of the sample period, 1951-1968. However, Logue and Willet (1976) and Foster (1978) confirmed Okun's findings.

uncertainty as explained by the theory. These conflicting evidences may be due to the sensitive nature of test results, the description of data and the measure of uncertainty used for investigations. Elder (2002) has shown that the estimated effects of inflation uncertainty on the real variables vary substantially in terms of magnitude and timing. So, a more scientific and convincing uncertainty measure is required to obtain reliable conclusions.

The existing literature on the relationship between inflation and inflation uncertainty is pertaining mainly to advanced industrialized economies, where the average inflation rates have been typically very low. Thornton (2005) pointed out that there is very little empirical evidence on the inflation and inflation uncertainty hypothesis with respect to developing countries. In the Indian context, however, there is no study that exclusively examines these relationships except Thornton (2006) and Chowdhury (2011) where conditional variance generated from the simple GARCH model is used as a measure of inflation uncertainty. Some studies are examining this association in Indian context empirically with a basket of countries, but there is no any exclusive study on Indian context[4]. With this backdrop, this chapter is focusing on examining this relationship between inflation and inflation uncertainty in India over the period from 1960 to 2011.

For this purpose, as a two-step procedure method first we have generated variance from the Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) model and Stochastic Volatility Model (SV) model as a measure of inflation uncertainty. Second, these measures are used in Granger causality tests to identify the causality with the inflation. Further to check the presence of structural break in the data, multiple structural breaks test proposed by Bai and Perron (1998, 2003) is employed.

The rest of the study is organized as follows: Section 2 provides an overview on select empirical studies on the relationship between inflation and inflation uncertainty; Section 3 deals with the issues in measuring uncertainty and explains the rationale for using conditional variance as a measure of uncertainty; Section 4

[4] Refer Rizvi et al. (2004), Milles et al. (2009) and Jiranyakul (2010).

outlines the modeling approach adopted for empirical verification; Section 5 discusses the data and presents the empirical results of different volatility models, structural break test and causality tests; and Section 6 provides concluding remarks.

2.2. Empirical Literature

There is plethora of empirical studies on the link between inflation and inflation uncertainty involving methodologies with different measures using various sample periods and data frequencies[5]. There are works that deals with cross country verifications where uncertainty is measured by a simple variance. Moreover, as a scientific measure of uncertainty, recent studies have used different class of ARCH-GARCH models[6] which is categorized into either the two-step procedures or the simultaneous-estimation approach. Few of the important empirical studies in the existing literature are listed below.

By using different cross country data sets, studies by Okun (1971), Logue and Willett (1976), Jaffe and Kleiman (1977), Foster (1978), Gale (1981), Ram (1985), Davis and Kango (1996), Hess and Morris (1996) and Yeh (2007) confirm the presence of significant positive link between the level of inflation and its variability. The early empirical studies of Engle (1982, 1983), Bollerslev (1996)[7] and Cosimano and Jansen (1988) for US data did not find any evidence of a link between inflation and inflation uncertainty. However, Ball and Cecchetti (1990) and Evans (1991) provided supporting evidence on the Friedman-Ball hypothesis, particularly for long-term uncertainty. Ungar and Zilberfarb (1993), Arnold and den Hertog (1995) and Davis and Kanago (2000) also confirm the Friedman-Ball hypothesis, but only for countries experiencing inflation rates above a certain threshold level.

---

[5] Holland (1993) and Golob (1993), Entezarkheir (2006) and Crawford and Kasumovich (1996) summarize the earlier literature with the specific measure of uncertainty employed in each paper. An extensive review of literature on the relationship between inflation and its uncertainty component, from the early-1970s till the mid-1990s, can also be found in Davis and Kanago (2000). Erkam and Cavusoglu (2010) provide a review on the link between inflation and inflation-uncertainty into two groups on the basis of their econometric methodology. Most of the studies suggest a positive relationship between inflation and variability.

[6] For more details, See Bollerslev (2008)

[7] Engle (1983) and Bollerslev (1986) did not perform statistical tests but only compared the estimated conditional variance series with the US average inflation rate over various time periods. They found no significant relation between the two series.

Caporale and McKiernan (1997) found evidence to support Friedman's view in US data for the period 1947-1994. Using G-7 countries' data, Grier and Perry (1998), found that inflation significantly raises inflation uncertainty in all the countries. The reverse causality, i.e., from uncertainty to inflation, was found in favour of Japan and France where as in the case of US, UK and Germany the rise in inflation uncertainty lowers the level of inflation. Nas and Perry (2000) provides a strong evidence to the notion that increased inflation significantly raises uncertainty in Turkey for the whole sample period of 1960-1998, but the evidence is found to be mixed in sub samples.

Fountas (2001), by using UK's data set for 100 years provides empirical evidence to support the Friedman-Ball hypothesis. Likewise, Thornton (2008) also found that an increase in inflation raises inflation uncertainty in Argentina for a period of more than a century. Kontonikas (2004) also derived similar conclusion for UK using 30 years of inflation data. Telatar and Telatar (2003) showed that inflation causes inflation uncertainty in Turkey for the period of 1987-2001.

Thornton (2007) used CPI monthly data for 12 emerging market economies including India and found mixed results. Rizvi and Naqvi (2009) employed asymmetric GARCH models for 10 Asian countries and found a bi-directional causality except for India, Pakistan, Indonesia and Thailand, where inflation causes inflation uncertainty. Thornton (2005) studied the relationship between inflation and inflation uncertainty in India using a simple GARCH-in-mean model and concludes in favour of both Friedman and Cukierman hypothesis. Similarly, Chowdhury (2011) provide evidence for both Friedman-Ball and Cukierman-Meltzer hypotheses in Indian context.

In spite of the above methods, it is argued in the literature that, the asymmetric models are providing consistence results than the simple GARCH models. Brunner and Hess (1993) was the first one to have found the results of simple GARCH model to be inconsistent for US inflation data, due to its symmetric restrictions on the conditional variance and also shows that asymmetric models provide much stronger evidence. Joyce (1995) tried to establish the same idea for UK inflation data and found that estimates of the conditional variance are positively associated with the level of inflation where the symmetrical restrictions imposed on the variance are rejected. Fountas and Karanasos (2004), using EGARCH model for six European countries, found that inflation causes inflation uncertainty for France and Italy, but not Germany and uncertainty causes inflation in France and Germany with a negative sign.

Daal et al. (2005) found that positive inflationary shocks have stronger impacts on inflation uncertainty in Latin American countries than the negative shock and found mixed evidence for Crukeriman hypothesis. Korap (2009) investigated the relationship between inflation and inflation uncertainty in the Turkish economy by using EGARCH model and found apparent evidence that inflation leads to inflation uncertainty, but not much evidence in the opposite direction. Nazar et al. (2010) found an asymmetric link between Iran's inflation and inflation uncertainty in a EGARCH model where the positive shocks to inflation has a significant effect on uncertainty than the negative shocks and there is no reverse causality.

Jiranyakul (2010), using EGARCH model, found both the hypothesis is valid in ASEAN countries and the inflation uncertainty of these countries is asymmetric in nature. Fountas and Karanasos (2000) studied the US inflation from 1960-1999, by using a GARCH-in-mean model as a simultaneous estimation method which allows for simultaneous feedback from conditional variance to mean of inflation. Findings of this study showed that there was a strong positive bi-directional link between inflation and inflation uncertainty. Ajevskis (2007) tested a GARCH in mean model for Latvia's data and supported the Friedman-Ball and Cukierman-Meltzer theories.

Berument and Dincer (2005), by using the Full Information Maximum Likelihood Method, found evidence in support of Friedman-Ball hypothesis for all the G-7 countries for the period of 1957 to 2001. Baillie et al. (1996) employed an Autoregressive Fractionally Integrated Moving Average (ARFIMA)-GARCH-in-mean model for 10 countries by assuming inflation as fractionally integrated and found that Friedman hypothesis is consistent only for three countries. Conrad and Karanasos (2005) using monthly data of USA, Japan and UK, employed a dual long memory model of the ARFIMA-FIGARCH for the period 1962-2001 and provides supporting evidence for Friedman's theory in all countries in contrary to bidirectional causality for Japan.

Ozer and Turkyılmaz (2005) examined the inflation and uncertainty relationship in Jordan, Philippines and Turkey using long memory models of ARFIMA-EGARCH and found that an increase in inflation raises its uncertainty, but shows weak evidence for reverse effect and no evidence for asymmetry. Jinquan (2008) used the ARFIMA-FIGARCH model to investigate China's monthly inflation rate and found that both the mean and variance of inflation have remarkable long memory, and supports Friedman hypothesis. In contrast to all these studies, Hwang (2001) by using US monthly inflation in ARFIMA-GARCH models, found no evidence for both Friedman-Ball and Cukierman-Meltzer hypothesis.

In addition to ARCH/GARCH class of model, there are few more methods used in verifying the association between inflation and inflation uncertainty. Empirical studies by, Evans and Wachtel (1993), Kim (1993), Bhar and Hamori (2004) and Zhao et al. (2005) adopted the Markov-Switching heteroskedastic model to find the association between inflation and inflation uncertainty. The flexible regression model of Hamilton's (2001) is used by Chen et al. (2008) to capture the nonlinear aspect of the relationship as well as regime shifts in four East Asian economies. Zang (2010) studied the role of inflation uncertainty in determining China's inflation with a Stochastic Volatility model. Berument et al. (2009, 2010), investigated the effect of inflation uncertainty on inflation for Turkish economy by employing a Stochastic Volatility in Mean model (SVM) and found mixed evidences.

The basic idea of the above discussed studies is all about the reactions of monetary policy during the higher inflationary periods. When the economy experiences high inflation, the central bank likes to adopt tight monetary policy measures, but the time of disinflation is uncertain due to the fear of recession. It creates uncertainty about future monetary policy and makes monetary policy less stable. Accordingly, these studies have also acknowledged the importance of inflation uncertainty in explaining the real effects of inflation.

2.3. Methodology

2.3.1. Measuring Inflation uncertainty

The fundamental issue in verifying the theories of inflation-uncertainty relationship necessitates the construction of proper uncertainty measure for inflation. By its subjective nature, generally different methods are used to measure uncertainty. Constructing an appropriate measure is the key issue to incorrect inferences about the association between inflation and inflation uncertainty. To obtain an appropriate measure, different types of methods are put into practice. The literature began with an assumption that the differences in standard deviations of inflation across countries as valid measure of variability.

Once the literature turned to time series, the most common way to estimate inflation uncertainty is the cross-sectional dispersion of survey-based individual forecasts and the moving standard deviation of inflation. Survey based measures summarize the dispersion among the individual forecaster's measure at a point of time but not the confidence intervals of each individual[8]. Bomberger (1996) pointed out that, though survey- based studies are good measure of variability of expected inflation, yet it is bounded with the problem of unreliability and of biased confidence intervals.

Moving standard deviation methods are criticized on the basis of its inability in differentiating the variability and uncertainty[9]. Simple variability need not necessarily be an inflation uncertainty, because rational agents may anticipate a high unconditional variance of inflation (Kontonikas, 2003). Grier and Perry (1998) pointed out that the uncertainty measure discussed in Friedman-Ball and in Cukierman-Meltzer model is not simply a moving average; it is the variance of a stochastic, unpredictable component of inflation.

[8]Zamowitz and Lambros (1987) provided a detailed discussion on using survey dispersion as a measure of uncertainty.
[9]See Driffill and Ulph (1990) for detailed discussions.

With the advent of Engle's (1982) on Autoregressive Conditional Heteroskedasticity (ARCH) model and subsequently the Generalized ARCH (GARCH) model of Bollerslev.et al. (1994), inflation uncertainty is generally measured by the estimated one-step ahead conditional variance. This technique estimates the variance of unanticipated shocks in a variable rather than simply calculating a variability measure from the past outcomes. One advantage of using the GARCH estimation is that it offers a direct test of statistical significance of time variation of conditional variance whereas survey based measure are not providing this (Grier and Perry, 1998; Evans, 1991).

However, the GARCH family of volatility models ignores the existence of structural instability in volatility due to changes in regimes. This shock in the volatility may have a dynamic effect on the relationship between variable of interest. This problem necessitating an alternative class of volatility models called a Stochastic Volatility (SV) model introduced by Taylor (1986) that allows the variance to be a random variable and the volatility changes stochastically rather than deterministically[10]. This Stochastic Volatility models (SV) are more sophisticated and important alternatives to the ARCH models[11]. Both models are having similar properties to some extent, but the distinction between the two relies on whether the volatility is observable or not.

2.3.2. Granger causality tests

Using causality tests for studying the relationship between inflation and inflation uncertainty is quite debatable under the problem of generated regressors. In causality type investigations, as a two step procedure, the measure of uncertainty is derived from a GARCH model and uses it in a granger causality test to explore the relationship. But, Pagan and Ullah (1984) have criticized this two-step procedure for its misspecifications due to the problem of using generated variables from the first stage as regressors in the second stage, which may have biased results of the

[10] For surveys of SV models, see Taylor (1994), Ghysels et al. (1996) and Shepard (1996).
[11] Danielsson (1994), and Kim et al. (1998) providing supportive evidence for empirical evidence of SV models as a better fit compared to ARCH models.

Granger causality tests[12]. They argued that, instead of a two-step procedure, such issues should be estimated jointly as a one step procedure where inflation should be in variance equation and variance should be in mean equation of inflation specifications.

Berument and Dincer (2005) pointed out that, if the inflation affects the inflation uncertainty, and the inflation uncertainty affects the inflation, then the inflation and the inflation uncertainty variable needs to be included in the inflation uncertainty (variance equation) and inflation (mean equation) specifications, respectively. As an alternative method, to check the validity of Friedman hypothesis, recent studies have used a bivariate GARCH-in-mean model, where the variance is included in the mean equation[13].

However, as pointed out by Grier and Perry (1998) and Fountas et al. (2004), these techniques avoid the problem of generated regressors but do not allow lagged effects in its specifications. Normally the effects of inflation on uncertainty are likely to take several periods and the usage of these models limits the ability to establish causality. Fountas et al. (2004) report the results of an EGARCH-M model, which confirm that a simultaneous approach does not detect the causal effect of inflation uncertainty on inflation. For these reasons, following Grier and Perry (1998), we also adopted the two-step procedure to capture the lagged effects of inflation.

2.4. The Model

2.4.1. Measuring Uncertainty

Firstly, the GARCH model for inflation is estimated using the following equation described by (Grier and Perry, 1999) and the time-varying conditional

[12] Pagan and Ullah (1984) suggest the Full Information Maximum Likelihood (FIML) method to address these issues.
[13] For example, John Thornton followed this type of methodology with Granger causality test in most of his papers. Grier and Perry (2000); Grier et al. (2004); Bredin and Fountas, (2005); Fountas et al., (2006) have also provided more details.

variance obtained from this GARCH model is used as a measure for inflation uncertainty. The model is

$$\pi_t = \beta_0 + \sum_{i=1}^{n} \beta_i \pi_{t-i} + \varepsilon_t$$
$$h_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1}^2 \qquad (2.1)$$

where π_t is the rate of inflation at time t ,n is the number of lags, and e_t is the shocks to the inflation process that cannot be forecasted with information known at time t. e_t is also assumed to be normally distributed with zero mean with a time-varying conditional variance h^2_t. Here, the conditional mean equation is simply an autoregressive representation inflation and the conditional variance is specified as a GARCH (*p, q*) of GARCH (1, 1) process, where only one lagged ARCH (ε_{t-1}^2) and GARCH (h_{t-1}^2) term are included in the variance equation. This GARCH process is a linear function of past squared forecasts errors and past variances.

This model assumes the constant and the coefficients in the equation to be positive for a non-negative conditional variance $(\alpha_0, \alpha_1, \alpha_2 \geq 0)$. In addition, to avoid the explosiveness in the conditional variance, the sum of the coefficients in variance equation except the constant should be less than one $(\alpha_1 + \alpha_2 \prec 1)$. The parameters of both mean and variance equations can be estimated simultaneously using the maximum likelihood method.

Next, we construct another measure for inflation uncertainty using log-normal AR (1) Stochastic Volatility model (SV), a more sophisticated model than the ARCH-type models which are due to Taylor (1986). The SV model depicted in equation 2.1 can be considered as an alternative to the ARCH models where the mean and volatility equations are estimated simultaneously. The mean equation of the SV model is similar to GARCH models and only the variance equation differs. The Stochastic Volatility model is as follows,

$$\pi_t = \alpha_0 + \sum_{i=1}^{k} b_i \pi_{t-i} + \sigma^* \exp(0.5 h_t)\varepsilon_t$$
$$h_t = \varphi h_{t-1} + \sigma_\eta \eta_t \qquad (2.2)$$

where α_0 is a constant term, π_t is the level of inflation which depends on a set of lagged exogenous variables π_{t-i} , $i = 1, . . ., k,$ and $b_1, b_{,}...., b_k$ are the other regression coefficients. The error term ε_t is independently and identically normally distributed with zero mean and unit variance. The term $h_t = \ln(\sigma_t^2 / \sigma^{*2})$ is a first-order autoregressive model of stochastic process; σ_t^2 is the volatility process, which is defined as the product of the positive scaling factor σ^{*2} and the exponential of the stochastic volatility process h_t. It is also assumed that the disturbances terms in mean and variance equations are mutually uncorrelated.

2.4.2. The relationship between inflation and inflation uncertainty: Granger causality tests

Following Granger (1969), the bivariate autoregressive model in equation 2.3 is used to test the causality between the inflation rate and its uncertainty.

$$\begin{bmatrix} \pi_t \\ h_t \end{bmatrix} = \begin{bmatrix} \alpha_\pi \\ \alpha_h \end{bmatrix} + \sum_{i=1}^{k} \begin{bmatrix} c_{\pi\pi}, i & c_{\pi h}, i \\ c_{h\pi}, i & c_{hh}, i \end{bmatrix} \begin{bmatrix} \pi_{t-i} \\ h_{t-i} \end{bmatrix} + \begin{bmatrix} e_{\pi t} \\ e_{ht} \end{bmatrix} \qquad (2.3)$$

where π_t is the inflation rate and h_t is conditional variance generated from GARCH and SV models, which is used as a measure for inflation uncertainty. $e_t = [e_{\pi t}, e_{ht}]'$ is a bivariate white noise with mean zero and non-singular covariance matrix $\sum_e$. The test of whether π_t (h_t) strictly Granger causes h_t (π_t) is simply a test of the joint restriction that all the $c_{h\pi};i$ ($c_{\pi h};i$), $i = 1,\ldots,k$, are zero. In each case, the null hypothesis of no granger-causality is rejected if the exclusion restriction is rejected. Bidirectional feedback exists if all the elements $c_{\pi h};i,\ c_{h\pi};i$), $i = 1,\ldots,k$, are jointly significantly different from zero. Akaike information criterion (AIC) and Schwartz Bayesian Criterion (SBC) are used to determine the optimum number of lagged variables in the test procedure.

2.4.3. Multiple Structural breaks test

Theoretical advances in the literature of unknown structural break tests[14], in particular the important contributions by Andrews (1993), Andrews and Ploberger (1994) and Bai and Perron (2002) enable us to identify changes and the associated timing in the underlying model with considerable precision. We prefer the tests of multiple structural changes proposed by Bai and Perron (1998, 2003) to determine the break dates. A key feature of the Bai and Perron procedure is that it allows testing for multiple breaks at unknown dates, so that it successively estimates each break point by using a specific-to-general strategy in order to determine consistently the number of breaks.

Following Bai and Perron (1998, 2003)[15], a multiple linear regression with *m* breaks (*m*+1 regime) is considered as below:

$$y_t = x_t^{'}\beta + z_t^{'}\delta + u_t \qquad t = T_{j-1} + 1,..., + T_j \tag{2.4}$$

where j =1,…, m +1; y_t is the explained variable; x_t (p×1) and z_t (q×1) are vectors of explanatory variables; β and δ_j (j=1,…, m+1) are the vectors of coefficients; u_t is the error term at time *t*. Equation (2.4) indicates a partial structural change model because the coefficient β is not subject to change; while p=0, a pure structural model is arrived since all parameters are subject to change. For each M-partition (T_1,., T_m), denoted $\{T_j\}$. The method of estimation for coefficients (β and δ_{j}) is based on minimizing the sum of squared residuals. $\sum_{i=1}^{m+1} \sum_{t=T_{i-1}+1}^{t} (y_t - x_t^{'}\beta - z_t^{'}\delta_j)^2$. We used the partial structural model for to verify the presence of breaks.

---

[14] Chow (1960) is the first one credited for the test for structural changes. His test procedures are criticized by Hansen (2001) for the assumption that the break dates are known a priori.

[15] For estimating the number of breaks, this procedure estimates small number of breaks in the model. While the first break point is identified, the sample is separated into two sub-samples by the first break point. For each sub-sample, the sup F_T ($m+1|m$) test is employed and the second break is obtained for which there is greatest reduction in the sum of squared residuals. The same procedure is employed for each sub-sample until the *m* breaks are arrived at.

2.5. Empirical Results

The estimates are obtained for seasonally adjusted[16] monthly Indian Wholesale Price Index (WPI) data for the time period from June 1961 to April 2011 yielding 599 observations[17]. The inflation variable (π_t) is defined as the logarithmic difference of the monthly point-to-point percentage change in seasonally adjusted price data. All the data is obtained from various issues of the Handbook of Statistics on Indian Economy and other publications of the Reserve Bank of India.

Table 2.1: Summary Statistics of Monthly Inflation

Mean	0.5882
Maximum	4.5080
Minimum	-2.4522
Std. deviation	0.8478
Skweness	0.3863
Kurtosis	5.2650
Jarque-Bera	142.94 (0.00)
Q (12)	70.91 (0.00)
Q^2(12)	220.64 (0.00)

Notes: Q (12) and Q^2 (12) are the 12 order of the Ljung-Box (LB) test for serial correlation in the residuals and squared residuals of the inflation rate from its sample mean. The numbers in parenthesis are *p* values.

First we examine some of the descriptive statistics for the inflation series and the results are presented in Table 2.1. The mean of the monthly inflation rate is 0.5882% with a standard deviation of 0.8478%. The positive value of Skweness and Kurtosis indicates that the distribution of the inflation series is skewed to the right with fat tails and the series is highly leptokurtic which means that the series is not normally distributed. The large value of the Jarque–Bera[18] statistic confirms the presence of non-normality in the series. The Ljung-Box Q statistic test is employed to check the presence of serial correlations. The high significant values of both the residual (Q (12) =70.91) and the squared residuals (Q^2 (12) = 220.64) indicates the

[16] The seasonal factors are adjusted by using both *X*-12-ARIMA routine and moving average methods. For both these methods the obtained results are similar, so we use seasonally adjusted price data from *X*-12-ARIMA method for its scientific nature.
[17] The whole sample period has been converted into 1993-94 base year prices, using the method of Splicing Index Numbers.
[18] The Jarque-Bera test checks the normality of a given sample by following a chi-square distribution with two degrees of freedom. Based on Skweness and Kurtosis calculated from the sample, it tests the null hypothesis that the data are from a normal distribution.

presence of higher order autocorrelation in the series. The significant higher order autocorrelation in the squared returns proves the presence of volatility clustering.

The stationary properties of the inflation series is tested by using augmented Dickey Fuller (ADF)[19], the Phillip-Peron (PP) unit root tests and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test[20] and the results are presented in Table 2.2. The optimum lag length for ADF is determined by the Schwartz Bayesian Criterion, while PP and KPSS test uses the optimal bandwidth determined by Newey-West bandwidth selection methods. Based on the respective procedures of accepting or rejecting the null hypothesis, all the test statistics confirms that inflation series is stationary at the conventional level of significance.

Table 2.2: Unit Root Test Statistics for Monthly Inflation

Unit root tests	Coefficients
ADF	-9.9032* (0.00)
PP	-18.3213* (0.00)
KPSS	0.1057*

Notes: Figures in parenthesis are *p* values; * indicates significance at the 1% level and '**' indicates 10% level of significance.

Usually, checking the presence of ARCH effects in the series is an essential precondition for any GARCH class of models. To check the presence of ARCH effect, the Engel's LM test statistic[21] (ARCH-LM) is used. The *F* statistic of the ARCH-LM test is presented in Table 2.3. The *F* statistic tests the null hypothesis of 'no ARCH effects in the errors'. In all the lags the null hypothesis is rejected at 1% level of significant from which it is understood that the presence of ARCH effect is very much evident for all the chosen lag orders. This implies that the variance of the inflation is heteroskedastic and hence, using ARCH/GARCH process will provide efficient estimates of the parameters concerned.

[19] See Dickey and Fuller (1979) for methodology and MacKinnon (1991) for critical values.

[20].Refer Phillips-Perron (1988) and Kwiatkowski, Phillips, Schmidt, and Shin (1992) for detailed methodology.

[21]The Engle's ARCH-LM test is a Lagrange multiplier test to measure the significance of ARCH effects. This test is based on residuals from the regression model and the null hypothesis is 'no ARCH effect'. A large critical value indicates rejection of the null hypothesis in favor of the alternative.

Table 2.3: The test results of ARCH effects -

Lags	Coefficients
2 lag	35.65 (0.00)
4 lag	21.77 (0.00)
8 lag	12.71 (0.00)
12 lag	9.43 (0.00)

Figures in parenthesis are *p* values

Subsequently, the presence of ARCH effects in the model leads to estimation of AR (q) - GARCH (1, 1) process for both the mean and variance equations of inflation using Maximum Likelihood function[22]. The estimated results of the model are summarized in Table 2.4. All the coefficients in mean and variance equations are statistically significant and the sum of the ARCH and GARCH coefficients ($\alpha + \beta$) in the conditional variance equation is 0.97 which indicates that the volatility exhibits high degree of persistence. The sum of ($\alpha+\beta$) is less than one which indicates the mean reverting character of the conditional variance of inflation series.

To test the validity of estimated model, a set of diagnostics tests are employed. The Ljung-Box Q-test[23] statistic is used to check the presence of higher order autocorrelation in standardized residuals and in standardized squared residuals. In addition, the ARCH-LM test has been carried out to check presence of remaining ARCH effects in the squared residuals. The reported Q statistic of standardized residual up to twelve lags is 10.43 with p-value 0.57 indicates the absence of serial correlation in the estimated residuals. The estimated Q statistic of standardized residual squares using 12 lags is 6.24 with p-value of 0.90 accepting the null of 'no autocorrelation' in the squared residuals[24].

[22] We have used Bollerslev-Woodbridge's Quasi-Maximum Likelihood (QML) method where Berndt-Hall-Hall-Hausman (BHHH) numerical algorithm is employed as an optimization procedure to compute non-linear estimations.

[23] The "portmanteau" test of Ljung and Box assesses the null hypothesis that a series of residuals exhibits 'no autocorrelation' for a fixed number of lags L, against the alternative that 'some autocorrelation coefficient ρ (k), $k = 1... L$, is nonzero'.

[24] The performance of the Ljung–Box test is affected by the number of lags (k) utilized. Tsay (2002) suggests that the choice of k =ln (sample size) provides better power performance. Though *ln* (sample size) = 6, we fix an upper limit for k equal to 12.

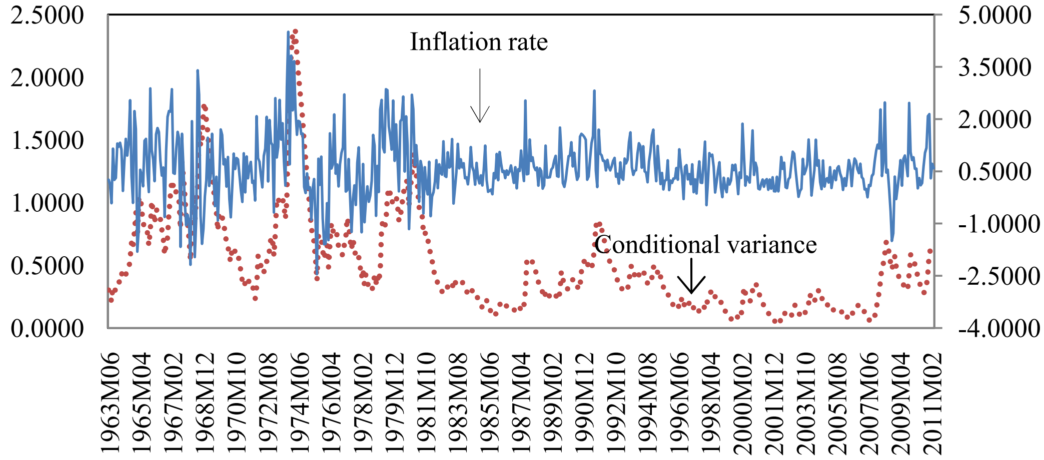
Table 2.4: The Symmetric GARCH Model for Monthly Inflation

Parameters	Symmetric model
Mean Equation	
b_0	0.3565 (0.00)
b_1	0.3026 (0.00)
b_3	0.1629 (0.00)
b_7	0.1042 (0.00)
b_{12}	-0.2291 (0.00)
b_{16}	0.1067 (0.00)
b_{24}	-0.0930 (0.00)
Variance Equation	
a_0	0.0129 (0.00)
a_1	0.1283 (0.00)
a_2	0.8499 (0.00)
Diagnostic Statistics	
Q(4)	2.3390 (0.67)
Q(12)	10.4360 (0.57)
$Q^2(4)$	3.0922 (0.54)
$Q^2(12)$	6.2409 (0.90)
ARCH-LM (4)	3.5586 (0.46)
ARCH-LM (12)	6.5326 (0.88)

Notes: Q (k) and Q^2 (k) are the Ljung-Box test statistic of the levels and the squared residuals respectively. LM (4) and LM (12) are ARCH-LM statistics of chi-squares. The figures in parenthesis are *p* values.

The LM test for neglected ARCH effect is 3.55 and 6.532 with *p*-value of 0.46 and 0.88 for 4^{th} and 12^{th} lag respectively indicating the absence of remaining ARCH effect in the model. All together, the insignificant Q statistic and LM test statistic indicates that the estimates of mean and variance equations do not suffer from any misspecification bias. The inflation rate and conditional variance generated from GARCH model, has been shown in Figure 2.1. The solid line indicates the inflation rate and while the dotted line indicates the conditional variance generated from GARCH models, which provides evidence that the higher inflationary periods are followed by periods of higher uncertainty about future inflation.

Figure 2.1: Inflation Rate and its Conditional Variance (GARCH)



Since the works of Brunner and Hess (1993) and Joyce (1995), it has been argued that the response of inflation uncertainty to inflation is asymmetric in nature; that is the magnitude of the effect of positive inflationary shocks on uncertainty is not similar to the negative shocks. But the simple GARCH model is bounded with a symmetric assumption of conditional variance for both positive and negative shocks. Hence, by using diagnostic tests suggested by Engle and Ng (1993) [25], we test whether there is any asymmetry in the response of volatility measure for the past shocks in inflation and the results are summarized in Table 2.5.

Table 2.5: Test for Asymmetries in Monthly Inflation

Parameters	Sign Bias Test	Negative Sign Bias Test	Positive Sign Bias Test	Join test for Sign and Size Bias
α_0	0.6804 (0.00)	0.5396 (0.05)	0.5405 (0.05)	0.6820 (0.00)
β_1	-0.2631 (0.00)	-0.0035 (0.96)	-0.0241 (0.80)	-0.2648 (0.00)
β_2	-	-	-	0.0001 (0.99)
β_3	-	-	-	-0.0361 (0.71)
TR^2	-	-	-	7.5068 (0.05)

Values in parenthesis are *p* –values

The test results show that both the positive and negative sign bias tests are insignificant, but the joint test shows some evidence in favour of the asymmetric response of inflation volatility at conventional level of significance. So we check the

[25] To check the presence of asymmetry in volatility series, Engle and Ng (1993) proposed a set of tests know as sign and size bias tests. These tests can be individually computed as a sign-bias test, a negative-size-bias test, a positive-size-bias test and jointly estimated as joint distribution test.

asymmetric behavior of uncertainty with asymmetric GARCH models, *viz*., EGARCH and TGARCH[26], where the non-negative constraints are not implemented in the estimated coefficients. The test results are presented in Table 2.6.

Table 2.6: The Asymmetric GARCH models

Parameters	EGARCH model	TGARCH model
Mean Equation		
b_0	0.3744 (0.00)	0.3639 (0.00)
b_1	0.2952 (0.00)	0.2998 (0.00)
b_3	0.1412 (0.00)	0.1599 (0.00)
b_7	0.1305 (0.00)	0.1102 (0.00)
b_{12}	-0.2336 (0.00)	-0.2347 (0.00)
b_{16}	0.0973 (0.01)	0.1096 (0.00)
b_{24}	-0.1125 (0.00)	-0.0946 (0.00)
Variance Equation		
a_0	-0.1863 (0.00)	0.0116 (0.00)
a_1	0.2152 (0.00)	0.1340 (0.00)
a_2	0.9772 (0.00)	0.8650 (0.00)
a_3	0.0356 (0.12)	-0.0443 (0.41)
Diagnostic Statistics		
Q(4)	2.5718 (0.63)	2.4908 (0.64)
Q(12)	10.342 (0.58)	10.000 (0.61)
$Q^2(4)$	2.9916 (0.55)	3.0764 (0.54)
$Q^2(12)$	6.3669 (0.89)	6.2864 (0.90)
ARCH-LM (4)	3.4184 (0.49)	3.5227 (0.47)
ARCH-LM (12)	6.6658 (0.87)	6.5710 (0.88)

Notes: Q (k) and Q^2 (k) are the Ljung-Box test statistic of the levels and the squared residuals respectively. LM (4) and LM (12) are ARCH-LM statistics of chi-squares. The figures in parenthesis are *p* values.

The Ljung-Box Q statistic indicates that the standardized errors are serially uncorrelated and LM statistics confirms that both the asymmetric GARCH (1, 1) models adequately capture the conditional variance. However, the asymmetric coefficients in both the models are insignificant, which doubts the presence of asymmetry in the variance equations. The different assumptions of error distributional have also provided same results of ‘no asymmetry’ in the variance

[26] To capture asymmetric responses of inflation volatility, we have employed exponential GARCH (EGARCH) model proposed by Nelson (1991) and the threshold GARCH (TGARCH) by Zakoïan (1994) and Glosten, Jaganathan, and Runkle (1993).

equations[27]. Since asymmetric GARCH models do not capture any asymmetric response of variance to inflation, we confine with the simple GARCH model[28] and use its variance as a measure for inflation uncertainty.

Table 2.7: Causality between Inflation and Uncertainty (GARCH) - Full Sample

Lag Length	Inflation does not Granger Cause Inflation Uncertainty	Inflation Uncertainty does not Granger Cause Inflation
4 lags	3.4037* (+) (0.00)	0.5244 (0.71)
8 lags	2.3965* (-) (0.01)	0.7082 (0.68)
12 lags	3.1342* (+)(0.00)	1.4221 (0.15)

Note: Given values are the *F*- static of Granger causality tests and. '*' indicates 1% level of significance. The figures in parenthesis are p values. The sign (+) or (-) indicates the direction of the relationship.

To check the direction of causality between inflation and GARCH (1, l) measure of inflation uncertainty, Granger-causality tests are conducted by employing the models specified in equation 2.3 and results are presented in Table 2.7[29]. The results show that the null hypothesis that inflation does not Granger-cause inflation uncertainty is rejected at the 1-percent level using four, eight or 12 lags. The null hypothesis that 'uncertainty does not Granger-cause inflation' cannot be rejected in all the lag orders. The sum of lagged inflation coefficients in nominal uncertainty equation is positive which indicate that positive nominal uncertainty effect of rise in inflation rates[30]. These results favor Friedman-Ball hypothesis that increased inflation raises inflation uncertainty.

Table 2.8 reports the test results of SV-model estimations. The parameters of the mean and variance equation are presented in the first column and the lower and

[27] The three most common distributional assumptions about the errors in ARCH models are normal (Gaussian) distribution, Student's t-distribution, and the Generalized Error Distribution (GED). We check all the distributions for all the different types of GARCH models employed and there is no change in the results for different distributional assumptions.
[28] Although we use the estimated conditional variance from GARCH models, the results need to be treated with causation. For example, Batchelor and Dua (1993) show that ARCH based measure can give misleading account of the causes of the changes in uncertainty.
[29] The AIC, SBC and HQ criterions are applied to find the optimum lag length. However, model selection criterions choose different lag order for different regimes as an optimum lag level; we verified the relationship up to 12 lags. The causal effects are also test for more lags for some models to understand the clear direction of the association.
[30] Throughout the study, the (+) or (-) notation indicates the sign sum of the lagged coefficients of the other independent variable.

higher critical values with the 95% confidence intervals are presented in the second and third column respectively. The mean specification includes a constant and 12th period lagged value of inflation with an error term. The variance specification includes only the lagged values of inflation volatility.

Table 2.8: Stochastic Volatility model for Monthly Inflation

Parameters	Coefficients	LCL	HCL
α	0.49494	0.57503	0.41486
y_{t-12}	0.00042	0.00046	0.00039
$\exp(0.5h_t)\,\varepsilon_t$	0.41814	0.49077	0.35626
ϕ	0.96054	0.96347	0.95739
η_t	0.08566	0.10054	0.07298
Q (12)Statistic = 133.02	Normality test statistic = 5.182		AIC= 1260.85

All the estimated parameters in the SV model are statistically significant because their confidence bands do not include zero. The volatility persistence parameter of the estimated series is statistically significant and less than one in absolute value implying that h_t is stationary. The presence of autocorrelation of the standardized residual is tested for 12 periods, by using Lagrangian Multiplier (LM) test, suggested by Wooldridge (1991). The null hypothesis of 'no autocorrelation' of the standardized residual cannot be rejected at the 5 % significance level. The smaller value of Jarque-Berra normality test statistic shows that the null hypothesis of 'normally distributed errors' cannot be rejected.

Figure 2.2: Inflation Rate and its Conditional Variance (SV)

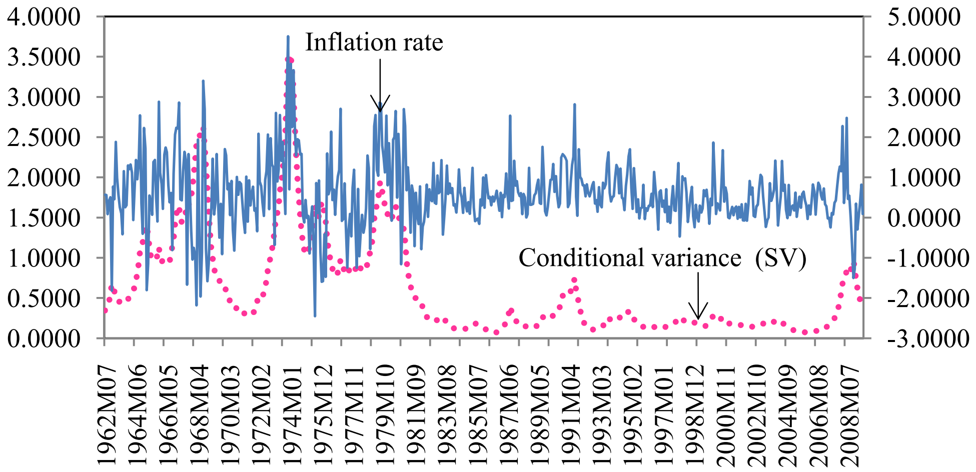


Figure 2.2 presents the association between the inflation and the variance generated from SV models. This shows similar movements between the variables like that of GARCH variance where the difference is exhibited only in the magnitude of the change. The Granger causality test results of the inflation and the uncertainty generated by using SV model is presented in Table 2.9.

Table 2.9: Causality between Inflation and Uncertainty (SV) – (Full Sample)

Lag Length	Inflation does not Granger Cause Inflation Uncertainty	Inflation Uncertainty does not Granger Cause Inflation
4 lags	9.4821* (+) (0.00)	3.5301* (-) (0.00)
8 lags	5.7766* (+) (0.00)	2.0381** (-) (0.04)
12 lags	4.0990* (+) (0.00)	2.0819* (-) (0.01)

Notes: Given values are the *F*- static of Granger causality tests and. '**', '*' indicates 5 %, and 1 % level of significance respectively. The figures in parenthesis are *p* values. The sign (+) or (-) indicates the direction of the relationship.

In contradiction to causality results established by GARCH models, the causality results of SV models show a bi-directional relationship between inflation and inflation uncertainty in all the lags. The null hypothesis of no inflation effect of nominal uncertainty was rejecting at conventional significant level across all lag lengths and provide support for the Friedman-Ball claim. On the other hand, the test results reject the null hypothesis that inflation uncertainty does not Granger-cause inflation and support Holland's hypothesis that an increase in inflation uncertainty lowers inflation and as a result of the policymakers' stabilization efforts, there may be a feedback effect from inflation uncertainty to inflation. These ambiguous results may be due to different measures of uncertainty[31] or because of the structural breaks existing in the system[32].

[31] Evans and Wachtel (1993) pointed out those conflicting results on the relationship between inflation and inflation uncertainty that may arise when differenced measures of uncertainties are used. Batchelor and Dua (1993, 1996) made a comparison of the performance of different methods of inflation uncertainty.

[32] Ungar and Zilberfarb (1993), Evans and Wachtel (1993), Garcia and Perron (1996) and, Chang and He (2010) claimed that structural shifts in inflation series may not only affect the estimates of uncertainty, but also the relationship between inflation and inflation uncertainty.

Table 2.10: Bai and Perron Test for Multiple Structural breaks

Specifications: $Y_t = \{\pi_t\}$ $Z_t = \{1, \pi_{t-1}\}$ $q = 2$ $p = 0$ $h = 89$		$M = 5$
SupF_T: no breaks vs. $m = k$ breaks		
$k = 1$		19.0653*
$k = 2$		12.0037*
$k = 3$		13.6286*
$k = 4$		13.4782*
$k = 5$		13.6601*
No breaks vs. a known number of breaks		
UD max		19.0653*
WD max		26.7832*
SupF_T: l breaks vs. $l + 1$ breaks (SupF_T $(l+1\|l)$)		
$l = 1$		14.1589*
$l = 2$		16.9773*
$l = 3$		10.4247
$l = 4$		9.4485
Selection with the sequential method		3
Selection with the SBIC & LWZ information criterion	SBIC	LWZ
$k = 0$	4.6123	4.6156
$k = 1$	4.6013*	4.6514
$k = 2$	4.6061	4.7038
$k = 3$	4.6245	4.7681
$k = 4$	4.6477	4.8381
$k = 5$	4.6738	4.9111

Notes**:** '*', denote significance at 5%, and the critical values are taken from Bai and Perron (1998).Changes in the mean are tested selecting a trimming = 0.15 with a maximum number of five structural breaks. Serial correlations in the errors are allowed for. The consistent covariance matrix is constructed using Andrews (1991) method.

This indistinct nature of the causality between inflation and uncertainty tempts us to re-estimate the whole analysis with possible structural breaks in the models. We apply the Bai and Perron (BP) test procedure with a constant and inflation as regressors (i.e., $z_t = \{1, \pi_t\}$) in a model which accounts for potential serial correlation via non-parametric adjustments. To find the breaks in the model, Bai and Perron (1998, 2003) introduced three formal F-related test statistics namely the sup F-type test, the double maximum tests (UD max and WD max) and the sequential test (sup $F_T(m+1|m)$, m=1, 2,…,n). A strategy for selecting the number of breaks recommended by Bai and Perron (1998, 2003) to first check the UD max or WD max tests to see if at least one break is present. Once the presence of a break is confirmed, the number of breaks can then be detected from the sequential examination of the sup $F_T(m+1|m)$ test.

In Table 2.10, the y_t, z_t, q, p, h, and M denote the dependent variable, the explanatory variable allowed to change, the number of regressors, the number of corrections included in the variance-covariance matrix, the minimum number of observations in each segment, and the maximum number of breaks, respectively. We impose 15 % trimming on each end of the sample and allow a maximum of five breaks; hence each segment has at least 89 observations. We also allow the variance of the residuals to be different across the segments with different distributions and the results are presented in Table 2.10. The documented test results in this table show that both *D*max and the WDmax confirm the presence of breaks.

The sup$F_T(k)$ appeared as highly significant for the five possible break points but at the same time sup$F_T(l+1/l)$ supports only for three break periods with the coefficient value of 16.97 which is significant at the 5% level. The SBIC information criterion selects one and the sequential procedure selects three break points corresponding to three regimes at the 5% level, although the LWZ information criterion detects none. Bai and Perron (1998, 2003), Perron (1997) documented that the information criteria are biased downward and that the sequential procedure and the supF_T(l +1/l) perform better than the former. So on the basis of sequential test supF_T $(l+1/l)$ we conclude the presence of three breaks at the 5 % level of significance.

Table 2.11: Break dates estimates

	Break dates
$\hat{T}_1$	1972:01 (1969:12 -1974:10)
$\hat{T}_2$	1980:08 (1978:01 -1983:11)
$\hat{T}_3$	1995:06 (1991:10 -2001:08)

Once the presence of breaks is located, the next procedure is to find the date of occurrence of the structural breaks. Table 2.11 reports the period of structural breaks in the inflation series. The breaks are estimated at 1972:01, 1980:08 and

1995:06. The first and second breaks are, however precisely estimated since the 95% confidence interval covers only two years before and after the break. The third break date has a rather large confidence interval before and after the break at the 95% significance level.

The three breaks located in the data classify it into four regimes and are closely associated with the most turbulent period of Indian inflation. In the first break (1972-1975), India's inflation was in double digit for a period of thirty months, which is highest ever in history since independence. In 1970's the inflation overshot to the level of 20%, i.e., 20.2% in 1973–1974 and 25.2% in 1974–1975 and the average inflation in the decade was 9%. During this period India has also experienced a severe drought and second Indo-Pak war, where as the world economy had been hit by the first oil price shock along with rising grain and metal prices. The second break point (1978-1980), witnessed a strong resurgence of inflationary tendencies due to poor agricultural output and the second shock in international crude oil prices. The third break was due to a substantial hike in administered prices, drastic shortfalls in the production of cash crops along with large monetary expansions and high fiscal deficits.

We re-estimate the causality tests with the two measures of uncertainty for all the four regimes and the corresponding results are presented in Table 2.12. The Granger causality test results of the first two regimes do not show any evidence for either Friedman-Ball or Cukierman-Meltzer arguments for both the uncertainty measures. The results pointed out that, there is no significant relationship existing between inflation and inflation uncertainty in India till late 80s', as advocated by different theories. In regime 3, when the GARCH generated uncertainty measures are taken into account, the F-statistic of Granger causality test does not reject Friedman's claim. On the contrary, the Granger causality test applying the uncertainty measure generated from SV models supports the views of Friedman argument and Holland '*Fed Stabilization Hypothesis'* at conventional significant levels. The results also show that it is the higher inflation that causes higher inflation uncertainty in the regime 4 following economic reforms of 1990s' and not the other way around in the shorter lags.

Table 2.12: Causality between Inflation, GARCH and SV for different Regime

	Generalized Auto Regressive Model (GARCH)		Stochastic Volatility Model (SV)	
Lags	$\pi_t \rightarrow h_{\pi_t}$	$h_{\pi_t} \rightarrow \pi_t$	$\pi_t \rightarrow h_{\pi_t}$	$h_{\pi_t} \rightarrow \pi_t$
		Regime 1 - (1963:05 - 1971:12)		
4	1.6635 (0.16)	0.7641 (0.55)	0.3978 (0.80)	0.7940 (0.53)
8	0.3161 (0.50)	0.8585 (0.95)	1.5171 (0.80)	0.5641 (0.16)
12	0.6403 (0.59)	0.5855 (0.91)	1.5868 (0.11)	0.7970 (0.65)
		Regime 2 - (1972:01 - 1980:07)		
4	0.6403 (0.63)	0.5854 (0.67)	2.1568** (0.08)	1.6154 (0.17)
8	1.0459 (0.40)	0.8360 (0.57)	1.3279 (0.24)	0.9833 (0.45)
12	0.4424 (0.93)	0.7816 (0.66)	0.8378 (0.61)	0.9484 (0.50)
		Regime 3 - (1980:08 - 1995:05)		
4	6.9818* (+) (0.00)	1.1006 (0.35)	12.9182*(+) (0.00)	5.1035*(-) (0.00)
8	4.8243* (-) (0.00)	1.1617 (0.32)	5.2791*(+) (0.00)	3.7175*(-) (0.00)
12	4.0370* (+) (0.00)	0.8511 (0.59)	4.2987*(+) (0.00)	3.5206*(-) (0.00)
		Regime 4 - (1995:06 - 2011:04)		
4	2.2542**(-) (0.06)	1.1763 (0.32)	4.5454*(-) (0.00)	1.1889 (0.31)
8	2.2404*(+) (0.02)	1.1996 (0.30)	2.5683*(+) (0.01)	1.5132 (0.15)
12	2.5205*(+) (0.00)	1.1410 (0.33)	2.2130*(+) (0.01)	2.0398*(-) (0.02)

Notes: Given values are the F- static of Granger causality tests and. '**', '*' indicates 10 %, 5 %, and 1 % level of significance respectively. π_t represents inflation and $h_{\pi t}$ indicates inflation uncertainty. The figures in parenthesis are *p* values. The symbol $\rightarrow$ indicates the direction of causality. The sign (+) or (-) indicates the direction of the relationship. $\pi_t \rightarrow h_{\pi t}$ indicates inflation does not Granger-cause inflation uncertainty; $h_{\pi t} \rightarrow \pi_t$ indicates inflation uncertainty does not Granger-cause inflation .

The Figure 2.3 to Figure 2.10 presents the plots of the association between GARCH and SV generated variance for all the four regimes. From these plots for both SV and GARCH variances, it is evident that for the first two regimes there is no relationship between inflation and its uncertainty. In these two regimes there are few episodes with high inflation and low uncertainty and vice versa. Altogether it is evident from these two regimes that the movements in inflation and its uncertainty are totally inconclusive. It is seen from the plots of 3rd and 4th regimes supports the view higher inflationary periods are followed by higher inflation uncertainty which is similar to the causality results.

2.6. Concluding remarks

This chapter examines the nature of the relationship proposed by various theories between inflation and its unexpected future uncertainty. To check this, we model India's inflation uncertainty using monthly price data for the period from

June 1961 to April 2011. The critical drawbacks of survey based indicators and moving average methods of measuring uncertainty pushed us to use the advanced time series models namely GARCH and SV type models for constructing the inflation uncertainty measure. The Bai and Perron multiple structural break tests are employed to verify the stability of the data and to check the presence of exogenous breaks in the system. As a two step procedure, Granger causality tests are used to check the presence causality between inflation and the variances generated from both GARCH and SV model.

Although diagnostic statistics suggest the presence of asymmetric response of inflation uncertainty, however, the asymmetric GARCH models did not. Granger causality results provided contradictory evidences for different uncertainty measures during the entire sample period. The Friedman-Ball hypothesis was supported by uncertainty measure obtained from GARCH models whereas the uncertainty obtained from SV model supports both the Friedman and Holland's hypotheses. The test results of Bai and Perron statistic provide evidence for the existence of three structural breaks in the inflation series. When the break dates are taken in to account, the causality results of both the models are similar except for the third regime. In this regime, the GARCH variance supports the Friedman-Ball claim whereas the variance from SV model provides valid evidence for Friedman and Holland's stabilization hypothesis. For the first two regimes, GARCH and SV model together pointed out the absence of any relationship between inflation and inflation uncertainty whereas both supports the argument of Friedman in the regime of post economic reforms.

Figure 2.3: Inflation and GARCH Variance (1963:05 - 1971:12)

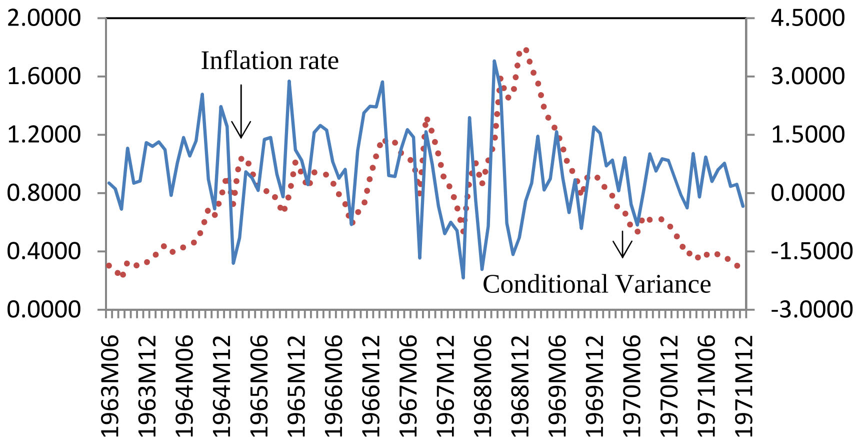


Figure 2.4: Inflation and GARCH Variance (1972:01 - 1980:07)

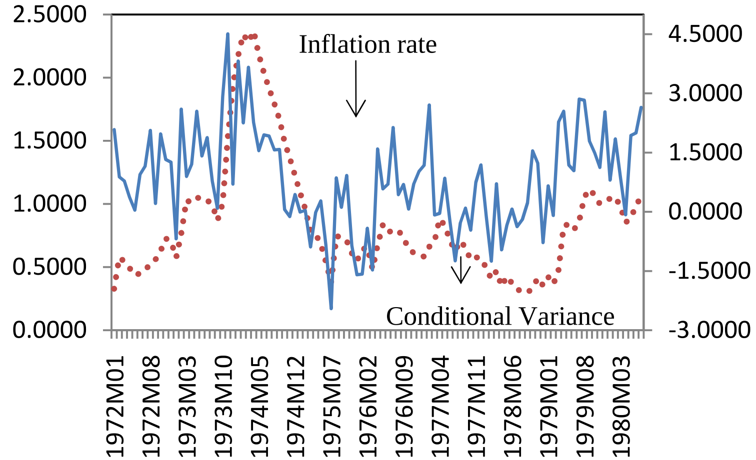


Figure 2.5: Inflation and GARCH Variance (1980:08 - 1995:05)

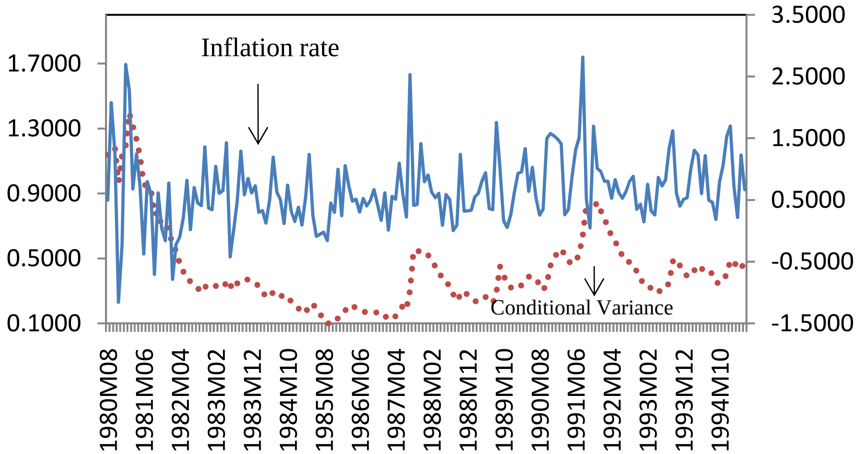


Figure 2.6: Inflation and GARCH Variance (1995:06 - 2011:04)

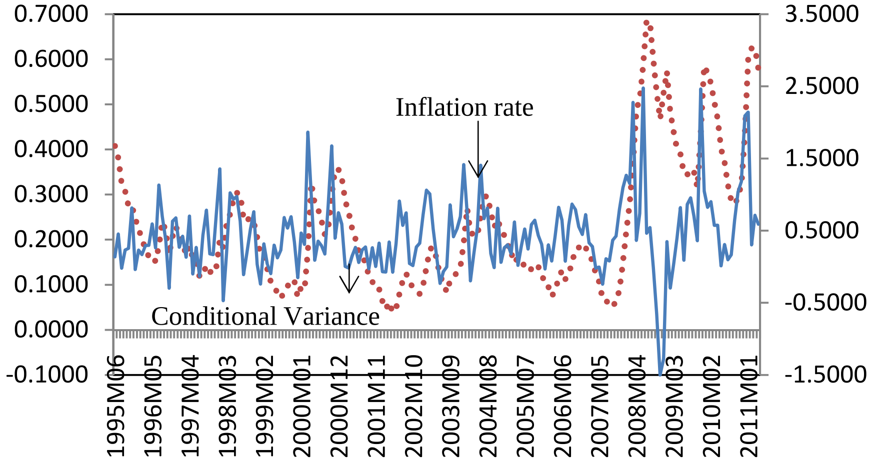


Figure 2.7: Inflation and SV Variance (1963:05 - 1971:12)

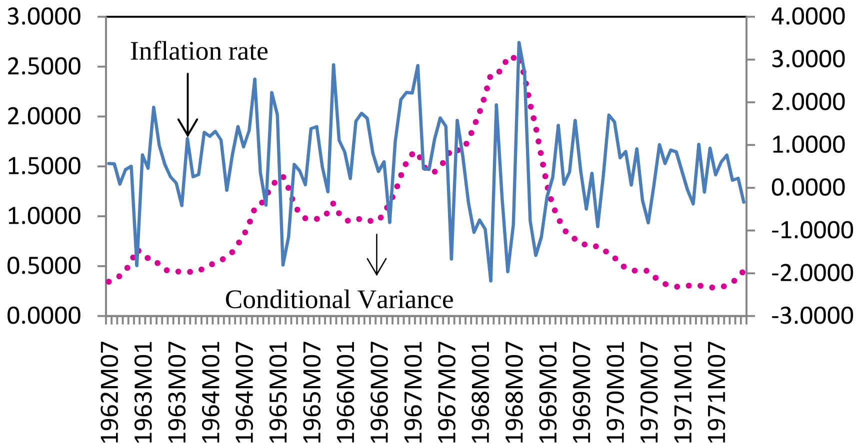


Figure 2.8: Inflation and SV Variance (1972:01 - 1980:07)

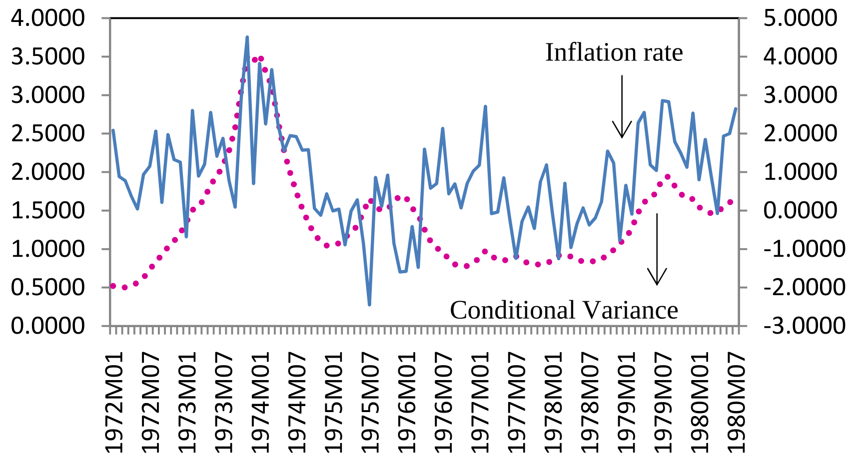


Figure 2.9: Inflation and SV Variance (1980:08 - 1995:05)

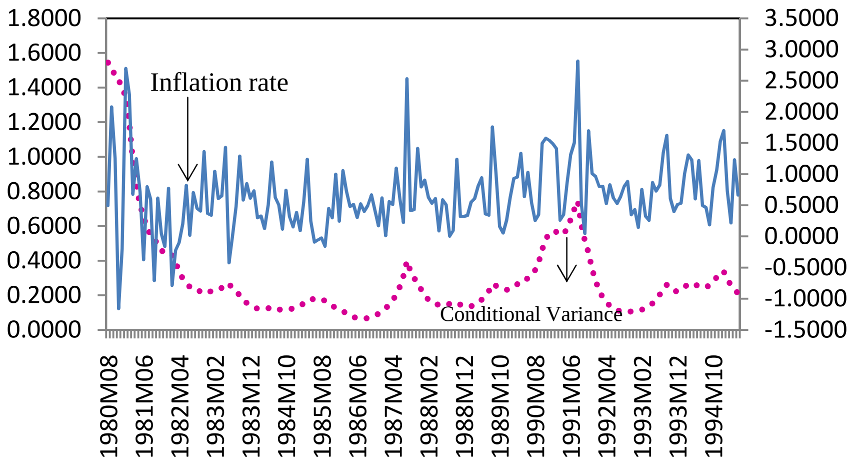
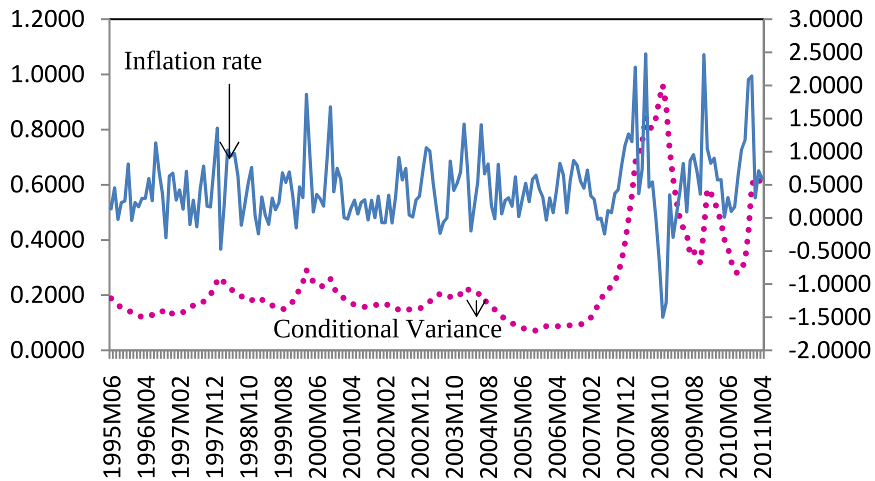


Figure 2.10: Inflation and SV Variance (1995:06 - 2011:04)



Chapter 3
OUTPUT AND OUTPUT UNCERTAINTY

3.1. Introduction

This chapter has been devoted to investigate the relationship between output and its volatility in Indian context. Traditionally, macroeconomic theories separated the fluctuations in output from the long run economic growth[1]. Until the early 1980's, the analysis of real business cycle theories and the growth theories are studied separately, where growth theories focused on the determinants of output growth and business cycles focused on the deviations of output from its trend. The important contributions of Nelson and Plosser (1982), Kydland and Prescott (1982), Long and Plosser (1983), and King et al.. (1988) in the field of real business cycle theories in early 1980's have changed the conventional outlook over the association between business cycle fluctuations and economic growth. They provide different models in which the theories of business cycles and long run economic growth are integrated together[2]. Only after the emergence of this idea in the business cycle literature, the issues of verifying the causal relationship between the instability in business cycles and growth have come into lime light[3].

In recent times, the nature of association between the growth rate of an economy and its deviations has received significant attention because of its commendable influence in framing growth policies. If there is positive liaison between growth and its volatility, then the policies attempt to stabilize the business cycles which may simultaneously damage the potential long run growth with the cost of slow future growth. Conversely, if there is a negative relationship, then the strategy designed to cut off the business cycle fluctuations will be consistent with the goal of a higher growth rates. Blanchard and Simon (2001) pointed out that the

---

[1] Solow (1957) argued that technological shocks are an important source of output variation and an important factor in determining long-run growth rates.
[2] Kydland and Prescott (1982) and Long and Plosser (1983) offered a new models for analyzing economic fluctuations that integrated growth and business cycle theories. According to these models, technological progress is the common source for both trend growth and cyclical fluctuations.
[3] See Aghion and Saint-Paul (1998) for detailed theoretical evolution.

volatility of output growth is profoundly important in assessing economic growth because it causes random shocks that contract the economy to fall into a recession.

Despite the important contributions in recent growth theories, still there is no concrete theoretical concurrence on the true nature of the relationship between growth rate and output variability. In this background, economic theory offers three different possible relationships between the effects of output fluctuations on growth[4]. The first possibility is the absence of any promising relationship between these two variables. The traditional business cycle models claimed an independent relationship between output fluctuations and economic growth and deny the possibility of any interdependence among these two variables. The business cycle models propounded by Friedman (1968) argued that the deviations of output from its natural rate are instigated by the price level misperception in response to monetary shocks, but the changes in the output growth arise from real factors and not at all influenced by any fluctuations in output growth[5].

The positive relationship between output variability and growth is due to a Schumpeterian '*cleansing effect*' of recessions (Caballero and Hammour, 1994). In his notation of '*creative destruction'* Schumpeter (1942) argues that uncertainty in economic activity improve the efficiency of the system by attracting more spending on research and development, thus improving the long-term growth. Sandmo (1970) claimed that through higher investments, the more variability in income end up with rise in output growth. Further, Mirman (1971) argued that the mechanism of precautionary savings and the consequent higher investments in the period of output fluctuations may lead to higher output growth

Further, Black (1987) claimed that the economic agents are interested to invest in riskier technologies only if the expected returns are sufficient enough to compensate the risk associated with the level of investment. Hence, the risk loving behavior of the investors would lead to more volatility and also higher growth rates.

---

[4] In this line of literature, the term growth rate and output are used as interchangeably. In addition, the terms, volatility of growth rate, output variability, fluctuations in output and business cycle volatility are used as an identical phrase for output uncertainty.

[5] Lucas (1987) also pointed out that long-run growth and business cycles as an independent occurrence from the output fluctuations and there is no trade-off between the two variables.

Aghion and Paul (1998) and Blackburn (1999) provided an alternative justification of how growth and volatility may be positively associated by using "*opportunity cost*" and "*knowledge accumulation*" approaches.

The other possibility is that the output fluctuations may lower the growth rates. The negative association between output variability and long run growth are attributed to Keynes (1936), who claimed that the variability in economic activity will create doubt in investors mind about the profitability of the future investments which may reduce the level of investment and negatively affect the output growth. Bernanke (1983) and Pindyck (1991) suggest that the existence of irreversibility in investment at firm level will result in an inverse relationship between volatility and investment[6]. Ramey and Ramey (1995) pointed out a volatility-induced productivity shock leads to fall in long run output growth.[7]

Stiglitz (1993) argued that output volatility may cut down the growth rate through its negative impact on research and development, which is contradictory to Schumpeter's point of creative destruction. Aghion and Howitt, (2006) put a different argument that the negative relation may not only due to the presence of irreversibility or diminishing returns to investment, but also from credit market imperfections that constrain investments during recessions[8]. In a stochastic monetary growth model, Blackburn and Pelloni (2004) come out with the different conclusion that the long run growth is negatively related to nominal shocks and positively related to the real shocks of the economy[9].

Most of the studies quoted above are concerned only about the possibilities of causal effect running from output uncertainty to output growth. However, there may be a possibility of reverse causality from growth to growth uncertainty. Alper

---

[6] This term irreversible investment is used to explain the situation in which it is impossible to cut down the installed investments. Generally, Firms have the funds available for investments during favorable economic circumstances and likes to withdrawn the funds during harsh economic conditions. But it is not possible in this scenario.

[7] They emphasize that if firms must make technology commitments in advance, then volatility will have firms producing at a sub-optimal level ex post. In their model, the negative impact of volatility on growth is decomposed into inefficiency effect and planning effect.

[8] Martin and Rogers (2000), Macri and Sinha (2000) and Rafferty (2005) provides a different argument for the negative relationship between output growth and economic fluctuations at the firm level.

[9] For more details refer Blackburn and Pelloni (2004, 2005)

(2002) claims that "since societies would prefer a relatively "steady" growth path with less uncertainty, it is important for a policy maker to know the sources of business cycles, that is, whether fluctuations in economic activity is primarily attributable to movements in, or shocks to, demand or supply." There is no solid theoretical consensus on this relationship and the sign and direction of the association between these two variables is quite ambiguous.[10]

Despite the several possibilities of the association put forward in the literature with different data sets for different economies, so far, the empirical works has not been able to supply consistent evidences on the sign and direction of the relationship between economic growth and cyclical fluctuations. Besides, the existing literature is mainly pertaining to advanced industrialized economies, where this line of research received stronger attention in framing growth policies. However, the lack of comprehensive empirical verifications and the ambiguous findings on the association motivated us to conduct this empirical exercise in Indian scenario.

To our knowledge, there is no empirical exercise exclusively discussing this issue in Indian context. However, Jiranyaukul (2011) studied this association in Indian scenario with a basket of five crises affected Asian countries which is criticized for testing only the possibility of Black's hypothesis and not considering the other prospects[11]. Earlier empirical studies tested the association between growth and the output variability, rather than the output uncertainty.[12] Recent studies measure output uncertainty, as different to output variability, by the conditional variance of unanticipated shocks to output growth that is estimated from Generalized Autoregressive Conditional Heteroskedasticity models.[13]

[10] This association is channeled through the inflation uncertainty and output uncertainty relationships. A detailed description of the theories advocating these channels are discussed in Chapter 1.

[11] This study is indented to verify only the possible positive effects of business cycle fluctuations on output growth. For more details, refer Jirayakul (2011).

[12] Methodologically, the unconditional volatility of macroeconomic aggregates has been computed using the standard deviation or variance of it (Fatas and Mihov, 2006).

[13] The conditional volatility has been captured by Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized ARCH (GARCH) models (Grier and Perry, 2000; Bredin and Fountas, 2005).

In this background, this chapter is aimed at understanding the direction and the association between output and output uncertainty in India for the period from 1980 to 2011. To test this relationship, we have used different types of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models and Stochastic Volatility models (SV model). Further, Granger causality tests are used to check the causality between output variability and output growth. Also Bai and Perron (1998, 2003) multiple structural breaks test is employed to check the presence of structural breaks in the data.

The reminder of this chapter is organized as follows: Section 2 provides a short overview of the relevant literature on the relationship between business cycle fluctuations and output growth; Section 3 presents the methodological issues and explains the model employed for empirical analysis; Section 4 discusses the data, reports the main empirical results and interpretations; and Section 5 summarizes the concluding remarks.

3.2. Empirical Literature

The section reviews some of the selected empirical surveys which integrated growth and business cycle fluctuations in a combined frame-work. Despite the literature is growing with different data sets for different countries with different methodologies, so far the empirical evidence on the association between output growth and its variability is quite uncertain.[14] Earlier empirical studies have focused on the cross-country variations of output and generally concluded that output volatility likely to be a destructive factor of the long term economic growth. Recent investigations in this line are using the time series techniques like Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models to obtain a more scientific measure of output uncertainty rather than the simple variance or standard deviation.

In their cross-country verification on the macroeconomic determinants of growth in 47 countries, Kormendi and Meguire (1985) found that countries with higher standard deviation of growth rates are enjoying the higher growth rates. But,

[14] A detail review of literature on growth and cycle is available in Gaggl and Steindl (2007).

Zarnowitz and Moore (1986) contradict that with U.S. output growth are high during the periods when the standard deviation of output is lower. Using pooled cross-section data of 113 countries, Grier and Tullock (1989) find a positive and significant relationship between growth and its standard deviation. On the contrary, Ramey and Ramey (1995) presented contradicting empirical evidence by using a panel of 92 nations and a sample of OECD countries, where the countries with higher output volatility have experienced lower growth rates and concluded that the negative effect of volatility came from the volatility of innovations to GDP growth. Aizenman and Marion (1997) confirm this result for a set of developing countries, for which they find that volatility also affects private investment negatively.

Martin and Roger (2000) tested the relationship for OECD countries and 90 European regions and found a significant negative relationship between these two variables. In panel of 24 OECD countries, Kneller and Young (2001) proved a negative effect of volatility on growth though the volatility has been separated as a long-run and short-run phenomenon. Turnovsky and Chattopadhyay (2003) also found a negative relationship between output volatility and growth for 61 developing countries in their model, in which different types of volatility have been allowed to influence the growth rates. Dejuan and Gurr (2004) find evidence for a weak positive association for Canadian provinces in a panel data framework. In a recent study, Lee (2010) found evidences in favor of the Black hypothesis in a dynamic panel GARCH framework, where the higher output growth is associated with higher volatility.

In time series models, different GARCH family models are used to study the linkage between volatility and growth. Using a GARCH-in-mean model, Caporale and McKiernan (1996) verified the linkage between growth and volatility in UK industrial production and found evidence in favor of Black's business cycle hypothesis. By employing the same methodology to annual US GDP data, Caporale and McKiernan (1998) reported a positive relationship.

However, in a GARCH-in-mean model, Speight (1999) does not able to found any significant evidence for a relationship between output uncertainty and growth in UK. Dawson and Stephenson (1997) also ended up with the same result in his volatility–growth study on 48 US states. Macri and Sinha (2000) studied this relationship in Australian context by using the ARCH-M model and found that the variability of output growth is to be significantly negatively related to the growth rate and supports the Keynesian view.

Henry and Olekalns (2002) studied this relationship with US postwar GDP data and found that output volatility is highest when the US economy is contracting. Fountas et al. (2004) examined the relationship by using quarterly GDP of Japan with three different specifications of GARCH models and found that output variability does not affect output growth and the results are similar even when asymmetries are taken into account. Beamont et al. (2008) investigated the volatility and growth link in 20 OECD countries with different GARCH models and not able to find any concrete evidence.

Grydaki and Fountas (2010) studied the impact of short-run and long-run output volatility for the G3 countries in a multivariate GARCH setup and found that the magnitude of nominal variability in explaining the output volatility is more significant than the other variables. Jiranyakul (2011) test the link between output growth and output volatility in five Asian countries with two-step approach and found mixed results. Berument et al. (2012) examined the relationship between growth and growth volatility in Turkey and found that growth volatility not only reduces growth but also cut down the total factor productivity, investment, and the foreign currency value of local currency.

In addition to the above discussed factors, which determine the sign of association between the volatility and growth rates, the following empirical studies have come out with different results and justifications. Kroft and Ellis (2002) found a significant negative association between growth and medium-term business cycle fluctuations and whereas a positive correlation between growth and short-term fluctuations. Imbs (2002) found that the sign of relationship depends on the level of aggregation. At the sectoral level, output fluctuations leads to higher growth but at the aggregated level, this link becomes negative.

Blackburn and Pelloni (2001) strongly believed that there is no fundamental reason for assuming that the relationship between volatility and growth should have one particular sign and concluded that long-run growth is negatively related to the volatility of nominal shocks, but positively related to real shocks. Rafferty (2005) found that unanticipated fluctuations in output volatility reduces the output and whereas expected volatility positively influences it. At the same time as the combined effect of anticipated and unanticipated fluctuations in output reduces the growth rates. In contrary, Rebello (2005) strongly argued that the output fluctuations are caused only by monetary, fiscal, oil or technology shocks and its impact on real uncertainty is ambiguous.

In the literature on the volatility-growth association, none of the study exclusively tested the reverse type of causality running from growth to output uncertainty. A very few empirical studies are pointed out this issue in addition to its primary objectives. Stiglitz (1993) claimed that the association between these two variables may run not only from volatility to growth but also from growth to volatility. Karanasos and Schures (2005) found a strong negative feedback between the two variables. Similarly, Fountas and Karanasos (2006) found that the output growth rate volatility exhibits no effect on the growth rate in G3, but the output growth rate affects its volatility negatively in the U.S. and bidirectional causality between output growth and its volatility in Germany. At the same time, in his Panel-GARCH approach Lee (2010), failed to found any significant relationship between these two variables in the G7 countries.

3.3. Methodology

We use both the simultaneous approach and the two step procedure methods for investigating the relationship between output growth and its volatility. In simultaneous approach method, different types of GARCH-in-mean models are used to verify the growth effects of output variability. Following GARCH family models, GARCH-in-mean models, (GARCH-M), Mean-in-GARCH model (M-GARCH) and comprehensive model of both the effects are used to study the relationship.

First, we test the empirical validity GARCH-in-mean specification model in the following equation, where

$$
\begin{aligned}
y_t &= \beta_0 + \sum_{i=1}^{n} \beta_i y_{t-i} + \delta h_t + \varepsilon_t \\
h_t^2 &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1}^2
\end{aligned}
\qquad (3.1a)
$$

only the GARCH term, h_t is included in the mean equation of the model. Further, the effects of output growth on volatility is measured in the model (3.1.b) where the lagged mean output growth, y_{t-1} is included in the variance equation,

$$
\begin{aligned}
y_t &= \beta_0 + \sum_{i=1}^{n} \beta_i y_{t-i} + \varepsilon_t \\
h_t^2 &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1}^2 + \gamma y_{t-1}
\end{aligned}
\qquad (3.1b)
$$

Following Caporale and McKiernan (1996), Fountas and Karanasos (2008), the subsequent comprehensive GARCH-M is used for testing the relationship between output and output uncertainty.

$$
\begin{aligned}
y_t &= \beta_0 + \sum_{i=1}^{n} \beta_i y_{t-i} + \delta h_t + \varepsilon_t \\
h_t^2 &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1}^2 + \gamma y_{t-1}
\end{aligned}
\qquad (3.1c)
$$

where y_t stands for the output growth at time t ,n is the number of lags, h_t symbolized the conditional variance of the errors which is referred as output uncertainty and the term y_{t-1} represents the one period lagged growth rate. This model allows us to simultaneously estimate the influence of uncertainty on output growth and the effects of growth fluctuations on output growth rate[15]. We test the influence of uncertainty on the growth rates, by only keeping the conditional variance (h_t) in the mean equation. The influence of growth on its uncertainty is verified by including only lagged growth rate y_t in the conditional variance equation

[15] Engle, Lilien, and Robins, (1987) has introduced ARCH-M model. For a detailed survey of the use of conditional variance in mean equation, see Bollerslev, Chou, and Kroner (1992).

and excluding the variance (h_t) from the mean equation. By keeping the variance in the mean equation and the lagged growth in the variance equation, the above model simultaneously tested the all the possible relationships between output growth and its uncertainty.

The validity of using GARCH-in-mean models are quite debatable in the literature, because these models does not allowed the lagged effects of more than one period conditional variance in the mean equation[16]. But the conditional mean values may be influenced by more than one period ahead conditional variance. Estimating GARCH-M models in such situation leads to a misleading conclusions. Hence, some studies examine the relationship between output growth and its volatility by using the two-step procedures, where a simple GARCH model is estimated in addition with the Granger causality tests.

Following Jiranyakul (2011)[17], we have estimated the following simple GARCH models for two-step procedures

$$\begin{aligned} y_t &= \beta_0 + \sum_{i=1}^{n} \beta_i y_{t-i} + \varepsilon_t \\ h_t^2 &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1}^2 \end{aligned} \tag{3.2}$$

where all the coefficients are similar to the above discussed GARCH model. Subsequently, as a robustness check, we construct another measure for output fluctuations by using the Stochastic Volatility model (SV) as follows:

$$\begin{aligned} y_t &= \alpha_0 + \sum_{i=1}^{k} b_i y_{t-i} + \sigma^* \exp(0.5 h_t) \varepsilon_t \\ h_t &= \phi h_{t-1} + \sigma_\eta \eta_t \end{aligned} \tag{3.3}$$

[16] A detailed discussion on this issue is available in the earlier chapter.
[17] Jiranyakul (2011), has pointed out that the two-step procedures are more superior than GARCH-M in studying the relationship, because this models are criticized for not including the lagged values of conditional variance in the mean equation.

where α_0 is a constant term, y_t is the output growth, k is the number of lagged output growth. The error terms, ε_t and η_t are assumed as mutually uncorrelated and independently, identically and normally distributed with zero mean and unit variance.

As a two step procedures, the following equations are employed to test the direction of causality between output growth and the variance generated from simple GARCH and SV models as a measure of output uncertainty.

$$\begin{bmatrix} y_t \\ h_t \end{bmatrix} = \begin{bmatrix} \alpha_y \\ \alpha_h \end{bmatrix} + \sum_{i=1}^{k} \begin{bmatrix} c_{yy},i & c_{yh},i \\ c_{hy},i & c_{hh},i \end{bmatrix} \begin{bmatrix} y_{t-i} \\ h_{t-i} \end{bmatrix} + \begin{bmatrix} e_{yt} \\ e_{ht} \end{bmatrix} \qquad (3.4)$$

where y_t is the inflation rate and h_t is conditional variance generated from GARCH and SV models.

To test the presence of structural breaks, Bai and Perron (1998, 2003), multiple structural break test is conducted by using the following regression:

$$y_t = x_t^{'}\beta + z_t^{'}\delta + u_t \qquad t = T_{j-1} + 1,..., +T_j \qquad (3.5)$$

where j =1,…, m +1; y_t is the explained variable; x_t (p×1) and z_t (q×1) are vectors of explanatory variables; β and δ_j (j=1,…, m+1) are the vectors of coefficients; u_t is the error term at time t. This equation is a partial structural change model where β coefficient is not subject to change. The models used here for empirical justifications are similar to those models explained in detail in the previous chapter on inflation and inflation uncertainty. In this chapter, we are presenting only the equations used for empirical estimations.

3.4. Empirical Results

The seasonally adjusted monthly time series data of Index of Industrial Production (IIP) is used as a proxy for output growth[18]. The sample covers the time period from April 1980 to April 2011. The real output growth (y_t) equals the monthly point-to-point percentage change in the logarithm of seasonally adjusted monthly IIP data with 1993-94 as base year prices. All the data series are obtained from various publications of Central Statistical Organization (CSO), Government of India and publications of Reserve Bank of India.

Table 3.1: Summary Statistics for Monthly Output

Mean	0.5577
Maximum	8.3349
Minimum	-10.870
Std. deviation	2.1707
Skweness	0.0070
Kurtosis	6.3471
Jarque-Bera	168.04 (0.00)
Q (12)	25.99 (0.01)
Q^2(12)	43.58 (0.00)

Notes: Q (12) and Q^2 (12)are the 12 order of the Ljung-Box (LB) test for serial correlation in the residuals and squared residuals of the inflation rate from its sample mean. The numbers in parenthesis are *p* values.

Summary statistics for the monthly output growth rate are reported in Table 3.1. The results show that monthly average rate of output growth is lower than 1% (0.5577) for the sample period with the highest rate of 8.3349 % and the lowest rate of -10.870 %. The measure of Standard deviation, which symbolizes the variability of the series, is 2.1707. The positive value of the Skweness exhibits that the output series is positively skewed to right and a high Kurtosis value indicates a leptokurtic series with fat tails. Both the test statistic disproves the presence of normality in the series.

The high and significant value of the Jarque–Bera test statistics is violated the null hypothesis of normal distribution of the series. When the seasonally

[18] The quarterly time-series data on real GDP is available only from 1996:Q2 and hence, we are using IIP as a proxy variable for growth.

adjusted series are tested by the Ljung-Box (LB) Q-statistic by using twelve lags, the presences of serial correlations are observed. The Ljung-Box (Q (12) = 25.99) statistics indicates the presence to higher order serial correlation in the residuals where as the Ljung-Box (Q^2 (12) = 43.58) provide evidence for the existence of time-varying conditional variance in the output series.

Table 3.2: Unit Root Test Statistics for Monthly Output

Unit root tests	Coefficient
ADF	-19.259* (0.00)
PP	-34.420* (0.00)
KPSS	0.0844*

Notes: '*' indicates significance at the 1% level and '**' indicates 10% level of significance. The figures in parenthesis are *p* values.

As a regular tradition of verifying the stationarity properties of the variable, we test the series by applying augmented Dickey–Fuller (ADF) and Phillips and Perron (1988) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests. It is evident from the results reported in the Table 3.2, that all the unit root tests reject the null hypothesis of a unit root at 1% level of significance.

Table 3.3: The test results of ARCH effects

Lags	Coefficients
2 lag	29.40 (0.00)
4 lag	31.06 (0.00)
8 lag	34.95 (0.00)
12 lag	45.70 (0.00)

Figures in parenthesis are *p* values

Prior to estimating GARCH models, it is necessary to check the presence of time varying heteroscedasticity in the series. The results reported in Table 3.3 are the *F* statistics of the ARCH-LM test, which tests the null hypothesis of 'no ARCH effects in the errors'. The test results confirm the presence of ARCH effects, where the null hypothesis is rejected at 1% level of significance irrespective of the different lag specifications. The significant higher order ARCH tests results indicates that the output series is conditionally heteroskedastic and justifies the usage of GARCH models as a measure of deriving conditional volatility over the OLS techniques.

Table 3.4 reported the results of the various GARCH models employed to verify the output –volatility relationships.[19] All the reported models are chosen on the basis of Akaike Information (AIC) and Schwarz (SC) model selection criterions. The necessary conditions ($\alpha_i \geq 0$), ($\beta_i \geq 0$) and ($\alpha_1+\beta_1 < 1$) that ensure a positive and stable conditional variances are satisfied in all the GARCH models. Moreover, the coefficients of the standardized (Q) and squared standardized residuals (Q^2) at various lag lengths indicates the absence of serial correlation at the conventional level of significance and the ARCH-LM test statistics also rejects the presence of remaining ARCH effects.

Table 3.4: The GARCH-in-Mean Models for Output

Parameters	**Model 3.1a**	**Model 3.1b**	**Model 3.1c**
Mean Equation			
b_0	0.9022 (0.00)	0.6491 (0.00)	0.9890 (0.00)
b_1	-0.5103 (0.00)	-0.4699 (0.00)	-0.4785 (0.00)
b_2	-0.2006 (0.00)	-0.1677 (0.00)	-0.1946 (0.00)
b_{11}	0.1040 (0.01)	0.0917 (0.06)	0.1269 (0.00)
b_{18}	-	0.0932 (0.09)	-
b_{24}	-	-0.1140 (0.02)	-
δ	-0.0066 (0.90)	-	-0.0331 (0.51)
Variance Equation			
a_0	0.0393 (0.10)	-0.0911 (0.00)	-0.0929 (0.00)
a_1	0.0719 (0.00)	0.0394 (0.00)	0.0362 (0.00)
a_2	0.9228 (0.00)	0.9478 (0.00)	0.9568 (0.00)
γ	-	0.2455 (0.00)	0.2201 (0.00)
Diagnostic Statistics			
Q(4)	1.8273 (0.76)	2.4863 (0.64)	1.5945 (0.81)
Q(12)	10.254 (0.59)	9.8016 (0.63)	10.252 (0.59)
$Q^2(4)$	1.6244 (0.80)	6.3000 (0.17)	2.0434 (0.72)
$Q^2(12)$	11.2380 (0.50)	18.5830 (0.09)	8.2657 (0.76)
ARCH-LM (4)	1.6414 (0.80)	1.5847 (0.17)	2.0304 (0.73)
ARCH-LM (12)	12.153 (0.43)	17.950 (0.11)	9.0933 (0.69)

Notes: Q (k) and Q^2 (k) are the Ljung-Box test statistic of the levels and the squared residuals respectively. LM (4) and LM (12) are ARCH-LM statistics of chi-squares. The figures in parenthesis are *p* values.

Model 3.1a reports the results of GARCH-in-mean specifications, where the impact of output fluctuations on output growth is examined. The results show that,

[19] For estimating the GARCH models, we use the Berndt et al. (1974) numerical optimization algorithm to get the maximum likelihood estimates of the parameters.

the estimated coefficient of the conditional variance (δ) in mean equation is negative and insignificant.[20] The results of the opposite type of causality running from output growth to output uncertainty is reported in Model 3.1b, where the lagged output growth (γ) is included in the conditional variance equation. The estimated results show that lagged output growth coefficient (γ) influences the conditional variance of the output growth positively and significantly, which implies a positive relationship running from output growth to output variability. These findings are in contradiction to most of the existing empirical studies.

The possible simultaneous feedback relationship between these two variables is examined in Model 3.1c, by including the conditional variance in the mean equation and the lagged output growth in the variance equation. Results show that the GARCH coefficient in the mean equation is negative and statistically insignificant which indicates that the output growth does not depend on the changes in its volatility. The output coefficient in the conditional variance equation is positive and statistically significant, which shows that the output growth does affect its volatility.

For the two procedures method, we are estimating a simple GARCH model and the results are presented in Table 3.5. The results show the coefficients of the mean and variance equation of the output model are highly significant and have satisfied all the necessary conditions of GARCH models. The intercept in the conditional variance equation is positive, which is consistent with the non-negativity condition of the variance.

The sum of the ARCH and GARCH coefficients in the conditional variance is 0.99, which proves that the conditional variance of the output series is stationary and the volatility measure shows a high degree of persistence. The reported Ljung-Box Q-test statistic for standardized residuals and standardized squared residuals indicate no serial correlation irrespective of the different lag orders. The ARCH-LM test results are also indicated the absence of any neglected ARCH effects in the model.

---

[20] The results of all the GARCH models estimated in this study are robust to the choice of the distribution of the error term.

Table 3.5: The Symmetric GARCH model for Output

Parameters	Symmetric model
Mean Equation	
b_0	0.8839 (0.00)
b_1	-0.5105 (0.00)
b_2	-0.2007 (0.00)
b_{11}	0.1030 (0.01)
Variance Equation	
a_0	0.0390 (0.10)
a_1	0.0726 (0.00)
a_2	0.9223 (0.00)
Diagnostic Statistics	
Q(4)	1.8235 (0.76)
Q(12)	10.227 (0.59)
$Q^2(4)$	1.6413 (0.80)
$Q^2(12)$	11.229 (0.50)
ARCH-LM (4)	1.6575 (0.79)
ARCH-LM (12)	12.133 (0.43)

Notes: Q (k) and Q^2 (k) are the Ljung-Box test statistic of the levels and the squared residuals respectively. LM (4) and LM (12) are ARCH-LM statistics of chi-squares. The figures in parenthesis are *p* values.

Prior to obtaining output uncertainty from the simple GARCH model, using Engle and Ng (1993) diagnostic statistic, we test whether there is any asymmetric response of the volatility to the past innovations and the results are reported in Table 3.6.

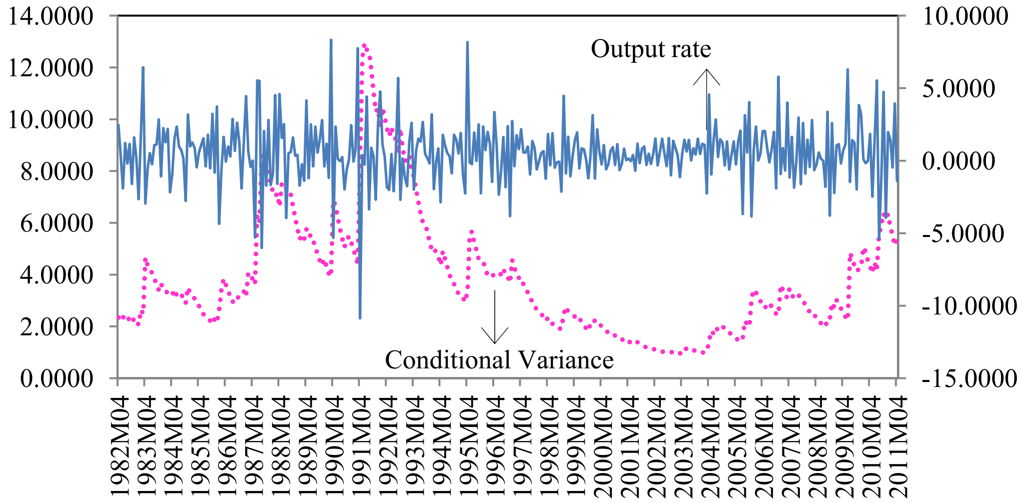
Table 3.6: Test for Asymmetries in Monthly Output

Parameters	Sign Bias Test	Negative Sign Bias Test	Positive Sign Bias Test	Join test for Sign and Size Bias
α_0	4.0310 (0.00)	3.6860 (0.00)	3.6915 (0.00)	4.0533 (0.00)
β_1	-0.6884 (0.39)	0.3505 (0.20)	0.2669 (0.41)	-0.7016 (0.38)
β_2	-	-	-	0.3485 (0.20)
β_3	-	-	-	-0.2759 (0.39)
TR^2	-	-	-	3.0603 (0.38)

Values in parenthesis are *p* –values

These results show that there is no evidence for the presence of considerable sign-bias, negative-size-bias and positive-size-bias which is also confirmed by the test of joint significance test. As a consequence we used the variance generated from the simple GARCH model as a proxy for output uncertainty in the two step procedures. Figure 3.1 plots the growth rate and the conditional variance generated from the simple GARCH model. Output growth rate is pointed out by the solid line where as the dotted line show the conditional variances of the output growth. It is evident from the figure that the higher growth periods are always followed by growth uncertainties.

Figure 3.1: Output Growth and its Conditional Variance (GARCH)



The second step of the two step procedure method, the relationship between output growth and its volatility generated from the simple GARCH model is tested by using a bivariate Granger causality tests and results are reported in Table 3.7. The lag orders are chosen on the basis of AIC and SBC criterions. Irrespective of the lag orders, causality test of the output- uncertainty relation indicates that it is strongly uni-directional positive causality running from output to output growth. Moreover, the acceptance of null hypothesis, output uncertainty does not Granger-cause output up to shorter lags indicates that there is no evidence for the reverse causality from output uncertainty to growth in the shorter period.[21] For the higher lag orders, the influence of real uncertainty on output growth is negative. These results indicate that

[21] The lag length criterions are suggesting up to 4 lags only. As a matter of intuition, we check the relationship up to 12 lags for all the causality models.

the Black's hypothesis of positive real effects of output uncertainty does not valid in Indian scenario even in the long run.

Table 3.7: Causality between Output and Uncertainty (GARCH) – Full Sample

Lag Length	Output does not Granger Cause Output Uncertainty	Output Uncertainty does not Granger Cause Output
4 lags	9.7594* (+) (0.00)	0.8105 (0.51)
8 lags	5.5308* (+) (0.00)	0.5809 (0.79)
12 lags	4.3544* (+) (0.00)	2.4030* (-) (0.00)

Notes: Given values are the *F*- static of Granger causality tests and '*' indicates 1% level of significance. The sign (+) or (-) indicates the direction of the relationship. The figures in parenthesis are *p* values.

In addition to the GARCH family models, as a robustness test, the SV models are used and the results are presented in Table 3.8. The mean equation of the SV model is estimated with a constant and 12th lag order of the output growth whereas the one period ahead lagged values volatility and an error term is included in the variance specifications. Empirical results indicate that the estimated parameters do not included zero in their confidence bands, which means a statistically significant mean and variance equations. The stationarity conditions of the volatility persistence parameter is also satisfied, where the parameter, (ϕ= 0.820) is less than one and statistically significant. The Jarque-Berra and Lagrangian Multiplier tests disprove the non-normality and the presence of autocorrelation in the residuals respectively.

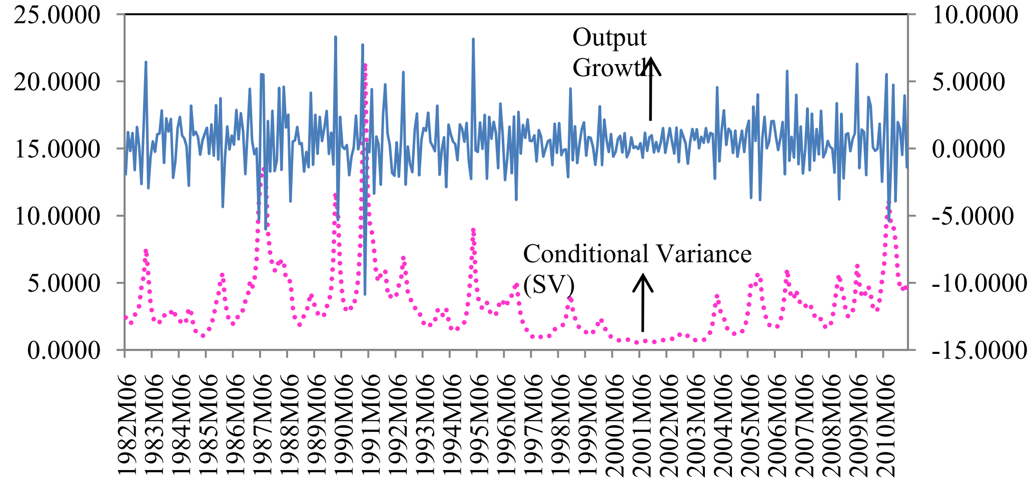
Table 3.8: Stochastic Volatility model for Monthly Output

Parameters	Coefficients	LCL	HCL
α	0.5286	0.4102	0.6470
y_{t-12}	0.0000017	0.0000016	0.0000019
$\exp(0\ .5h_t)\ \varepsilon_t$	2.9407	2.3169	3.7325
ϕ	0.8205	0.7995	0.8398
σ_η	0.2944	0.2051	0.4226
Q (12)Statistic = 81.39	Normality test statistic = 5.065		AIC= 1459.58

Figure 3.2 depicts the association between ouput growth and the volatility component genrated from the SV model. The ploted varibles in this figure shows a

smiliar visulaliztion to Figure 3.1 and the only difference is the change in magnitude of the association.

Figure 3.2: Output Growth and its Conditional Variance (SV)



To check the robustness of the causality test results obtained from the GARCH model variance, we use the conditional variance of SV model as a measure of uncertainty and the estimated results are provided in Table 3.9. As like earlier models, the lag orders are chosen on the basis of lag selection criterions. Reported test results are consistent with the causality established by GARCH models where there is a positive unidirectional causality operates from output growth to output uncertainty. Similar to earlier causality results, the causality is not running from output uncertainty to output. When the lag orders are increased further, estimated results shows a significant negative association. These results are not found any evidence in favor of Black's claim of positive causal effects of output uncertainty on real growth rates.

Table 3.9: Causality between Output and Uncertainty (SV) – Full Sample

Lag Length	Output does not Granger Cause Output Uncertainty	Output Uncertainty does not Granger Cause Output
4 lags	4.6016* (+) (0.00)	1.1551 (0.33)
8 lags	2.3614* (+) (0.01)	1.7036**(-) (0.09)
12 lags	2.0125* (+) (0.02)	2.3501* (-) (0.00)

Notes: Given values are the *F*- static of Granger causality tests and. '**', '*' indicates 5 %, and 1 % level of significance respectively. The sign (+) or (-) indicates the direction of the relationship. The figures in parenthesis are *p* values.

To check the possibilities of the presence of structural breaks in the output series, we have employed the Bai and Perron (1981) test for multiple breaks. The sample has been trimmed by 15 % on both the sides with the maximum of five breaks which ends up with 54 observations in each segment. The results are reported in Table 10, where the test procedures for choosing number of break points (*D*max , WDmax, sup$F_T(k)$ and sup$F_T(l+1/l)$) did not locate any significant break point in the output series. The coefficients of all the statistics are insignificant and disprove the presence of conventional output shocks for the period under investigation.

Table 3.10: Bai and Perron test for Multiple Structural Breaks in Output

Specifications: $Y_t = \{O_t\}$ $Z_t = \{1, O_{t-1}\}$ $q = 2$ $p = 0$ $h = 54$ $M = 5$		
SupF_T: no breaks vs. $m = k$ breaks		
$k = 1$		7.6875
$k = 2$		3.7450
$k = 3$		3.5326
$k = 4$		4.6427
$k = 5$		3.5838
No breaks vs. a known number of breaks		
UD max		7.6875
WD max		7.6875
SupF_T: l breaks vs. $l + 1$ breaks (SupF_T $(l+1\mid l)$)		
$l = 1$		1.2365
$l = 2$		1.1602
$l = 3$		4.9976
$l = 4$		0.0836
Selection with the sequential method		3
Selection with the SBIC & LWZ information criterion	SBIC	LWZ
$k = 0$	1.5485	1.5541
$k = 1$	1.5768	1.6448
$k = 2$	1.6206	1.7511
$k = 3$	1.6630	1.8561
$k = 4$	1.7054	1.9611
$k = 5$	1.7540	2.0725

Notes: '*', denote significance at 5%, and the critical values are taken from Bai and Perron (1998). Changes in the mean are tested selecting a trimming =0.15 with a maximum number of five structural breaks. Serial correlations in the errors are allowed for. The consistent covariance matrix is constructed using Andrews (1991) method.

Though the Bai and Perron multiple break tests found no breaks in the output growth, we verified whether the historical break such as the economic reforms implemented in the early 1990s, has any influential impact on the association between output and growth. Hence, we employ Granger causality test with the pre and post reforms periods separately for both the GARCH and SV measures of uncertainty and the results are presented in Table 3.11. It is understood from the documented results that, in the pre economic reforms period, the causality test of GARCH measures rejects only the null hypothesis of output and does not cause uncertainty at the conventional level of significance, whereas the SV measure of uncertainty rejects both the null hypothesis.

Table 3.11: Causality between Output and GARCH & SV for different Regimes

	Generalized Auto Regressive Model (GARCH)		Stochastic Volatility Model (SV)	
Lags	$y_t \rightarrow h_{y_t}$	$h_{y_t} \rightarrow y_t$	$y_t \rightarrow h_{y_t}$	$h_{y_t} \rightarrow y_t$
Regime 1 - (1981:04 - 1991:03)				
4	3.7008* (+) (0.00)	1.5477 (0.19)	1.8066 (0.13)	1.2253 (0.30)
8	2.2995* (+) (0.02)	1.3626 (0.22)	1.3932 (0.21)	1.0373 (0.41)
12	1.5978** (+) (0.10)	1.3542 (0.20)	1.2373 (0.27)	0.7944 (0.65)
Regime 2 - (1991:04 - 2011:04)				
4	9.5740* (+) (0.00)	1.9084 (0.11)	4.6029* (-) (0.00)	0.9838 (0.41)
8	4.3458* (+) (0.00)	1.2054 (0.29)	3.0313* (+) (0.00)	1.2281 (0.28)
12	3.1057* (+) (0.00)	1.8472*(-) (0.04)	2.0451* (+) (0.02)	1.612** (-) (0.09)

Notes: Given values are the *F*- static of Granger causality tests and. '**', '*' indicates 10 %, 5 %, and 1 % level of significance respectively. The sign (+) or (-) indicates the direction of the relationship. The figures in parenthesis are *p* values. $y_t \rightarrow h_{yt}$ indicates output does not Granger-cause output uncertainty; $h_{yt} \rightarrow y_t$ indicates output uncertainty does not Granger-cause output.

However, for the post economic reform period, both the uncertainty measures proved the presence of causality running from output growth to uncertainty and not the other way around. However, there was a slight difference in the direction of the effect in the earlier lags; these results are identical to the findings of the full sample analysis for both uncertainty measures. The causality running form output to uncertainty holds good when the historical breaks are taken into account. The insignificant impact of variance to growth disproves Black's hypothesis of positive uncertainty effects of output growth and provide strong evidence for Friedman's misperceptions hypothesis. These results are similar to the empirical works of Grier and Perry (2000), Fountas and Karanasos (2006) and Speight (1999) who claims an independent association between business cycle fluctuations and output growth. These results are consistent with the earlier real business cycle theories.

3.6. Concluding remarks

This chapter examines the nature of the relationship between cyclical volatility and output growth rate for India using monthly time series data for the period from April 1980 to April 2011. We employ various GARCH models that allows lagged growth rate to appear in the conditional variance equation and the conditional variance of the output growth to be included in the mean equations. As a robustness measure, Stochastic Volatility model is estimated as an alternative specification. The presences of asymmetry in the GARCH models are tested with the Engle and Ng sign-bias test. The possible breaks in the output series is verified by adopting Bai and Perron multiple structural break tests. Finally, we adopt a two step procedure method, where causality between output volatility and growth is investigated by Granger causality tests where the output volatility is generated from a simple GARCH model and a SV model.

The empirical results show that output volatility has a negative and insignificant impact on economic growth whereas there is strong evidence to claim positive effects of output growth on its own uncertainty. There is no evidence for the presence of asymmetry in the errors which justifies the validity of using simple GARCH model in generating output volatility. The causality test results based on the uncertainty measures of both the GARCH and SV models indicates the causation running from output growth to its volatility and not from the former to the later. This finding is consistent with some of the earlier works and real business cycle theories. The results are also consistent for pre and post reform period analysis. All together, we find strong evidence in favour of a unidirectional causality running from output growth to its variability.

Chapter 4
INFLATION, OUTPUT AND THEIR UNCERTAINTIES

4.1. Introduction

The previous two chapters dealt with the individual effects of inflation, output growth and their respective uncertainties. The main aim of this chapter is to understand the cross relationship among these four variables. The spillover effects and the causality between inflation, output growth, and macroeconomic uncertainties has become an important theoretical issue and testing these effects offer a significant knowledge about the potential effects of uncertainties on the growth of an economy. A substantial research has been focused on these relationships in both theoretical and empirical literature of macroeconomics. This chapter observes the causality between real and nominal uncertainties in addition with the effect of volatility spillovers of real uncertainty to inflation and nominal uncertainty to real output growth.

A number of different arguments are put forward in the economic theory on the association between these macroeconomic variables.[1]It is generally accepted in the literature that there is no long-run tradeoff between inflation rate and output growth, but, most of the economists believe that the uncertain future inflation and the corresponding stabilization polices have their own impact on the real economic variables. Fuhrer (1997) indicates that when an economy is continually buffeted by economic shocks, then a short-run relationship between uncertainties and real variables may end up with a permanent variability tradeoff. Marhubi (1998) pointed out that there may be at least three main channels through which inflation uncertainty could affect growth rates. First, uncertainty about future inflation make it difficult to differentiate between the changes in aggregate and relative price level which consequently shows a poor response of economic agents to relative price changes[2]. The other mechanism by which inflation uncertainty could affect growth

[1] In total, there are 12 types of possible relationships that exist between these four variables. But, empirical validity of many of these relationships remains scant or nonexistent. A detailed description of some of the valid theories is discussed in Chapter 1.

[2] This issue is the so called typical Lucas (1973) signal-extraction problem faced by economic agents.

rate is through its influence on the pattern of asset accumulation and with the irreversibility in investment[3].

The idea of the negative impact of inflation uncertainty on output growth is originally attributed to Okun (1971) and Friedman (1997) where an argument is made that prevailing uncertainty about inflation will have higher risk on the returns on the capital which may delay the future investments and lower the growth rates consequently. Cukierman and Meltzer (1986) presented a model in which surprise money shocks by monetary authorities' increases inflation uncertainty and in turn affects output growth. Pindyck (1991) claimed that inflation uncertainty increases the uncertainty associated with potential returns to investment, thus adversely affecting the output growth.

On the other hand, some studies hold a view that uncertainty about future inflation rates will affect real variables in a positive manner. In a model with symmetric adjustment costs of investment, Abel (1983), show that growth rates are positively influenced by inflation uncertainty through increase in investments. In the same fashion, Dotsey and Sarte (2000) demonstrates that higher inflation uncertainty leads to higher output growth as a result of higher precautionary savings which in turn leads to higher investment. This finding is also supported by Varvarigos (2008) with a human capital accumulation channel.

The positive effect of real uncertainty on inflation is advocated by Devereux (1989) in an extended Barro-Gordon model by introducing an endogenous wage indexation. He pointed out that though Fed dislikes inflation, volatility in real uncertainty reduces the optimal amount of wage indexation and induces the policymaker to create more inflation surprises in order to obtain favorable real effects. Cukierman and Gerlach (2003) also recognized the Deveraux (1989) claim on the positive association between output uncertainty and rate of inflation. In

[3] For more details refer, Fisher and Modigliani (1978), Fisher (1984; 1993), Romer (1986; 1989), Lucas (1988). Pindyck (1991), and Pindyck and Solimano (1993)

contrast, output uncertainty may also lead to lower the inflation rate via the combined effect of Taylor (1979) with the Cukierman-Meltzer hypothesis channel[4].

Logue and Sweeney (1981) argued that greater inflation uncertainty leads to greater uncertainty in production, investment and market decisions which cause a greater variability in real growth. They claimed the positive impact of nominal uncertainty over the real uncertainty where, higher relative price variability makes more difficult for the producers to distinguish between nominal and real demand shifts, thus leading to more variability in all economic activities. In contrast, Taylor (1979) argued that more inflation uncertainty would be accompanied by less output growth uncertainty as a result of the tradeoff between inflation uncertainty and output growth uncertainty (the so-called Taylor curve). In addition, Cecchetti and Ehrmann (1999) also find that the aggregate supply shocks create a positive trade-off between nominal and real variability which is confirmed by Clarida et al. (1999) where they derive a short-run positive inflation–output variability tradeoff.

In economic literature, the empirical validity of above discussed theories is still under ambiguity because of non-availability of suitable measure for macroeconomic uncertainties. The existing empirical studies are providing conflicting results for the same group of countries with same data periods, when the uncertainties are obtained from different conditional variance-covariance models.[5] Hence, constructing an appropriate measure for the real and nominal uncertainties is the crucial factor in studying the association between uncertainties and macroeconomic performances[6].

In this background, this chapter examines the relationship between macroeconomic uncertainties, inflation and output growth in India, using both simultaneous approach and two-step procedure method. Absence of comprehensive

---

[4] The Taylor effect claimed a negative association between output volatility and inflation volatility and the Cukierman-Meltzer suggest a positive effect of inflation uncertainty on inflation. The combination of these two channels causes a negative impact of output growth uncertainty on the average rate of inflation.

[5] Neanidisa and Savvab (2010) tabulated the list of studies which gives different results for same countries when the method of uncertainty measure differs.

[6] The problems with the conventional method of uncertainties and superiority of GARCH models over the conventional measures are documented in Chapter 2.

empirical studies with respect to Indian situation is the motivating factor behind this study. A bivariate GARCH-M model with BEKK[7] variance representation is employed as a simultaneous estimation method, where the conditional variances are allowed to influence the conditional mean. This model has an advantage of measuring both direct and effects of uncertainty on the variables on the mean values.

For two-step procedure method, the conditional variances and covariances of inflation and output growth are obtained from a bivariate GARCH model and the causal relationship between the variables are examined by performing Granger causality tests. The effects of structural breaks in the relationship are also taken into account by splitting the sample period into two sub-periods with the last break point identified for inflation in Chapter 2.

This Chapter is structured as follows: Section 2 briefly reviews the empirical literature on the relationship between the real and nominal uncertainties with their mean values; Section 3 describes the econometric model used for estimation; Section 4 outlines the data and reports the empirical results of various specifications of the multivariate GARCH models and the causality tests; and Finally, Section 5 summarizes with a conclusion.

4.2. Empirical studies

The empirical literature that examines the effects of macroeconomic uncertainties on inflation and output growth are rich in terms of numbers. Generally, the empirical literature on this subject matter is classified into two groups of studies on the basis of methodology employed.

The first group of studies is the one that uses simultaneous models where the mean and conditional variances of both the variables are estimated simultaneously with different variance parameterizations and the effects of uncertainties are measured by including conditional variance in the mean equation of the model. On the other hand, the effects of uncertainties are studied by adopting a two-step

[7] The acronym BEKK is used to refer Baba, Engle, Kraft, and Kroner (1990).

procedure method like univariate or bivariate GARCH modes where the conditional variances obtained from the GARCH models are taken as an uncertainty measure and use it in a simple causality tests to verify the relationship.

Darrat and Lopez (1989) test the validity of Friedman hypothesis in 12 Latin American countries and found that erratic inflationary environment have played a significant role in hampering the economic development. Davis and Kanago (1996) also hold the similar view, but argue that the effect of inflation uncertainty on real GNP growth is purely temporary. By using univariate GARCH model, Jansen (1988) found no evidence to the claim that uncertainty in inflation cuts down the output growth in US. In contrary, Grier and Perry (2000) conclude that inflation uncertainty significantly lowers real output growth in US and not backing up the other possible relationships. In a bivariate conditional Constant Conditional Correlation model (CCC), Fountas et al (2002) provide evidence for Friedman's argument on inflation-uncertainty relationship in Japanese economy and fail to find any impact of output uncertainty on inflation and output. Lee (2002) investigates volatility tradeoff between inflation and output in the US and confirming the presence of temporal dependencies among the variables for pre and post monetary policy regime changes.

In a pioneering work, Grier et al (2001, 2004) studied the effects of macroeconomic volatility on the output growth and inflation for post-war US data in a multivariate asymmetric GARCH-M model, where the validity of diagonality and symmetry covariance restrictions are tested in contrary to the earlier studies. They found that higher inflation uncertainty negatively affects the growth rates of the economy, whereas, there is a positive association between growth uncertainty and output. Using the same methodology and non-diagonal variance structure, Bredin and Fountas (2005) investigates the above effects in G7 economies and concludes that macroeconomic uncertainty tends to influence macroeconomic performance and importantly, in some countries the former may even improve the later.

Karanasos and Kim (2005) examined the relationship between nominal and real uncertainties in the G3 countries and found few associations between these two variables only in the sub-samples. In the augmented multivariate GARCH-M system model, Grier and Grier (2006) support the validity of Friedman hypothesis in Mexican economy. In a bivariate EGARCH-M model, Wilson (2006) claimed strong evidence for the predictions that uncertainty about future inflation raises the average inflation and lowers the growth rate and no significant evidence for the other possible relationships.

By employing a Constant Correlation model (CCC) Fountas et al. (2006) found that in G7 countries, inflation and its uncertainty do have real effects and real uncertainty is a positive determinant of the output growth. In contrast, with same set of countries and with similar methodology, Fountas and Karanasos (2007) conclude that uncertainty about future inflation may not be necessarily harmful to the output. In an Unrestricted Extended Constant Conditional Correlation GARCH model, Conrad and Karanasos (2008) observe that inflation uncertainty affects output variability positively, while output variability has a negative effect on inflation uncertainty in the US. Berdin and Fountas (2009) came out with the mixed evidence in the US output growth-uncertainty relationship and not able to notice any significant relationship between inflation uncertainty and growth performance.

In contrary to earlier literature, with VAR-GARCH-M model of five Asian countries, Berdin et al. (2009) found that inflation uncertainty does not affect the growth performance in most of the economies, whereas the output growth uncertainty negatively affects the growth rate. In an EGARCH-model, Bhar and Mallik (2010) show that, in US, inflation uncertainty has a positive and significant effect on the level of inflation and a negative and significant effect on the output growth. However, output uncertainty has no significant effect on output growth or inflation. By using an annual historical data on both developing and developed countries, Jha and Dang (2011) found that inflation uncertainty affects the growth rate only in the developing countries when inflation exceeds a certain threshold level. In a bivariate CCC model, Jiranyakul and Opiela (2011) found an association between inflation, inflation uncertainty and output growth in Thailand.

In addition to standard methodologies, some studies have investigated the association with different approaches. In a combined model of panel data and Least Absolute Deviation Autoregressive Conditional Heteroscedastic Model (L-ARCH)

Baharumshah (2010) confirmed the presence of significant negative role of inflation uncertainty in determining the economic growth in five ASEAN economies. Chang and He (2010) applied a bivariate Markov switching model to investigate the effects of uncertainties on macroeconomic performance and observed that the inflation uncertainty will affect the growth rate only in the low inflation regimes.

Neanidis and Savva (2010) analyze the causal effects by employing a bivariate Smooth Transition VAR GARCH-M model for the G7 countries and found that on the one hand, inflation uncertainty lowers the growth rate in the high inflation periods while on the other hand growth uncertainty enhances output growth only in the low growth regimes. Moreover, the real and nominal uncertainties have mixed effects on average inflation. In an augmented version of the Unrestricted Extended Constant Conditional Correlation (UECCC) GARCH model, Conrad and Karanasos (2010) conclude that high inflation is detrimental to output growth both directly and indirectly via the nominal uncertainty and output growth boosts inflation indirectly through reduction in real uncertainty.

It is understood from the discussed literature that the evidences are mostly associated with the developed countries and there is a lack of concrete evidence on effects of macroeconomic uncertainties on inflation and output growth in the context of developing countries. The other important point of concern is the validity of the results of the above documented empirical studies due to ambiguity surrounds measures for uncertainties. For this reasons, the following bivariate VAR GARCH models are used to verify the association in Indian scenario.

4.3. Methodology

4.3.1. Simultaneous estimation method

Following Grier et al. (2004) and Bredin et al. (2009), the subsequent bivariate VAR-GARCH-M (Vector Autoregressive GARCH-in-Mean) model has been employed to simultaneously investigate the dynamics of the relationship between real and nominal uncertainties and their influence on output growth and inflation rate. The specification of bivariate VAR (*p*)-GARCH-M model is written as follows

$$x_t = \alpha + \sum_{i=1}^{p} \Gamma_i x_{t-i} + \psi \sqrt{h_t} + \varepsilon_t \tag{4.1}$$

in which,

$$x_t = \begin{pmatrix} y_t \\ \pi_t \end{pmatrix}; \alpha_t = \begin{pmatrix} \alpha_y \\ \alpha_\pi \end{pmatrix}; \Gamma_i = \begin{pmatrix} \Gamma_{11,i} & \Gamma_{12,i} \\ \Gamma_{21,i} & \Gamma_{22,i} \end{pmatrix}; \psi = \begin{pmatrix} \psi_{11} & \psi_{12} \\ \psi_{21} & \psi_{22} \end{pmatrix}; \sqrt{h_t} = \begin{pmatrix} \sqrt{h_{y,t}} \\ \sqrt{h_{\pi,t}} \end{pmatrix}; \text{and } \varepsilon_t = \begin{pmatrix} \varepsilon_{y,t} \\ \varepsilon_{\pi,t} \end{pmatrix}$$

where x_t is a 2 × 1 column vector, that is (y_t, π_t), symbolize the output growth and inflation rate respectively, α is the 2 × 1 vector of constants and $\Gamma_{i,}\ i = 1,\ldots,p,$ is the 2 × 2 matrix of parameters. The 2 × 1 vector ψ represents the uncertainties and e_t is the vector of residuals. The residual vector ε_t is assumed to be normally distributed with its corresponding conditional variance covariance matrix $H_t = \begin{pmatrix} h_{y,t} & h_{\pi y,t} \\ h_{y\pi,t} & h_{\pi,t} \end{pmatrix}$ that is $(\varepsilon_t | \Omega_{t-1}) \sim N(0, H_t)$, where Ω_{t-1} is the information set up to time *t*-1.

4.3.2. Two-step procedure method

For computing two-step procedure method, the Karanasos and Kim (2004), is modified into following bivariate GARCH model as,

$$x_t = \alpha + \sum_{i=1}^{p} \Gamma_i x_{t-i} + \varepsilon_t \tag{4.2}$$

where all the elements and coefficients in this model holds same characteristics of the equation. (4.1) and the only difference is the exclusion of GARCH variance coefficient (ψ) from the model.

4.3.3. Variance-Covariance method

To model the second moment (variance) of the series, there are several well known multivariate-GARCH models with different parameterizations available in the time series literature[8]. The common practice in this approach of research is by following the diagonal-GARCH representations suggested by Bollerslev et al (1988) where the off-diagonal elements of the matrices in variance equations are restricted to zero. In this diagonal representation, the conditional variance of each series depends only on its past values and its own lagged squared residuals and the conditional covariance depends on past values of itself with the lagged cross product of residuals.

To overcome these limitations, Engle and Kroner (1995) proposed a new class of procedures called as BEKK representations. This specification ensures a positive definite for all values of e_t, by imposing quadratic forms on the matrices coefficients and allow the conditional variance-covariance to interact with each other[9]. This model allows for non-diagonality in the covariance process and provides an appropriate framework to check the volatility linkage between the variables and also reduces the computational complexity of estimating a large number of parameters. Hence, to model the variance-covariance matrix (H_t) of equation (4.1) and equation (4.2), a bivariate GARCH (1, 1) – BEKK representation proposed by Engle and Kroner (1995) is employed.

In their pioneering work, Grier et al. (2004) indicated that the imposing of invalid diagonal restrictions in covariance structure may create series specification errors in the model. Thus, following Grier et al. (2004), the diagonal restrictions in covariance structures of the BEKK model is tested here instead of simply assuming *a priori* diagonality.[10]

---

[8] The other famous multivariate GARCH specifications are the VECH model of Bollerslev et al (1988), the CCC model of Bollerslev (1990), the asymmetric BEKK model of Kroner and Ng (1998), the DCC model of Engle (2002) and so on. Each model offers different restrictions on the conditional covariance.

[9] In this diagonal representation, the conditional variances are functions of their own lagged values and own lagged returns shocks, while the conditional covariances are functions of the lagged covariances and lagged cross-products of the corresponding shocks.

[10] For more details, see Grier et al. (2004), Shields et al. (2004) and Berdin et al. (2009, 2005).

The BEKK parameterization for a bivariate VAR-GARCH (1, 1) model is written as

$$H_t = C_0^{'} C_0 + \sum_{i=1}^{p} A_{11}^{'} \varepsilon_{t-1} \varepsilon_{t-1}^{'} A_{11} + \sum_{i=1}^{p} B_{11}^{'} H_{t-1} B_{11} \tag{4.3}$$

where, **C**, **A**, **B**, are the 2 × 2 parameter matrices of the variance equations in which C_{11} is restricted to be lower triangular matrix and A_{11} and B_{11} are the other two unrestricted matrices. The parameters of matrix A_{11} measure the degree of the effects of shocks or news on the conditional variance and measure the extent to which the conditional variances are associated with past squared errors. The elements of square matrix B_{11} indicate the persistence in conditional volatility between the variables and measure the influence of past conditional variances over the conditional variance of the present period[11].

The complete representation of the second moment of the bivariate VAR-GARCH with BEKK representation will take the following expansion as follows[12]:

$$\begin{pmatrix} h_{11,t} & h_{12,t} \\ \cdot & h_{22,t} \end{pmatrix} = \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{pmatrix}^{'} \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{pmatrix} + \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}^{'} \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{pmatrix}$$

$$\begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}^{'} \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \tag{4.4}$$

It is necessary to expand the conditional variance of each equation of the bivariate GARCH models by the matrix multiplication method, because the

---

[11] The covariance in the BEKK model is stationary only if all the Eigen values of $A \otimes A + B \otimes B$ (where $\otimes$ stands for Kroner product) are less than one in modulus. (Engle and Kroner, 1995)

[12] For simplicity, the individual elements of the matrices, C, A and B are taken as

$$C_{11} = \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{pmatrix},\ A_{11} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix},\ B_{11} = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}$$

parameters in the BEKK representation cannot be inferred on individual basis[13]. Hence the variance system H_t is further expanded as the following equations;

$$
\begin{aligned}
h_{11,t} &= c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + b_{11}^2 h_{11,t-1}^2 \\
&\quad + 2b_{11}b_{12}h_{12,t-1} + b_{21}^2 h_{22,t-1}^2
\end{aligned} \tag{4.5}
$$

$$
\begin{aligned}
h_{22,t} &= c_{12}^2 + c_{22}^2 + a_{12}^2\varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2\varepsilon_{2,t-1}^2 + b_{12}^2 h_{11,t-1}^2 \\
&\quad + 2b_{12}b_{11}h_{12,t-1} + b_{22}^2 h_{22,t-1}^2
\end{aligned} \tag{4.6}
$$

The above equations measure the spillover effects and volatility transmissions across the variables over a period of time. The coefficients of the above equation (4.5) and equation (4.6) are the non-linear function of the elements in the BEKK-GARCH equation (4.3). Finding the standard errors for these coefficients involves a first order Taylor series expansion of the function around its mean. Following Kearney and Patton (2000), the standard errors of this non-liner function, has been calculated by applying the Delta method[14].

The estimates of the above discussed equations are obtained by using the following maximum likelihood function;

$$
L(\theta) = -\frac{TN}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(\ln\left|H_t\right| + \varepsilon_t' H_t^{-1}\varepsilon_t\right) \tag{4.7}
$$

where the notation *T* symbolize the number of observations, θ is the estimated parameter vector and *N* represents the number of variables in the estimated system and the errors in the estimation process are assumed to be normally distributed. Simplex algorithm is used to obtain the initial starting values for the estimations and then the final parameters of the mean and variance–covariance matrix with

---

[13] Kearney and Patton, (2000) pointed out that the parameters in the BEKK representations are cannot be interpreted on an individual basis and the inference is based on the functions of the parameters form the intercept and the coefficients of the lagged variance, covariance, and error terms of the respective equations.

[14] For details, refer Oehlert (1991), Kearney and Patton (2000), Hassan (2007) and Malik(2009).

respective standard errors are simultaneously estimated by using BFGS (Broyden, 1970;-Fletcher, 1970;-Goldfarb, 1970; Shanno, 1970) algorithm. [15]

4.3.4. The Causality tests

Although the simultaneous estimation method in equation (4.1) avoids the problem of generated repressors, it does not allow for the lagged influence of uncertainties in the model. The influence of real and nominal uncertainties on output growth and inflation rate may exist for prolonged period of time. The restrictions imposed in the lagged uncertainties in the simultaneous approach may have an edge over the ability to establish proper association between the pair of variables considered. To overcome this problem, as a two-step approach, a bivariate GARCH model in equation (4.2) is employed to obtain the conditional variances of the inflation rate and output growth with the BEKK representations. The causal nexus between uncertainties and macroeconomic performance are studied by using Granger causality tests.[16]

4.4. Data and Empirical results

4.4.1. Data

The seasonally adjusted data of Index of Industrial Production (IIP) and Wholesale Price Index (WPI) are used for analysis. The real output growth is measure by the monthly percentage change in the natural logarithm of IIP and inflation is computed as natural logarithm of monthly difference in the WPI[17]. The sample covers the period from April 1980 to April 2011 and consists of 360 observations in each series[18].

---

[15] Weiss (1986) and Bollerslev and Wooldridge (1992) pointed out that valid inference on normal quasi-maximum likelihood estimates may be based on robustified versions of the standard test statistics. So, the robust standard errors were calculated by following Bollerslev and Wooldridge (1992).

[16] A detailed discussion on the Granger causality models is available in Section 3 of Chapter 1.

[17] The data source, method of measuring real activity and inflation rate and rest of the other computation procedures are well documented in the earlier chapters.

[18] The time series starts from the year 1980, because, prior to 1980, the proxy for growth rates (IIP or GDP) is not available on monthly basis.

Table 4.1: Summary Statistics

A. Summary Statistics					
Variable	Mean	Std. Deviation	Skewness	Kurtosis	J-B Normality
Y	0.5577	2.1707	0.0070	6.3471	168.04 (0.00)
π	0.5291	0.5397	0.7699	5.3988	121.58 (0.00)

B. Unit root and stationarity tests			
Variable	ADF test	PP test	KPSS tests
Y	-19.259*	-34.420*	0.083*
π	-12.880*	13.021*	0.224*

C. Test for serial correlation and ARCH effects					
Variable	$Q(4)$	$Q(10)$	$Q^2(4)$	$Q^2(10)$	ARCH(4)
Y	14.69 (0.00)	22.91 (0.01)	26.19 (0.00)	38.36 (0.00)	23.06 (0.00)
π	8.33 (0.80)	17.28 (0.06)	9.16 (0.05)	10.70 (0.08)	7.58 (0.10)

Table 4.1 presents the descriptive statistics of real economic activity and inflation rate and offer preliminary insights about the data. The reported summary statistics and the Jarque- Bera (JB) normality test[19] fails to provide evidence for normality in both real activity and inflation rate. A set of unit root tests and the test for stationarity is displayed in Panel B of Table 4.1 showing that both the variables are stationary at their levels.

The Ljung-Box tests for serial correlation presented in Panel C firmly reject the null hypothesis of no autocorrelation for both the variables and show a significant amount of serial dependence in the conditional mean. Similarly, it also provides strong evidence for the presence of conditional Heteroskedasticity in the squared errors of inflation and output growth. The reported test statistic of the ARCH-LM test for various lags also provides evidence for the presence of ARCH effects in the model.

[19] The summary statistics and the unit root properties of the growth rate are already discussed in Chapter 2.

4.4.2. Results

The Equations (4.1) and (4.2) are estimated by using normal quasi-maximum likelihood method proposed by Bollerslev and Wooldridge (1992)[20]. To check the adequacy of the specifications, the following nested models, a diagonal VAR, a homoskedastic model, a GARCH model without mean, and a diagonal GARCH model are estimated. The results of the estimated parameters from the bivariate GARCH-M model with BEKK specification are reported in Table 4.2 in addition with the residual diagnostic statistics[21]. The elements of matrix ψ in mean equation measures the impact of uncertainties on output growth and inflation. The effects of real uncertainty on output growth are captured by the elements ψ_{11} and ψ_{21} whereas the elements ψ_{12} and ψ_{22} test the influence of nominal uncertainty[22].

The negative and insignificant influence of real uncertainty on output growth implies that there is no evidence for Black hypothesis of positive association between output uncertainty and growth. The positive and significant value impact of real uncertainty on inflation rate indicates support for the Devereux prediction of ‘increased growth uncertainty raises average inflation rate’. On the other hand, the negative and significant effect of nominal uncertainty on the output growth provides strong evidence to Friedman and Okun’s argument regarding the real effects of inflation uncertainty. On the contrary, the statistically insignificant coefficient of inflation uncertainty indicate that nominal uncertainty do not have any impact on the inflation rate, which is contradictory to both the Cukierman–Meltzer and the Holland hypotheses of positive influence.

[20] As a robustness test, in addition with the assumption of normally distributed errors, maximum likelihood estimation with conditional Student *t* distribution is also performed for all the BEKK-GARCH equations. The results are similar for both the distributional assumptions in all the models.

[21] On the basis of the AIC, SBC and HQ lag length criterions, in this chapter, three lags is chosen as an optimal lag length for all the bivariate VAR-BEKK-GARCH models.

[22] The reported results are based on the order of variables shows in the equations. Changing the order of variables is also given the same results not only for the impact of uncertainties on macroeconomic performance but also for the sign and significance of the BEKK coefficients.

Table 4.2: Bivariate Symmetric GARCH-M model

A. Conditional mean equation

$$x_t = \alpha + \sum_{i=1}^{p} \Gamma_i x_{t-i} + \psi \sqrt{h_t} + \varepsilon_t$$

$$x_t = \begin{pmatrix} y_t \\ \pi_t \end{pmatrix}; \alpha_t = \begin{pmatrix} \alpha_y \\ \alpha_\pi \end{pmatrix}; \Gamma_i = \begin{pmatrix} \Gamma_{11,i} & \Gamma_{12,i} \\ \Gamma_{21,i} & \Gamma_{22,i} \end{pmatrix}; \psi = \begin{pmatrix} \psi_{11} & \psi_{12} \\ \psi_{21} & \psi_{22} \end{pmatrix}; \sqrt{h_t} = \begin{pmatrix} \sqrt{h_{y,t}} \\ \sqrt{h_{\pi,t}} \end{pmatrix} \text{;and } \varepsilon_t = \begin{pmatrix} \varepsilon_{y,t} \\ \varepsilon_{\pi,t} \end{pmatrix}$$

$$a = \begin{pmatrix} 2.3008 \\ (0.61) \\ \\ 0.0120 \\ (0.12) \end{pmatrix} \quad \Gamma_1 = \begin{pmatrix} -0.5007 & 0.1770 \\ (0.05) & (0.18) \\ \\ -0.0064 & 0.3733 \\ (0.01) & (0.05) \end{pmatrix} \quad \Gamma_2 = \begin{pmatrix} -0.1855 & 0.4943 \\ (0.05) & (0.18) \\ \\ -0.0250 & 0.0046 \\ (0.01) & (0.04) \end{pmatrix}$$

$$\Gamma_3 = \begin{pmatrix} -0.0566 & -0.0557 \\ (0.05) & (0.16) \\ \\ 0.0038 & 0.0797 \\ (0.01) & (0.04) \end{pmatrix} \quad \psi = \begin{bmatrix} -0.2037 & -2.5136 \\ (0.20) & (0.06) \\ \\ 0.1190 & 0.1610 \\ (0.04) & (0.20) \end{bmatrix}$$

B. Conditional variance – covariance matrix

$$H_t = C_0^{'} C_0 + \sum_{i=1}^{p} A_{11}^{'} \varepsilon_{t-1} \varepsilon_{t-1}^{'} A_{11} + \sum_{i=1}^{p} B_{11}^{'} H_{t-1} B_{11}$$

$$C_{11} = \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{pmatrix}, \ A_{11} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}, \ B_{11} = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}, \ \varepsilon_{t-1} = \begin{pmatrix} \varepsilon_{y,t-1} \\ \varepsilon_{\pi,t-1} \end{pmatrix}$$

$$C_0 = \begin{pmatrix} 1.2961 & -0.0428 \\ (0.15) & (0.09) \\ \\ 0 & 0.0000 \\ & (0.04) \end{pmatrix} \quad A_{11} = \begin{pmatrix} 0.5409 & 0.1242 \\ (0.09) & (0.02) \\ \\ -0.8454 & 0.8227 \\ (0.27) & (0.09) \end{pmatrix}$$

$$B_{11} = \begin{pmatrix} 0.04242 & -0.0034 \\ (0.06) & (0.01) \\ \\ -0.1116 & 0.2718 \\ (0.51) & (0.09) \end{pmatrix}$$

C. Residual diagnostics

	$Q(4)$	$Q(10)$	$Q^2(4)$	$Q^2(10)$
$\varepsilon_{1,t}$	2.314 [0.68]	8.018 [0.63]	4.855 [0.30]	8.142 [0.61]
$\varepsilon_{2,t}$	0.957 [0.92]	10.577 [0.39]	2.913[0.57]	6.169[0.80]

D. Hypothesis testing

Diagonal VAR	$H_0 : \Gamma_{12}^{i} = \Gamma_{21}^{i} = 0$	[0.02]
No GARCH	$H_0 : \alpha_{ij} = \beta_{ij} = 0$ for all *i, j*	[0.00]
No GARCH-M	$H_0 : \psi_{ij} = 0$ for all *i, j*	[0.03]
Diagonal GARCH	$H_0 : \alpha_{12}^{*} = \alpha_{21}^{*} = \beta_{12}^{*} = \beta_{21}^{*} = 0$	[0.00]

Notes: Standard errors displayed as ( ). Marginal significance levels are displayed as [ ]. Q and Q^2 are the Ljung– Box tests for p^{th} order of serial correlation.

The estimates of the variance coefficient matrices provide strong evidence for the existence of heteroscedasticity in variances of the series. The homoscedasticity assumption in variance requires the matrices in the variance equation to be jointly insignificant but the results shows that they are jointly significant at 1% level and individually significant at conventional level for most of the coefficients. The individual and joint significance of the off-diagonal elements of the two matrices in the variance equation displays that the lagged conditional variances and lagged squared innovations in each series influencing the conditional variance of the other series. The joint significant of the coefficients of GARCH-M matrix proved that macroeconomic performances are influenced by macroeconomic uncertainties. The values of Ljung-Box test statistics in Panel C ensure the absence of serial correlation in the mean and variance equations of both the output and inflation series.

The empirical validity of the results obtained from GARCH-M models is quite debatable, because of the restrictions imposed on the effect of the lagged uncertainties. The influence of real and nominal uncertainties on output growth and inflation rate may exist for a prolonged period of time. Hence the restriction imposed may limit the ability of this simultaneous estimation approach in establishing real factual associations between the pair of variables under consideration. To overcome this problem, as a two-step approach, a bivariate GARCH model in equation (4.3) is used to obtain the conditional variances of the inflation rate and output growth with the BEKK representations where there are no any restrictions on the diagonal values of the conditional variance-covariance matrices[23].

[23] To check the presence of asymmetry in BEKK GARCH, the sing and size bias test proposed by Engle and Ng (1993) was used. The test result does not provide any evidence for asymmetry in the output series. Thus a symmetric VAR-BEKK GARCH model is estimated.

Table 4.3: The Bivariate Symmetric GARCH Model - VAR-BEKK-GARCH

A. Conditional mean equation

$$x_t = \alpha + \sum_{i=1}^{p} \Gamma_i x_{t-i} + \varepsilon_t$$

$$x_t = \begin{pmatrix} y_t \\ \pi_t \end{pmatrix}; \alpha_t = \begin{pmatrix} \alpha_y \\ \alpha_\pi \end{pmatrix}; \Gamma_i = \begin{pmatrix} \Gamma_{11,i} & \Gamma_{12,i} \\ \Gamma_{21,i} & \Gamma_{22,i} \end{pmatrix}; \sqrt{h_t} = \begin{pmatrix} \sqrt{h_{y,t}} \\ \sqrt{h_{\pi,t}} \end{pmatrix} \text{;and } \varepsilon_t = \begin{pmatrix} \varepsilon_{y,t} \\ \varepsilon_{\pi,t} \end{pmatrix}$$

$$a = \begin{pmatrix} \underset{(0.10)}{0.9747} \\ \underset{(0.04)}{0.3066} \end{pmatrix} \quad \Gamma_1 = \begin{pmatrix} \underset{(0.05)}{-0.5084} & \underset{(0.15)}{-0.0339} \\ \underset{(0.01)}{-0.0079} & \underset{(0.03)}{0.3416} \end{pmatrix} \quad \Gamma_2 = \begin{pmatrix} \underset{(0.05)}{-0.1286} & \underset{(0.18)}{0.6687} \\ \underset{(0.01)}{-0.0276} & \underset{(0.04)}{-0.0290} \end{pmatrix}$$

$$\Gamma_3 = \begin{pmatrix} \underset{(0.04)}{-0.0896} & \underset{(0.14)}{-0.3966} \\ \underset{(0.01)}{-0.0031} & \underset{(0.05)}{0.1169} \end{pmatrix}$$

B. Conditional variance – covariance matrix

$$H_t = C_0^{'} C_0 + \sum_{i=1}^{p} A_{11}^{'} \varepsilon_{t-1} \varepsilon_{t-1}^{'} A_{11} + \sum_{i=1}^{p} B_{11}^{'} H_{t-1} B_{11}$$

$$C_{11} = \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{pmatrix}, \; A_{11} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}, \; B_{11} = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}, \; \varepsilon_{t-1} = \begin{pmatrix} \varepsilon_{y,t-1} \\ \varepsilon_{\pi,t-1} \end{pmatrix}$$

$$C_0 = \begin{pmatrix} \underset{(0.08)}{0.2128} & \underset{(0.03)}{0.0973} \\ 0 & \underset{(0.52)}{0.0000} \end{pmatrix} \quad A_{11} = \begin{pmatrix} \underset{(0.03)}{0.5272} & \underset{(0.01)}{0.2147} \\ \underset{(0.16)}{-2.8592} & \underset{(0.03)}{0.5378} \end{pmatrix}$$

$$B_{11} = \begin{pmatrix} \underset{(0.06)}{0.2431} & \underset{(0.01)}{-0.0248} \\ \underset{(0.17)}{-1.0374} & \underset{(0.05)}{-0.0264} \end{pmatrix}$$

C. Residual diagnostics

	$Q(4)$	$Q(10)$	$Q^2(4)$	$Q^2(10)$
$\varepsilon_{1,t}$	0.694 [0.95]	6.925 [0.73]	5.474 [0.24]	1.834 [0.77]
$\varepsilon_{2,t}$	0.957 [0.92]	10.577 [0.39]	10.013[0.44]	6.142 [0.80]

D. Hypothesis testing

Diagonal VAR	$H_0 : \Gamma_{12}^{i} = \Gamma_{21}^{i} = 0$	[0.00]
No GARCH	$H_0 : \alpha_{ij} = \beta_{ij} = 0$ for all i,j	[0.00]
Diagonal GARCH	$H_0 : \alpha_{12}^{*} = \alpha_{21}^{*} = \beta_{12}^{*} = \beta_{21}^{*} = 0$	[0.00]

Notes: Standard errors displayed as ( ). Marginal significance levels are displayed as [ ]. Q and Q^2 are the Ljung– Box tests for p^{th} order of serial correlation.

The estimated parameters from simple VAR-BEKK GARCH model with associated robust standard errors and error diagnostic test results are presented in

Table 4.3. The estimates from the mean equation rejects the diagonal restrictions in the data ($H_0 : \Gamma^i_{12} = \Gamma^i_{21} = 0$) and provide strong support for the presence of dynamic interactions between output growth and inflation rate. The elements in A_{11} and B_{11} matrix confirm the existence of strong conditional heteroskedasticity jointly in both the series, where the null hypothesis of no GARCH ($H_0 : \alpha_{ij} = \beta_{ij} = 0$) is rejected at the conventional level of significance.

The joint significance of off-diagonal elements of both the two matrices strongly rejects the null of diagonal covariance process ($H_0 : \alpha^*_{12} = \alpha^*_{21} = \beta^*_{12} = \beta^*_{21} = 0$) which implies that the lagged squared innovations in real activity (inflation rate) significantly influence the conditional variance of inflation rate (output growth). Except the two coefficients (a_{21}, b_{21}), all individual coefficients in these two matrices are statistically significant. The reported residual diagnostic tests indicate no remaining autocorrelation in the standardized and squared standardized residuals in output growth and inflation equations up to 12^{th} lag order[24].

The conditional variances and covariance of output growth and inflation obtained from VAR-BEKK GARCH model are displayed in Figure 4.1, to Figure 4.3. The visual inspection of this plots show that both output growth and inflation volatility is high in the period from 1990 to 1993. In this period, Indian economy experienced biggest economic turbulence followed by new economic reform process. Also both growth and inflation volatility is showing consistency in ups and downs up to 2007 and higher variance thereafter due to the fall-out of global financial crisis. The conditional variance and covariance do not remain constant over time and showed a clear cluster.

[24]To make a comparison with the results of BEKK specifications, different volatility models like Diagonal VECH model of Bollerslev et al. (1988) and the CCC model of Bollerslev (1990) are also estimated by following the two step procedure methods. The VAR-GARCH models are also estimated with CCC GARCH specifications. Results obtained from these models are similar to the VAR-BEKK representations.

Figure 4.1: Conditional Variance of Real Output Growth

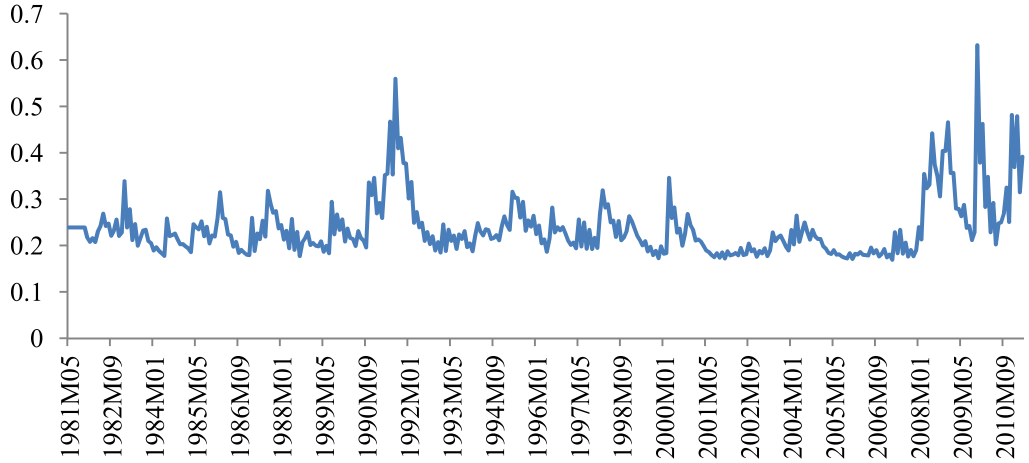


Figure 4.2: Conditional Variance of Inflation Rate

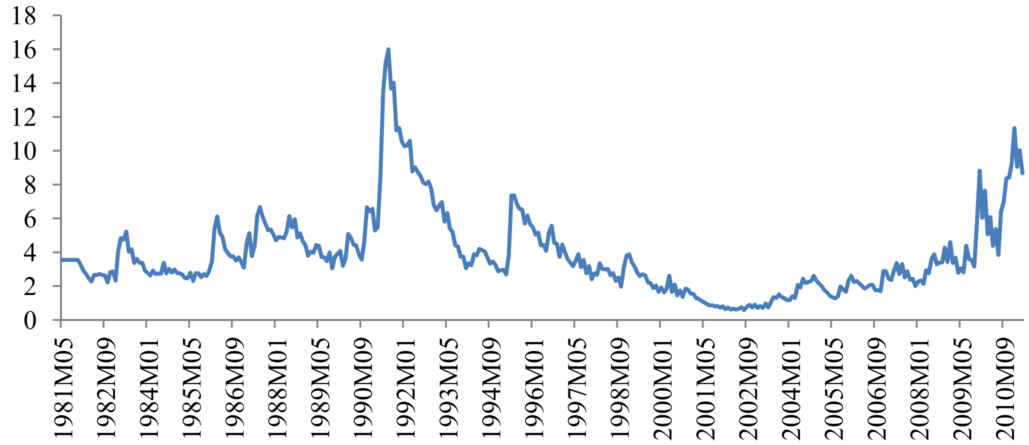
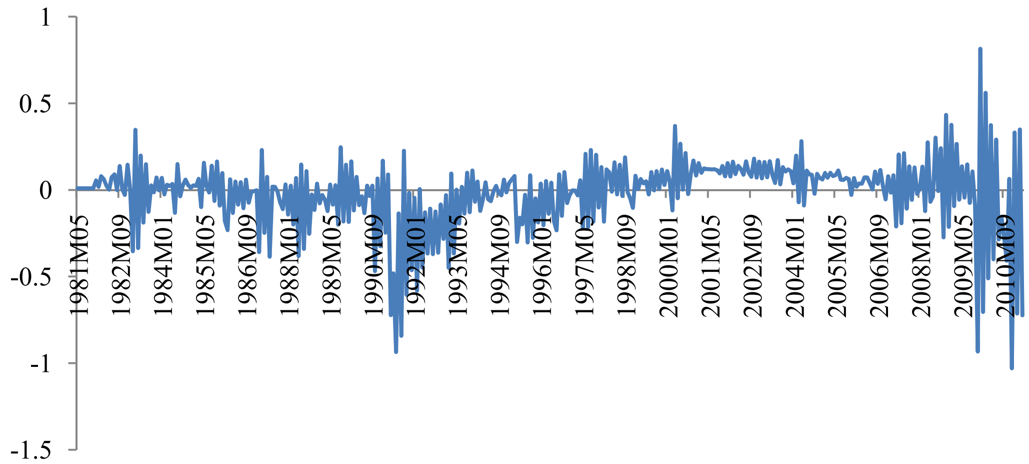


Figure 4.3: Covariance between Output Growth and Inflation Rate



The above presented VAR-BEKK-GARCH model does not fit enough to verify the impact of macroeconomic uncertainties on inflation and output growth. The exclusion of uncertainty coefficients from the mean equation departed its ability of explaining the effects of uncertainty on macroeconomic variables. This model only explains the cross volatility effects of the lagged series with each other. In other words, the results presented in Table 4.4 explain only the volatility transmissions between output growth and inflation and not the mean effects of volatility. The other important point to remember is that as mentioned in the methodology, the estimated BEKK parameters (*A* and *B* matrices) cannot be interpreted on the individual basis, because these parameters involve nonlinear functions of the original parameters[25].

The spillover effects between real and nominal uncertainties are investigated from the specification denoted in equation (4.5) and (4.6) gives an expanded parameters of the conditional variance in the BEKK representation. The standard errors for this non linear function are obtained by using the delta method and the first-order Taylor approximation, which yields an approximate formulation of the variance of the non linear functions[26]. The results are presented in Table 4.4.

Table 4.4: Volatility Spillovers between Real and Nominal Uncertainties

Variable	$h_{11,t+1}$	$h_{22,t+1}$
$h_{11,t}$	0.0798 (1.761)	0.2475 (3.635)
$h_{12,t}$	-0.2811 (2.318)	-0.2592 (-3.289)
$h_{22,t}$	0.0012 (3.166)	0.0678 (10.318)
$\varepsilon_{1,t}^2$	0.6441 (1.662)	2.2424 (27.649)
$\varepsilon_{1,t}\varepsilon_{2,t}$	2.4037 (1.621)	-2.6238 (-2.052)
$\varepsilon_{2,t}^2$	0.0068 (0.711)	1.7521 (1.549)

Notes: h_{11} denotes the conditional variance for output series and h_{22} is the conditional variance for inflation series. The corresponding *t*-values for each coefficient are given in parenthesis.

[25] For more details refer, Kearney and Patton (2000) and Oehlert (1991).

[26] Applying delta method to a nonlinear function like h_{tt} yields the following $\mathrm{var}(h(\theta) = \left(dh/d\theta\right)^2 \mathrm{var}(\theta)$ equation. Correspondingly, applying the delta method to a function of two variables $h_{tt}(\theta_1, \theta_2)$, gives the following equation $var(h(\theta_1,\theta_2) = \left(\partial h/\partial\theta_t\right)^2 var(\theta_1) + \left(\partial h/\partial\theta_2\right)^2 var(\theta_2) + 2\left(\partial h/\partial\theta_t\right) + \left(\partial h/\partial\theta_2\right) cov(\theta_1,\theta_2,)$.

The reported results indicate two transmission mechanism channels of the volatility spillovers. First channel includes direct and indirect transmissions of conditional volatility where in direct volatility transmission, the conditional variance directly ($h_{11,t+1,}$) responds to its own volatility ($h_{11,t}$) and/or to the volatility of the other variables ($h_{22,t}$). The indirect volatility transmission mechanism is the situation, where $h_{11,t+1}$ responds to the volatility of the conditional covariance ($h_{12,t}$) of the two variables. In the second mechanism, the squared error term "ε" in each model represents the transmission of *direct news effect*, where the conditional variance ($h_{11,t+1}$) responds directly to its own shocks/news ($\varepsilon_{1,t}^2$) and/or to the shocks/news in the other variable ($\varepsilon_{2,t}^2$). The response of ($h_{11,t+1,}$) to the indirect transmission of shocks is measured by the cross values of the error terms of the two variables ($\varepsilon_{1,t}$ $\varepsilon_{,2t}$) which represents the *indirect news effect* of the two variables of interest.

The results presented in the first column of Table 4.4 indicate that the conditional variance of real uncertainty responds directly to its own past volatility and to its own news effect. This conclusions are evident from the significant coefficients of the, $h_{11,t}$, and $\varepsilon_{1,t}^2$. In addition, the real uncertainty is directly affected by the volatility of nominal uncertainty and indirectly affected news effect of nominal uncertainty which is indicated by the significant coefficients of the, $h_{22,t}$ $h_{12,t}$ and $\varepsilon_{1,t}\varepsilon_{2,t}$. This finding is consistent with the earlier results that the positive shocks in inflation uncertainty are associated with a rise in output uncertainty. The shocks in nominal uncertainty, ($\varepsilon_{2,t}^2$) do not significantly affect the conditional variance of real uncertainty.

The behavior of the nominal volatility model substantially differs from the results of real volatility model. The results depicted in column two shows that all the coefficients of the nominal volatility transmission model show significant values. This finding indicates that the volatility of nominal variable is directly and indirectly affected by the volatility and news effect of the real uncertainty as well as the volatility and news of its own. Further, this observation implies that the nominal volatility declines significantly, when the volatility and the news of output growth rate are reacting good which is evident from the negative and significant $h_{12,t}$ and $\varepsilon_{1,t}\varepsilon_{2,t}$ coefficients. Overall, there is a significant volatility transmission and the spillovers between the real and nominal uncertainties and the vital finding is that the volatility in nominal uncertainty directly affects volatility of the real growth rates.

Hence as a two-step approach, the tradeoff between uncertainties and macroeconomic performance are studied in the causality tests where the conditional variances obtained from the BEKK-GARCH model are used as proxies for macroeconomic volatility[27]. Table 4.5 reports the results of pair wise *F* statistics of Granger-causality analysis between macroeconomic uncertainties, inflation and output growth for four, eight and twelve lag periods. Panel A reports causality test results of the nexus between nominal uncertainty and output growth. The results in Panel B displays the causal effects of real uncertainty on inflation and the results reported in Panel C examines the nexus between real and nominal uncertainties.

The reported results in Panel A provide evidence that the null hypothesis of nominal uncertainty does not Granger-cause output growth cannot be rejected up to 8 lags at the conventional level of significance. The effect of inflation uncertainty on output growth is statistically significant only after 12 lags. The negative sum of the lagged nominal uncertainty coefficients in the output equations for all lag periods indicate the adverse impact of the uncertainty on the output growth. These results do not locate any concrete evidence for Friedman (1977) and Pindyck (1991) claim on the negative real effects of inflation uncertainty in the shorter time span. The key finding here is that the inflation uncertainty significantly lowers the output growth only when there exists uncertainty persistence for longer time periods and there is no any influence in the short durations. In other words, the inflation uncertainty influences the output growth rate only in the long run.

[27] A detailed discussion on the causality tests is available in Section 3 of Chapter 2.

Table 4.5: Causalities between Inflation, Output and their Uncertainties

Panel (A)	$y_t \rightarrow h_{\pi_t}$	$h_{\pi_t} \rightarrow y_t$
4 lags	2.6607**(-) (0.03)	1.7166 (-) (0.15)
8 lags	1.8833*** (-) (0.06)	1.6613(-) (0.11)
12 lags	1.4312 (-) (0.15)	2.1505* (-) (0.01)
Panel (B)	$\pi_t \rightarrow h_{y_t}$	$h_{y_t} \rightarrow \pi_t$
4 lags	9.5943* (+) (0.00)	3.3086* (+) (0.01)
8 lags	6.0451* (+) (0.00)	2.2936* (+) (0.02)
12 lags	4.2158* (+) (0.00)	2.4692* (+) (0.00)
Panel (C)	$h_{\pi_t} \rightarrow h_{y_t}$	$h_{y_t} \rightarrow h_{\pi_t}$
4 lags	89.203* (+) (0.00)	1.3569 (+) (0.25)
8 lags	47.245* (+) (0.00)	4.0338* (+) (0.00)
12 lags	30.169* (+) (0.00)	2.3957* (+) (0.01)

Notes: Reported values are the *F* statistics of Granger causality tests and '***', '**'and '*' denotes 10%, 5 %, and 1 % level of significance respectively. The symbol $\rightarrow$ indicates the direction of causality and the sign (+) or (-) indicates the direction of the relationship. π_t □ $h_{\pi t}$ indicates inflation does not Granger-cause inflation uncertainty; $h_{\pi t} \rightarrow \pi_t$ indicates inflation uncertainty does not Granger-cause inflation. . $y_t \rightarrow h_{yt}$ indicates output does not Granger-cause output uncertainty; $h_{yt} \rightarrow y_t$ indicates output uncertainty does not Granger-cause output.

In contrast, the reverse causality results provide strong evidence for the significantly negative influence of the output growth to nominal uncertainty only in the short span and not in the higher orders. The sum of the lagged output coefficients in the nominal uncertainty equation is negative for all the lag periods and the null hypothesis of no causality is rejected only at the 4th lag at the conventional level of significance. This association is channeled through the short-run Phillips curve and Friedman's hypothesis where higher output growth leads to higher inflation rate and increase in rate of inflation summoned more uncertainty about future rate of inflation and thus, increasing output growth grounded more nominal uncertainty.

The results presented in Panel B verified the impact of growth uncertainty on average inflation rate. The sum of the lagged output uncertainty coefficients in the inflation equation is positive and the null hypothesis of no causality between real uncertainty and inflation is rejected for all the lags at the much conventional significant level. This evidence provides strong empirical support for Deveraux

(1989) and Cukierman and Gerlach (2003) claim of positive causal effect of growth uncertainty on the inflation rate. The causality results of inflation-real uncertainty displays a strong positive impact of inflation over the output growth rate[28]. For all the different lag periods, the alternative hypothesis of causality between inflation and output growth uncertainty is accepted at the highest conventional level of statistical significance.

Panel C present the test results of the two null hypotheses that 'nominal uncertainty does not cause real uncertainty' and the null hypothesis that 'the real uncertainty does not cause nominal uncertainty'. The results show that at each lag length, the claim of inflation uncertainty does not influence output variability is rejected at 1% level of significance and the former has a strong, positive and significant impact on latter. This evidence support the hypothesis advocated by Logue and Sweeney (1981) where higher inflation uncertainty leads to higher variability in real growth. The reverse type causality from output volatility to inflation uncertainty also reports similar results where the real uncertainty positively and significantly influences the nominal uncertainty at all the lags. The null hypothesis is rejected for all the lag periods and these results provide strong supportive evidence for the Devereux (1989) hypothesis of positive nexus between output volatility and the variability of inflation.

As pointed out in the earlier chapters, structural changes are common in the macroeconomic interrelationships and the gain of using a long time series data may be offset by the possibility of structural breaks. Hence, the results obtained from the long time span data should be interpreted with caution. Instead of choosing a priori break point, the Bai and Perron multiple structural break tests are applied to both the series which obtained a break in inflation series at the year 1995:06.[29] For this reason, the whole sample period is broken into two sub-periods where the first sub-period starts from the beginning of the sample to the end of 1995:05 and the second

[28] Theoretically, there is a no any direct mechanism are available to explain the effect of inflation on output uncertainty and the sign of the effect is quite ambiguous. The interaction of Friedman hypothesis and Logue and Sweeney effects or Ungar and Zilberfarb and Taylor effect may channeled this association.

[29]A detailed discussions and test results of multiple structural break tests are presented in the earlier chapters.

sub-period starts from 1995:07 and continue till the end of the sample. To investigate the role of break point in determining association between the spillovers and the causalities of the variables of interest, a separate granger causality test and volatility spillover test are conducted for each subsample.

The Table 4.6 reports the causality test results of the relationship between average inflation, output growth, nominal uncertainty, and real uncertainty for the pre and post break period. The results reported in Panel A shows that inflation uncertainty influence the output growth only at the higher levels in both the pre and post break periods. This finding is consistent with the results of the full sample period but the sign of the effect differs. Likewise, the reverse causality from output growth to inflation uncertainty in post break period replicates the same association resembling to the full sample period where the effect of output growth on nominal uncertainty is only for a shorter period of time.

Table 4.6: Causalities between Real and Nominal Uncertainties with Inflation and Output for Pre and Post break periods

	Pre break period (1980:01 - 1995:05)		Post Break period (1995:07 - 2011:04)	
	$y_t \rightarrow h_{\pi_t}$	$h_{\pi_t} \rightarrow y_t$	$y_t \rightarrow h_{\pi_t}$	$h_{\pi_t} \rightarrow y_t$
4 lags	1.0690 (-) (0.37)	1.6610 (-) (0.16)	2.1580*** (-) (0.08)	0.6563 (-) (0.62)
8 lags	0.5752 (+) (0.80)	1.8138*** (+) (0.08)	1.8137***(+) (0.08)	0.9875 (+) (0.45)
12 lags	0.6746 (-) (0.77)	1.885**(+) (0.04)	1.4123 (-) (0.17)	2.533*(+) (0.00)
	$\pi_t \rightarrow h_{y_t}$	$h_{y_t} \rightarrow \pi_t$	$\pi_t \rightarrow h_{y_t}$	$h_{y_t} \rightarrow \pi_t$
4 lags	3.6942*(-) (0.01)	3.8973*(+) (0.00)	7.4710*(+) (0.00)	1.6527(-) (0.16)
8 lags	2.9845*(+) (0.00)	2.1327**(+) (0.00)	3.9002*(+) (0.00)	1.461(+) (0.17)
12 lags	2.0025**(+) (0.03)	2.3116*(+) (0.00)	2.3684*(+) (0.01)	1.2711(+) (0.24)
	$h_{\pi_t} \rightarrow h_{y_t}$	$h_{y_t} \rightarrow h_{\pi_t}$	$h_{\pi_t} \rightarrow h_{y_t}$	$h_{y_t} \rightarrow h_{\pi_t}$
4 lags	30.352*(-) (0.01)	3.3316*(+) (0.01)	81.536*(+) (0.00)	1.5949(+) (0.18)
8 lags	14.411*(+) (0.00)	2.3015**(+) (0.02)	54.734*(+) (0.00)	6.0918*(+) (0.00)
12 lags	9.5942*(+) (0.00)	1.7493**(+) (0.06)	34.484*(-) (0.00)	2.9420*(+) (0.00)

Notes: Reported values are the *F* statistics of Granger causality tests and '***', '**'and '*' denotes 10%, 5 %, and 1 % level of significance respectively. The symbol $\rightarrow$ indicates the direction of causality and the sign (+) or (-) indicates the direction of the relationship

The causality results of pre break period presented in Panel B find the strong positive evidence of the line of causation running from output uncertainty to inflation. In contrast to the full sample and pre break analysis, the null hypothesis of no causality between output growth uncertainty and inflation is accepted by the post break causality test results. It fails to find any evidence to support Deveraux's hypothesis, positive effect of growth uncertainty on inflation, which means that after the break point, the growth uncertainty may not have any role in determining the average rate of inflation. The reverse causality test result also shows a positive and significant impact of inflation on output growth uncertainty in both the sub sample analysis, which is similar to the results of full sample period.

The reported causality test results between the real and nominal uncertainties in Panel C provide strong evidence for positive bidirectional causality between real and nominal uncertainties in pre and post break analysis. These results supports both the Logue and Sweeney (1981) and Devereux (1989) hypothesis of positive association between real and nominal uncertainty as well as the positive association from nominal to real uncertainty. The reported sign and direction of the association between these two variables in the both the sample period is very much equivalent to the results of the full sample analysis.

In sum, the validity of the causality test results between macro uncertainties and macroeconomic variables in pre and post break analysis provided much similar results like the full sample period with the exception on the output growth uncertainty and inflation relationship in the post break tests. Consequently these results tempt to conclude that the structural change in the economic system during the period of study does not have any significant impact on the association between the uncertainties and macroeconomic variables.

Table 4.7: Volatility Spillovers between Real uncertainty and Nominal uncertainty for Pre and Post break analysis

	Pre break (1980:01 - 1995:05)		Post Break (1995:06 - 2011:04)	
Variable	$h_{11,t+1}$	$h_{22,t+1}$	$h_{11,t+1}$	$h_{22,t+1}$
$h_{11,t}$	0.2084 (45.556)	0.0008 (0.863)	0.2127 (3.355)	0.0015 (0.417)
$h_{12,t}$	-0.0262 (-1.123)	0.0056 (-1.915)	-0.0365 (-0.967)	0.0469 (0.758)
$h_{22,t}$	1.3791 (8.753)	0.0349 (1.574)	0.8799 (3.203)	0.3516 (4.363)
$\varepsilon_{1,t}^2$	0.1058 (1.894)	0.0269 (4.373)	0.5501 (2.770)	0.0038 (16.35)
$\varepsilon_{1,t}\varepsilon_{2,t}$	0.1069 (0.386)	0.0777 (2.694)	0.0925 (0.281)	0.0835 (1.810)
$\varepsilon_{2,t}^2$	14.744 (4.678)	-0.4731 (10.68)	0.7752 (2.219)	1.3396 (10.62)

Notes: h_{11} denotes the conditional variance for output series and h_{22} is the conditional variance for inflation series. The corresponding t-values for each coefficient are given in parenthesis.

The results of pre and post break volatility spillovers of real and nominal uncertainties are given in Table 4.7. The second and third column of the tables studied the pre break volatility spillovers whereas fourth and fifth columns discuss the results of post break volatilities.

The reported results in column two shows that the volatility of real uncertainty in pre break period is directly affect by the news and volatility of its own. Also, it is directly affected by the volatility and news effect from the nominal uncertainty model. In addition, it is also found that the estimated volatility and the unexpected news of nominal uncertainty do not have any significant influence on the real uncertainty. Likewise the results of pre break nominal volatility h_{22}, shown in column three is also impacted by its own past volatility and its own shocks. The significant $h_{12,t}$ and $\varepsilon_{1,t}\varepsilon_{2,t}$ coefficients indicates the indirect influence of volatility and news effect of the real variance on the nominal variable. The direct influence of real volatility on the nominal uncertainty is denoted by the significant values of $\varepsilon_{1,t}^2$.

The given results of post break real volatility spillovers in column four of Table 4.7 shows that growth sector is directly affected by its own news effect and volatility as well as the volatility and unexpended news or shocks in the nominal uncertainty. There is no any indirect effect of the covariance volatility and the cross values of error terms. The volatility spillover effects of nominal variable in column four indicate that the lagged nominal uncertainty significantly influence its mean value where as real volatility coefficients and the covariance volatility between real and nominal uncertainty does not have any impact on the nominal variable. Besides, the direct and indirect news effects of both real and nominal uncertainties are also significantly influencing the nominal uncertainty coefficient h_{22}.

The estimated results of both the sample period confirms the presence of significant spillover effects between the real and nominal uncertainties and most importantly it substantiate the vital influence of nominal uncertainties over the real growth uncertainty. The depicted results of real volatility model in both the sample periods confirm the direct and significant influence of news effect of nominal variable in addition to the influence of volatility. Furthermore, in pre and post break periods, the real and nominal uncertainties are significantly affected by their own news effects as well as the unexpected shocks from other variable. All together, the results of the subsample analysis of volatility spillovers provided similar findings like that of full sample period with very minor exceptions. Thus, these results may lead to conclude that the structural break does not have any significant impact on the volatility transmissions and spillover effects between the real and nominal uncertainties.

4.5. Concluding remarks

This chapter examines the nexus between real and nominal uncertainties and its association with real output growth and inflation rate. The bivariate GARCH models with BEKK representation has been employed to generate the conditional variances of output growth and inflation. The Granger causality tests are performed to examine the causal relationships between real and nominal uncertainties and to verify the association between macroeconomic uncertainties and macro variables where the conditional variances generated from GARCH models are used as proxies of real and nominal uncertainties. The volatility transmissions and spillover effects between this real and nominal uncertainty is examined in expanded GARCH volatility equations derived from delta method. To check the influence of structural breaks, the entire sample is divided into two subsamples and the entire analysis is re-estimated for the pre and post break samples.

The findings show that the Friedman's claim of negative influence of nominal uncertainty on output growth is valid only in the long run where as the reverse causality from output to inflation uncertainty holds only in the short run for the entire sample as well as the subsamples. The results of growth uncertainty – inflation rate nexus provide evidence for the positive causal effect of real uncertainty over the inflation rate for all the sample periods except post break analysis. There is a significant bidirectional association existing between the real and nominal uncertainties for the entire sample as well as the sub sample analysis. The tests of volatility spillovers in all sample periods provide evidence for significant influences of nominal uncertainty over the real uncertainty and show a significant volatility transmission between the real and nominal uncertainties. Overall the findings conclude that the inflation uncertainty has stronger negative effects on real economic activity in the long run and the volatility and unexpected news effect in the nominal uncertainty significantly influences the real volatility. These results are holding well even when the structural breaks are taken into account.

Chapter 5
Summary, Findings and Conclusion

5.1. Introduction

Price stability is the primary objective of all the central bank around the world and price stability has assumed to be an essential precondition for sustainable economic growth. The common credence is that the high rate of inflation is potentially detrimental to the output growth of an economy. The theoretical and empirical macroeconomics has different standpoints on the nature of the tradeoff between inflation and economic growth. Originating from the Latin American context from the 1950s, there is an everlasting debate among the structurlists and monetarists on this tradeoff where structuralist see rising prices as an essential indicator for output growth whereas monetarists believe inflation as inimical to social justice as well as to the economic growth.

The effects of inflation on output growth have been studied in different theoretical macro models and a set of different possibilities, a positive, negative or zero effect of inflation on economic growth are drawn. Tobin (1965) reported a significant positive output effect of inflation where higher inflation raises precautionary savings which in turn enhances economic growth via investment channel. The negative effects of inflation on output growth have been in a Cash-In-Advance model, Stockman (1981) reports a negative influence of inflation on economic growth where as Sidrauski (1967) established super-neutrality of inflation.

In addition, a new class of models are emerged in which inflation has a negative effect on long-run growth, but only if the level of inflation is above a threshold level. The studies by Barro (1995, 1996) and Bruno (1998) found that the relationship between inflation and output growth may not be linear in nature. Friedman (1973) briefly condenses the indecisive nature of the relationship between inflation and economic growth as follows: *historically, all possible combinations have occurred: inflation with and without development, no inflation with and without development*. Though considerable research efforts have been directed through the years, the direction of the impact of the average rate of inflation on the rate of economic growth is quite ambiguous (Solow, 1990).

A decline in both real variability and inflation in the 1990s stimulated another less studied theoretical links between macroeconomic uncertainties and economic performances. The development of theories regarding the relationship between uncertainties and macro variables gives rise to number of interesting facts. Studying these relationships is not just a simple research issue and it provides significant knowledge of whether or not the associated volatilities tend to have potential effects on the growth process as well as the rate of inflation. Even though, economic theory postulates different possibilities of associations, theoretically, the relationships between real and nominal uncertainties with the rate of inflation and output growth received more attention.

Several theories have been advanced in the literature to test all possible empirical relatinships among these four variables. The idea of significant positive association between inflation and its variability was initiated by Okun's (1971) claim. Milton Friedman (1977) provided an intuitive argument towards a positive correlation between inflation and nominal uncertainty and Ball (1992) offers a formal derivation of Friedman's hypothesis in a game theoretic model, where the effective influence of monetary authority in a high inflation regime ends up with higher uncertainty about the future rate of inflation.

In contrary to the causation link proposed by Friedman and Ball, Cukierman and Meltzer (1986) and Cukierman (1992) claim that Central banks tend to create inflation surprises in the presence of more inflation uncertainty. Holland (1995) asserts that in a high inflation uncertainty environment, monetary authorities respond by contracting the money supply growth in order to eliminate the associated negative output effects. Further, Pourgerami and Maskus (1987) and Zilberfarb (1993) pointed out that in an environment of accelerating inflation agents may invest more resources in inflation forecasting, thus reducing inflation uncertainty.

The negative impact of inflation uncertainty on output growth is supported by Friedman (1977) informal argument that rising inflation uncertainty reduces the effective allocation of resources and hinders long-term contracting, thus reducing output growth. In addition, Cukierman and Meltzer (1986) claimed that surprise money shocks increases inflation uncertainty and in turn affects output growth. Further, Pindyck (1991) pointed out that the uncertainty associated with the returns on investment due to uncertain future prices adversely affects the growth rates.

On the Contrary, Abel (1983), Dotsey and Sarte (2000) and Blackburn and Pelloni (2004) showed that inflation uncertainty raises investment and growth via precautionary in savings channel. In a extend Barro-Gordon model, Devereux (1989) delivers a positive inflationary effects of real uncertainty where real uncertainty encourages Fed to create surprise inflation for to keep positive output effects. Cukierman and Gerlach (2003) also supports this claim where as the negative inflationary effects of real uncertainty are channeled through the combination of Taylor effect with Cukierman-Meltzer hypothesis.

Macroeconomic analysis before 1980s treated the business cycle theories and economic growth independently. The class of business cycle models strongly believes that there is no relationship between real uncertainty and growth and the transitory instability in growth rate is the results short run monetary shocks. The idea of positive nexus between real uncertainty and output growth rates was attribute to Schumpeter's (1942) for his claim of 'creative destruction'. Similar to Sandmo (1970) and Mirman (1971), converse to existing business cycle models, Black (1987) provide a more formal argument that increasing output uncertainty leads to more output growth where investment in riskier technology would followed by higher output growth rate.

On the contrary, Keynes (1936) pointed out an inverse relationship between output volatility and growth where uncertainty in growth rates lower investment which causes lower further growth rates. Similarly, Bernanke (1983) and Pindyck (1991) show that irreversibilities in investments at firm level at the time of uncertain growth periods, cut short the future investment projects and output growth rates. Finally, Ramey and Ramey (1991) offer a negative relationship between real uncertainty and output growth by pointing out the firms commit on technological advancement.

In a same fashion, Logue and Sweeney (1981) predicts a positive impact of nominal uncertainty over the real uncertainty, where that the difficulties in identifying the difference between the nominal and real demand shifts results more relative price variability which upshot the real activity. In addition, Devereux (1989) supports the positive causal effects between real and nominal uncertainty in a Barro and Gordon model. In contradictory to Logue and Sweeney, Taylor (1979) predicts a negative trade-off between inflation and output variability and hence uncertainty. Similarly, Fuhrer (1997), Cecchetti and Ehrmann (1999) and Clarida et al (1999) also derive a negative trade-off between real nominal and real uncertainties.

Testing the transmissions between unexpected variations and macroeconomic aggregates become a vital research issue because the direction and significance of the association depends on the strength of the country specific policy instruments. Against this backdrop, the present study, intended to evaluate the all possible associations between real and nominal uncertainties with inflation and output growth in the Indian context from a developing country perspective. To do so, the empirical complexity make the present study to examine the individual nexus between nominal uncertainty and inflation and real uncertainty and output growth in the as a first phase. The second part examined the combine association between macro uncertainties with their mean values in the addition with the spillover effects between the uncertainties.

To investigate the above discussed issues, the present study uses three different sample periods. The monthly WPI data for the sample period from 1st June 1961 to 1st April 2011 and the monthly IIP data for the sample period from 1st April 1980 to 1st April 2011 are used in the first two chapters. The monthly data of WPI and IIP for the sample period from 1st April 1980 to 1st April 2011 is used for empirical exercises in chapter three. The rate of inflation and output growth are measured as the logarithmic first difference of the monthly WPI and IIP respectively. The data on all the variables used in the empirical exercises are collected from various issues of Handbook of Statistics on Indian Economy, Reserve Bank India (RBI) and various sources of Central Statistical Organisation (CSO), Government of India.

The Autoregressive Conditional Heteroskedasticity (ARCH) models of Engle (1982) and Generalized Autoregressive Conditional Heteroskedasticity models of Bollerslev (GARCH) and Stochastic Volatility (SV) models are used to derive an appropriate measure for both inflation and growth uncertainties. In order to assess the nexus between the uncertainties and their respective mean values, the Granger causality tests are employed and to evaluate the positive or negative causality, the sigh of the coefficients are taken into account. The Bai and Perron (1998, 2003) multiple structural break tests are used to investigate the presence of structural changes in model. To identify the influence of structural breaks, all the models are re-estimated for various sub-samples during the sample period.

To identify the causal nexus and volatility spillovers between macroeconomic uncertainties, inflation and output growth the study has used the bivariate BEKK- GARCH model proposed by Grier et al. (2004). This model simultaneously estimates the conditional mean and variance of the model and allows the testing of diagonality restrictions in the covariance structure. Similar to earlier chapters, the presence of causal relationship between the variables are estimated in Granger causality tests. The volatility transmissions between the real and nominal uncertainties are tested in a first order Taylor expansion method and the standard errors for those nonlinear coefficients are obtained from delta method. Furthermore, the model is estimated for pre and post break periods by taken the structural breaks into account.

5.2. Major Findings

The results in chapter two on the relationship between nominal uncertainty and inflation rate revealed that there is an asymmetry in the mean inflation. Even though the joint test for sign and size bias are significant, the asymmetric coefficients in EGARCH and TGARCH models are insignificant in different distributional assumptions which indicate superiority of symmetric GARCH models. Moreover, the estimates of the various models show that the results are very much sensitive to different methods of uncertainty measures. For the whole sample period, the uncertainty generated by GARCH models supports the Friedman hypothesis whereas the uncertainty generated through SV models favors both Friedman hypothesis as well as Holland 'Stabilization Fed' hypothesis.

The Bai-Perron test for exogenous breaks found three structural breaks i.e, 1972:01, 1980:08 and 1995:06 in the inflation data and Indian economy has experienced a most difficult era during these breaks. The first break is period of high inflation in Indian history after independence and the entire world is shuffled by the first oil price shocks. The second break period hit by a poor agricultural output and second crude oil shocks whereas the final break period experienced large fiscal deficits with large monetary expansions in addition to drastic shortfall in food production.

When these exogenous breaks are taken into account for different measures of uncertainty, the sign and direction of the causation are similar to both the measures of uncertainties except the third regime period. In sum, the results show that there is a positive relationship between inflation and inflation uncertainty i.e., inflation causes inflation uncertainty during the whole sample and sub-sample analysis the reverse causality with negative sign is evident only in a whole sample and in a particular sub-sample period of SV model analysis.

The results presented in Chapter three show that there is no evidence for the asymmetry in output growth i.e, insignificant sign and test bias and symmetric GARCH models have an edge over the asymmetric models. For the relationship between real uncertainty and output growth, the results of GARCH and SV models, for the whole sample period, validate that there is no causal relationship between output uncertainties and output growth in India. The direction of causality is running from output to output uncertainty. These results are also confirmed by the estimated simultaneous equation models where the influence of conditional variance which is measured by output uncertainty in the mean equation is insignificant in all the models whereas the coefficient of output growth positively and significantly influences the output uncertainty.

The Bai-Perron test has not found any structural breaks in the data. It is found that even the historical breaks (Post liberalization period) do not have any significant effects on the relationship with both the measures of uncertainty. Over all there is a positive association runs form output growth to output uncertainty and there is no evidence of any of the claims regarding reverse causality from real uncertainty to growth rate. These results are consistent with the real business cycle theories where the variations in output growth are treated independently from the mean growth rate.

Chapter four reports the results of the bivariate BEKK-GARCH model that estimate the interrelationship between the real and nominal uncertainties with their respective mean values for the whole sample as well as the sub-sample periods. The estimated results show that Friedman's claim of negative output effects of nominal uncertainty is valid only in the long run for both the whole sample and sub-sample analysis.

On the contrary, the growth rates are negative influencing the inflation only in the shorter period. Except post break analysis, the documented results found strong evidence for the positive impact of real uncertainty over the rate of inflation. For the whole sample as well as sub sample periods, test results found a significant positive bidirectional association between the real and nominal uncertainties. In addition, the tested diagonal restrictions strongly reject the assumption of non-diagonality in covariance structure and provide evidence for spillover effects between the covariances of the two series.

The key finding from the results is that Friedman's claim of negative real effects of nominal uncertainty holds only for the longer period and results are robust even when the structural breaks are considered into account. The results from the first order Taylor expansion method of BEKK variances model show that innovations to inflation and output growth significantly influence the conditional variance of output growth (real uncertainty) and inflation (nominal uncertainty). It is found that the though volatility transmission between inflation and output growth is felt on both the directions and the unexpected shocks in the nominal uncertainty significantly influences the real volatility. So there is need for a policy that balances these shocks that affects inflation and the output growth.

5.3. Policy Suggestions

1) The positive association between inflation and nominal uncertainty would create suspicions in the minds of public and economic agents, whether the central bank implements a tight monetary policy to restrain inflation or compromise with inflation for higher growth rates. Thus, to strengthen public's confidence, RBI has to formulate more specific policy objectives to ensure stability in prices.

2) RBI able to accomplish its twin objectives by reacting to rising nominal uncertainties. Responding to inflation uncertainty by reducing inflation, the goals of stable prices as well as higher output growth will be achieved.

3) The absence of real uncertainty influences on output growth implies that the policy makers need not to account for the influences of business cycle fluctuations in growth policies.

4) Stabilization polices aiming at reducing inflation may lower the effective functioning of price system and have its own real effects through uncertainty channel. Hence policies must be framed with more caution about the future course of the real economic activity.

5) The significant volatility transmissions and spillover effects between the real and nominal uncertainties need a policy that balances these shocks that affects inflation and the output growth.

6) Finally, incorporating macroeconomic uncertainties in economic models will avoid the model misspecification bias and measure the influences of these elements.

5.4. Directions for Future research

In this study only the structural breaks in mean equation of the model is considered but there exists structural breaks in variance also. Hence, considering the structural breaks in variance can also be employed in future studies. Also, the thesis has treated low and high inflation regimes as identical but nominal uncertainties in different regimes may have different real effects. So, the regime dependant models can be employed to show refinement. To investigate the dynamics of the relationship, as a sensitivity test the Generalized Impulse Response Function (GIRF) and the Volatility Response Functions (VIRF) may be used. Generally, the Granger causality tests are imposing linear restrictions on the nexus between the variables. But the causality between macroeconomic uncertainties and macroeconomic variables may be non linear in nature. Hence, studying this association in a non-linear causality tests may improve the elegance of the results.

REFERENCES

Abel, A. (1983). Optimal investment under uncertainty. *American Economic Review,* 73, 228– 233.

Aghion, P., and Howitt, P. (2006). Joseph Schumpeter lecture appropriate growth policy: A unifying framework. *Journal of the European Economic Association*, 4(2-3), 269-314.

Aghion, P., and Saint Paul, G. (1998). On the virtue of bad times: An analysis of the interaction between economic fluctuations and productivity growth. *Macroeconomic Dynamics*, 2, 322–344.

Aizenman, J. and Marion. N. (1999). Volatility and investment: Interpreting evidence from developing countries. *Economica*. 66. 157-79.

Ajevskis, V. (2007). *Inflation and inflation uncertainty in Latvia*. Bank of Latvia, Working Paper No. 4/2007.

Akerlof, G., Dickens, W., and Perry, G. (1996). The macroeconomics of low inflation. *Brookings Papers on Economic Activity*, 1, 1-59.

Al-Marhubi, F. (1998). Cross-country evidence on the link between inflation volatility and growth. *Applied Economics,* 30, 1317–1326.

Alper, E. (2002). Business cycles, excess volatility, and capital flows: Evidence from Mexico and Turkey, *Emerging Markets Finance and Trade*, 38(4), pp.25–58.

Andrews, D. (1993). Tests for parameter instability and structural change with unknown change point. *Econometrica*, 61, 821-856.

Apergis, N. (2004). Inflation, output growth, volatility and causality: Evidence from panel data and the G7 countries. *Economics Letters*, 83, 185-191.

Arnold, I.J.M., den Hertog, G.J.R. (1995). European time-series relationships between inflation and inflation uncertainty: In search of threshold levels. *De Economist*, 143, 495.

Baharumshah, A.Z., Hamzah, A.N., and Sabri, S.R.M. (2011). Inflation uncertainty and economic growth: Evidence from the LAD ARCH model. *Journal of Applied Statistics*, 38, 195-206.

Bai, J. and Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, *18*, 1-22.

Bai, J. and Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, 66, 47-78.

Bailey, M. (1956). The welfare cost of inflationary finance. *Journal of Political Economy,* 73, 93–110.

Baillie, R., Chung, C., Tieslau, M. (1996). Analysing inflation by the fractionally integrated ARFIMA-GARCH model. *Journal of Applied Econometrics*,1, 23-40 .

Ball, L. (1992). Why does high inflation raise inflation uncertainty?, *Journal of Monetary Economics*, 29, 371-388.

Ball, L., Cecchetti, S., Gordon, R.J. (1990). Inflation and uncertainty at short and long horizons. *Brookings Papers on Economic Activity*, 1, 215-254.

Barro, R., and Gordon, D. (1983). A positive theory of monetary policy in a natural rate model. *Journal of Political Economy*, 91, 589-610.

Barro, R.J. (1995). Inflation and economic growth. *Bank of England Quarterly Bulletin*, 35, 166–76.

Batchelor, R., and Dua, P. (1993). Survey vs ARCH measures of inflation uncertainty. *Oxford Bulletin of Economics and Statistics*, 55, 341–353.

Batchelor, R., and Dua, P. (1996). Empirical measures of inflation uncertainty: A cautionary note. *Applied Economics*, 28, 333–341.

Beaumont, P., Norrbin, S.C., and Yigit, F.P. (2008). Time series evidence on the linkage between volatility and growth of output, *Applied Economic Letters*, 15, 45-48.

Bernanke, B. (1983). Irreversibility, uncertainty, and cyclical investment. *Quarterly Journal of Economics*, 98, 85–106.

Bernanke, B. S. (2011).The near- and longer-term prospects for the U.S. Economy. *Speech at the Federal Reserve of Kansas City Economic Symposium*, Jackson Hole, Wyoming.

Berument, H., Dincer, N.N. (2005) Inflation and inflation uncertainty in the G-7 countries. *Physica,* 348: 371.

Berument, H., Yalcin, Y., and Yildirim, Y. (2009). The effect of inflation uncertainty on inflation: Stochastic volatility in mean model within a dynamic framework. *Economic Modeling,* 26, 6, 1201-1207.

Berument, H., Yalcin, Y., and Yildirim,Y. (2011). The inflation and inflation uncertainty relationship for Turkey: A Dynamic framework. *Empirical Economics*, 41, 293–309.

Bhar, R. and Hamori, S. (2004). The link between inflation and inflation uncertainty: Evidence from G7 countries, *Empirical Economics,* 29, 825–853.

Bhar, R., and Mallik, G., (2010). Inflation, inflation uncertainty and output growth in the USA. *Physica*, 5503–5510.

Bhattacharya, B.B., and Lodh, M. (1990). Inflation in India: An analytical survey. *Artha Vijnana*, *32*, 25-68.

Black, F. (1987). *Business Cycles and Equilibrium*. Basil Blackwell, New York. Basil

Blackburn, K. (1999). Can stabilization policy reduce long-run growth? *Economic Journal,* 109, 67-77.

Blackburn, K. and A. Pelloni A. (2001), *On the Relationship between Growth and Volatility in Learning-by-Doing Economies*, Centre for Growth and Business Cycle Research Discussion Paper Series, University of Manchester,1.

Blackburn, K. and Galindev, R. (2003). Growth, volatility and learning. *Economics Letters*, 79, 417-421.

Blackburn, K. and Pelloni, A. (2004). On the relationship between growth and volatility. *Economics Letters, 83*, 123–127.

Blanchard, O., and Simon, J. (2001). The long and large decline in U.S. output volatility. *Brookings Papers on Economic Activity*, 32, 135-174.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*, 307–328.

Bollerslev, T. (1990). Modeling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH model. *Review of Economics and Statistics*, 72, 498–505.

Bollerslev, T. and Wooldridge, J. M. (1992). Quasi-maximum likelihood estimation and inference in dynamic models with varying covariances, *Econometric Reviews*, 11,143-172.

Bollerslev, T., Engle, R.F., and Nelson. (1994). *ARCH model* in Engle R. and McFadden D. (eds), Handbook of Econometrics, Vol. IV, North Holland, Amsterdam, pp. 2959–3038.

Bomberger, W.A. (1996). Disagreement as a measure of uncertainty. *Journal of Money, Credit and Banking*, 28, 381-392.

Bredin, D., Elder, J., and Fountas, S (2005). Macroeconomic uncertainty and macroeconomic performance: Are they related?. *The Manchester School*, 73, 58–76.

Bredin, D., Elder, J., and Fountas, S. (2009). Macroeconomic uncertainty and performance in Asian countries. *Review of Development Economics*, 13, 215– 229.

Briault, C. (1995). The costs of inflation. *Bank of England Quarterly Bulletin*. 33–45.

Brunner, A. D., and Hess, G. D. (1993). Are higher levels of Inflation less predictable? A state-dependent conditional heteroscedasticity approach. *Journal of Business & Economic Statistics*, 11, 187-97.

Brunner, A., D. (1993). Comment on Inflation Regimes and the Sources of Inflation Uncertainty. *Journal of Money, Credit and Banking*, 25, 512-520.

Bruno, M., and Easterly, W. (1996). Inflation and growth: In search of a stable relationship. *Federal Reserve Bank of St. Louis*, 139–146.

Caballero, R., and Hammour., M. (1994). The Cleansing effect of recessions. *American Economic Review*, 84, 350-368.

Caporale, G., M., and Kontonikas, A., (2008). The Euro and inflation uncertainty in the European Monetary Union. *Journal of International Money and Finance*.

Caporale, T. and McKiernan, B. (1996). The relationship between output variability and growth: evidence from post-war UK data. *Scottish Journal of Political Economy*, 43, 229-236.

Caporale, T. and McKiernan, B. (1998). The Fischer Black hypothesis: Some time-series evidence, *Southern Economic Journal*, 63, 765-771.

Caporale, T., and McKiernam, B. (1998). High and variable inflation: Further evidence on the Friedman hypothesis. *Economic Letters*,65-68

Caporale, T., and McKiernan, B. (1997). High and variable inflation: Further evidence on the Friedman hypothesis. *Economics Letters*, 54, 65-70

Cecchetti, S. and Krause, S. (2001). *Financial structure, macroeconomic stability and monetary policy.* NBER Working Paper, No. 8354.

Cecchetti, S. and M. Ehrmann. (1999). *Does inflation targeting increase output volatility? An international comparison of policymaker's preference and outcomes*. NBER Working Paper No: 7426.

Chen, S., Shen, C., and Xie, Z. (2008). Evidence of non-linear relationship between inflation and inflation uncertainty: The Case of four little dragons. *Journal of Policy Modeling*, 30, 363-376.

Chow,G.C.(1960).Tests of Equality between sets of coefficients in two linear regressions. *Econometrica*, 28, 591–605.

Chowdhury, A. (2011). *Inflation and inflation uncertainty in India: The policy implications of the relationship*. Department of Economics, Working paper 2011-01 Marquette University.

Clarida, R., Gali,J., and Gertler, M.(1999). The science of monetary policy: A New Keynesian perspective. *Journal of Economic Literature.* XXXVII, 1661–1707.

Conrad, C., and Karanasos, M. (2005). On the inflation uncertainty hypothesis in the USA, Japan, and the UK: a long memory approach. *Japan and the World Economy*, 17, 327-343.

Conrad, C., and Karanasos, M. (2008). *Modeling volatility spillovers between the variability's of US inflation and output: The UECCC GARCH model*. University of Heidelberg, Department of Economics, Discussion Paper No. 475.

Conrad, C., Karanasos, M., and Zeng, N. (2010). The link between macroeconomic performance and variability in the UK. *Economics Letters*, 106, 154-157.

Cosimano, T., Jansen, D. (1988). Estimates of the variance of U.S. inflation based upon the arch model: Comment. *Journal of Money, Credit and Banking*, 20, 409-421

Crawford, A.,and M. Kasumovich. (1996). *Does inflation uncertainty vary with the level of inflation?* Bank of Canada, Working Paper No. 96–9.

Cukierman, A., and Gerlach, S. (2003). The inflation bias revisited: Theory and some international evidence. *The Manchester School*, 71, 541–565.

Cukierman, A. (1992). *Central bank strategy, credibility, and independence: Theory and evidence*. Cambridge, Massachusetts: MIT Press.

Cukierman, A., and Meltzer, A. (1986). A theory of ambiguity, credibility, and inflation under discretion and asymmetric information. *Econometrica*, 54, 1099–1128.

Daal, E., Naka, A.T., Sanchez, B. (2005). Re-examining inflation and inflation uncertainty in developed and emerging countries. *Economics Letters*, 89(2): 180

Danielsson, J. (1994). Stochastic volatility in asset prices: estimation with simulated maximum likelihood. *Journal of Econometrics*, 64, 375-400.

Darrat, A.F., and Lopez, F.A. (1989). Has inflation uncertainty hampered economic growth in Latin America?. *International Economic Journal*, 3, 1–14.

Davis, G., and Kanago, B. (1996). On measuring the effect of inflation uncertainty on real GNP growth. *Oxford Economic Papers*, 48, 163-175.

Davis, G., and Kanago, B. (2000). The level and uncertainty of inflation: Results from OECD forecasts, *Economic Inquiry*, 38, 58-72.

Dawson, J.W., and Stephenson, E.F. (1997). The link between volatility and growth: evidence from the States. *Economics Letters*, 55, 365-369.

De-Chih, Liu. (2009). Structural changes in job creation and destruction. *Economics Letters*. 34-36.

Dejuan, J. and Gurr, S. (2004) On the link between volatility and growth: Evidence from Canadian Provinces. *Applied Economics Letters*,11, 279–82.

Devereux, M. (1989). A Positive theory of inflation and inflation variance. *Economic Inquiry, 27*, 1- 10.

Dickey, D.A., and Fuller, W.A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74, 427-431.

Dixit,A.K., and Pindyck, R.S. (1994). *Investment under uncertainty.* Princeton University Press, Princeton.

Dotsey, M. and Ireland, P.(1996). The welfare cost of inflation in general equilibrium. *Journal of Monetary Economics*, *37*, 29-47.

Dotsey, M., and Sarte, P.D. (2000). Inflation uncertainty and growth in a cash-in-advance economy. *Journal of Monetary Economics, 45*, 631– 655.

Driffill, J., Mizon, G.E. *and* Ulph, A. (1990), *Costs of Inflation*. In: *B.M. Friedman* and. *F.H. Hahn* (*eds*), *Handbook of Monetary Economics* Vol II, chapter 19, pages 1013-1066 *North* Holland

Elder, J. (2004). Another perspective on the effects of inflation uncertainty. *Journal of Money, Credit and Banking*, 36, 912-928.

Engle, R. (1983). Estimates of the variance of U.S. inflation rates based on the ARCH model. *Journal of Money Credit and Banking*, 15, 286–301.

Engle, R. and Kroner, K. (1995).Multivariate simultaneous generalized ARCH. *Econometric Theory,* 11, 122–150.

Engle, R.F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50, 4, 987-1007

Entezarkheir,M.(2006). The relation between inflation and inflation uncertainty in Iran. *Iranian Economic Review*, 10, 1–20.

Erkam, S. and Çavuşoğlu, T. (2008). Modeling inflation uncertainty in Transition Economies: The case of Russia and the former Soviet Republics. *Economic Annals*, 53, 178-179, 44-71.

Evans, M. (1991) Discovering the link between inflation rates and inflation uncertainty. *Journal of money credit and banking*, 23, 169-182

Evans, M., and Wachtel, P. (1993). Inflation regimes and the sources of inflation uncertainty. *Journal of Money, Credit, and Banking*, 25, 475-51

Fatas, A. and Mihov.I. (2006). *Policy volatility, institutions, and economic growth.* Centre for Economic Policy Research (CEPR) Discussion Paper 5388. London, CEPR.

Fischer, S., and Modigliani, F. (1975). Towards an understanding of the real effects and costs of inflation. Weltwirts chaftliches Archive, 114, 810–33.

Fischer, S. (1993). The role of macroeconomic factors in growth. *Journal of Monetary Economics, 32*, 485–512.

Fischer, S. and Modigliani, F.(1978). Towards an understanding of the real effects and costs of inflation. *Review of World Economics*, 114, 810-833.

Foster, E. (1978). The variability of inflation. *Review of Economics and Statistics*, 60, 346

Fountas, S. (2001). The relationship between inflation and inflation uncertainty in the UK: 1885-1998, *Economics Letters*, 74, 77-83.

Fountas, S. and Karanasos, M. (2006). The relationship between economic growth and real uncertainty in the G3. *Economic Modeling*, 23, 638-647.

Fountas, S. and M. Karanasos. (2007). Inflation, output growth, and nominal and real uncertainty: empirical evidence for the G7.*Journal of International Money and Finance,* 26, 229-250

Fountas, S. and Karanasos, M. (2008). Are economic growth and the variability of the business cycle related?. Evidence from five European countries. *International Economic Journal,* 22, 445-459.

Fountas, S., Karanasos, M., and Kim, J. (2002). Inflation and output growth uncertainty and their relationship with inflation and output growth. *Economics Letters,* 75, 293–301.

Fountas, S., (2010). Inflation, inflation uncertainty and growth: Are they related?. *Economic Modelling.* 27, 896–899.

Fountas, S., Ioannidi, A.,and Karanasos, M. (2004) Inflation, inflation uncertainty and a common European monetary policy. *Manchester School*, 72(2): 221

Fountas, S., Karanasos, M. and Kim, J.(2006). Inflation uncertainty, output growth uncertainty and macroeconomic performance. *Oxford Bulletin of Economics and Statistics*, 68, 319-343.

Fountas, S., Karanasos, M. and Mendoza, A. (2004). Output variability and economic growth: The Japanese case, *Bulletin of Economic Research*, 56,353–63.

Fountas, S., Karanasos, M., and Karanassou, M. (2000). *A GARCH model of inflation and inflation uncertainty with simultaneous feedback.* The University of Melbourne, Department of Economics - Working Papers Series No.818

Friedman, M. (1968). The role of monetary policy. *The American Economic Review,* 58, 451–472.

Friedman, M. (1977). Nobel lecture: Inflation and unemployment. *Journal of Political Economy*, 85, 451–472.

Friedman, M.(1969). T*he Optimum quantity of money and other essays*. Chicago, Aldine.

Fuhrer, J.(1997). Inflation/output variance trade-offs and optimal monetary policy. *Journal of Money, Credit, and Banking,* 29, 214–234.

Gaggl, P., Steindl, S., (2007). *Business cycles and growth: A Survey*. WIFO Working Paper 308, Vienna.

Gale, W. A., (1981). Temporal variability of United States consumer price index. *Journal of Money, Credit and Banking*. 13, 273-297.

Ghysels, E., Harvey, A., and Renault. E. (1996). *Stochastic Volatility*. In Handbook of Statistics. Vol. 14: *Statistical Methods in Finance*, Maddala, G.S. (ed.) North-Holland, Amsterdam, pp. 119-91.

Glosten L., Jagannathan, R. and Runkle, D. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance*, American Finance Association, 48, 1779-1801.

Golob, J. (1994). Does inflation uncertainty increase with inflation?. *Federal Reserve Bank of Kansas City Economic Review,*79, 27–38.

Gordon, R.J. (1971) Steady anticipated inflation: Mirage or oasis?. *Brookings Papers on Economic Activity*, 1971(2): 499

Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica,* 37 (3), 424–438.

Greenspan, A. (2004). Risk and uncertainty in Monetary Policy. *American Economic Review,* 94,33–40.

Grier, K. B. and Tullock, G. (1989). An empirical analysis of cross-national economic growth, 1951-80. *Journal of Monetary Economics*, 24, 259-276.

Grier, K. B., Henry, Ó. T., Olekalns, N., and Shields, K. (2004). The asymmetric effects of uncertainty on inflation and output growth. *Journal of Applied Econometrics,* 19,551-565.

Grier, K.B., and Perry, M. J. (1999). The effects of uncertainty on macroeconomic performance: Bivariate GARCH evidence, *Journal of Applied Econometrics*, 15, 45-98.

Grier, K.B., and Perry, M.J. (1996). Inflation, inflation uncertainty, and relative price dispersion: evidence from bivariate GARCH-M models. *Journal of Monetary Economics,* 38, 391-405.

Grier, K.B., and Perry, M.J. (1998). On inflation and inflation uncertainty in the G7 countries. *Journal of International Money and Finance*, 17, 671-689.

Grier, R., and Grier, K., B., (2006). On the real effects of inflation and inflation uncertainty in Mexico. *Journal of Development Economics.* 80. 478– 500.

Haslag, J. H. (1997). Output, growth, welfare, and inflation: a survey. *Economic Review, Federal Reserve Bank of Dallas*, 11–21

Hassan., S.A., and Malik., F. (2007). Multivariate GARCH modeling of sector volatility transmission. *The Quarterly Review of Economics and Finance*. 47, 470-480

Henry, O.T., and Olekanls, N. (2002). The effect of recessions on the relationship between output variability and growth. *Southern Economic Journal,* 68, 683-692.

Hess, G.D., and Morris, C.S. (1996).The long-run costs of moderate inflation. *Economic Review*, Federal Reserve Bank of Kansas City,71-88.

Holland, S. (1993). Comment on inflation regimes and the sources of inflation uncertainty. *Journal of Money Credit Banking,* 25,514–520.

Holland, S. (1995). Inflation and uncertainty: Tests for temporal ordering. *Journal of Money, Credit, and Banking*, *27*, 827-837

Hughes, D.(1982). The costs of inflation: An analytical overview. *Economic Review,* Federal Reserve Bank of Kansas City. 3-14.

Huizinga, J. (1993). Inflation uncertainty, relative price uncertainty, and investment in US manufacturing. *Journal of Money, Credit, and Banking*, 25,521–549.

Hwang, Y. (2001). Relationship between inflation rate and inflation uncertainty, *Economics Letters*, 73, 179-186.

Imbs, J. (2007), Growth and volatility, Journal of Monetary Economics, 54(7),pp. 1848-1862

Jansen, D.W. (1989). Does inflation uncertainty affect output growth? Further evidence. *Federal Reserve Bank of St Louis Review*, 43–54.

Jha, R., and Dang., Tu. (2011). *Inflation variability and the relationship between inflation and growth,* CAMA Working Papers 2011-08, *Centre for Applied Macroeconomic Analysis*, Crawford School of Public Policy, The Australian National University.

Jiranyakul, K. and Opiela, T. P. (2010). Inflation and inflation uncertainty in the ASEAN-5 economies, *Journal of Asian Economics*, 21, 105-112.

Jiranyakul, K., (2011). The link between output growth and output volatility in Five crisis-affected Asian countries. *Middle Eastern Finance and Economics*, 12, 1450-2889..

Jiranyakul, K., and Opiela, P.T. (2010). Inflation and inflation uncertainty in the ASEAN-5 economies. Journal of *Asian Economics*, 21, 105-12.

Jiranyakul, K., and Opiela, P.T. (2011). The Impact of inflation uncertainty on output growth and inflation in Thailand. *Asian Economic Journal,*,25,291-301.

Joyce, M. (1994). *Modelling UK inflation uncertainty: The impact of news and the relationship with inflation*, Bank of England. Mimeo,

Kannan, R., and Joshi, H. (1998). Growth-Inflation trade-off: Empirical estimation of threshold rate of inflation for India. *Economic and Political Weekly,* 33, 2724–2728.

Karanasos, M, Karanassou M, Iza and Fountas S, (2004). Analyzing US inflation by a GARCH model with simultaneous feedback. *WSEAS Transactions on Information Science and Application*, 1, 767-772.

Karanasos, M., and Schurer,S.(2006). Is the relationship between inflation and its uncertainty linear*?. Computing in Economics and Finance. 463-470,*

Karanasos,. M., and Kim, J. (2005). The inflation-output variability relationship in the G3: A bivariate GARCH (BEKK) approach. *Risk Letters*, 1, 17-22.

Karanasos, M., and Schurer, S. (2008). Is the relationship between inflation and its uncertainty linear?. *German Economic Review,* 9, 265–286.

Kearney, C. and Patton, A. J. (2000) Multivariate GARCH modeling of exchange rate volatility transmission in the european monetary system. *The Financial Review,* 41, 29-48.

Keynes,J.M.(1936). *The General Theory of Employment, Interest, and Money*. Macmillan, London.

Khan, M. S. and Senhadji, A.S. (2001). Threshold effects in the relationship between inflation and growth. IMF Staff Papers, 48, 1–21.

Kim, S., Shephard., N. and Chib., S. (1998). Stochastic volatility: Likelihood inference and comparison with ARCH models, *Review of Economic Studies*, 65, 361-93.

Kim.,S.J. (2003). The Spillover effects of us and japanese public information news in advanced Asia-Pacific stock markets. *Pacific-Basin Finance Journal*, 11, 611-630.

King, R., Ploser, C.I., and Rebelo, S. (1988). Production, growth and business cycles II: New directions. *Journal of Monetary Economics*. 21, 195-232.

Kneller , R. and Young, G. (2001). Business cycle volatility, uncertainty and long-run growth. *Manchester School* 69, 534-552.

Komain., J. and Opiela., P. (2010). Inflation and inflation uncertainty in the ASEAN-5 economies. *Journal of Asian Economics*, 21, 105-112.

Kontonikas, A. (2004). Inflation and inflation uncertainty in the United Kingdom, Evidence from GARCH modeling. *Economic Modelling*, 21, 524-543.

Korap, L. (2009).On the links between inflation, output growth and uncertainty system-Garch evidence from the Turkish economy. *MPRA Paper No. 19054*.

Kormendi, R. and Meguire,P. (1985). Macroeconomic determinants of growth: Cross-country evidence. *Journal of Monetary Economics*. 16, 141-163.

Krause, S. (2003). *Measuring monetary policy efficiency in European Union countries*. Department of Economics, Emory University, Working Paper No. 03-11.

Kroner, K.F. and Ng., V.K. (1998). Modeling asymmetric co-movements of asset returns. *Review of Financial Studies,* 11, 817–844.

Krugman, P.(1996). Stable prices and fast growth: Just say no, *The Economist*,15-18.

Kuang, L.C., and Chi., He (2010). Does the magnitude of the effect of inflation uncertainty on output growth depend on the level of inflation?. *The Manchester School,* 78, 126–148,

Kwiatkowski, D., Phillips, P.C.B., Schmidt, P., and Shin, Y. (1992) Testing the null hypothesis of stationary against the alternative of a unit root. *Journal of Econometrics*, 54, 159-178

Kydland, F.E., and Prescott, E.C. (1982). Time to build and aggregate fluctuations. *Econometrica*, 50, 1345–1370.

Lee, Jim. (2002). The inflation-output variability tradeoff and monetary policy: evidence from a Garch model. *Southern Economic Journal*, 69, 175-188.

Levi, M., and Makin.J. (1980). Inflation uncertainty and the Phillips curve: Some empirical evidence. *American Economic Review*, 1022-27.

Logue, D. and R. Sweeney (1981) Inflation and real growth: Some empirical results. *Journal of Money, Credit and Banking*, 13, 497-501.

Logue, D.E., and Willett, T.D. (1976). A note on the relation between the rate and variability of inflation. *Economica,* 43, 151–158.

Long, J.B. and Plosser., C.I. (1983). Real business cycles. *Journal of Political Economy,* 91, 39-69

Lucas, R.E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, 22, 3-42.

Lucas, R.E.(1973). Some international evidence on output-inflation trade-offs. *American Economic Review*, 63, 326–334.

Lucas, R.E.(2000). Inflation and welfare. *Econometrica*, 68, 247-274.

Lucas,R.E. (2000) Inflation and welfare. *Econometrica,* 68, 247–74

Macri, J. and Sinha, D. (2000). Output variability and economic growth: The case of Australia. *Journal of Economics and Finance*. 24, 275-282.

Makin, J.(1982). Anticipated money, inflation uncertainty, and real economic activity. *Review of Economics and Statitstics*.126-34

Malik., F. and Ewing., T.B. (2009). Volatility transmission between oil prices and equity sector returns. *International Review of Financial Analysis*. 18, 95-100.

Mallkiel, B. (1979). The capital Formation problem in the United States. *Journal of Finance,* 291-306.

Mankiw,N.G.(2006) *Macroeconomics*, sixth edition. NewYork: Worth Publishers.

Martin, P., and Rogers, C.A. (2000). Long-term growth and short-term economic instability. *European Economic Review*, 44, 359-381.

Miles,W.,and Schreyer,S.,(2009). Inflation costs, uncertainty costs and emerging markets. Journal of Economic Development,34,1-15.

Mirman, L. (1971). Uncertainty and optimal consumption decisions, *Econometrica* 39(1), 179-85.

Mullineaux, D.J.(1980). Unemployment, industrial production, and inflation uncertainty in the United States. *Review of Economics and Statistics*. 163-69.

Nachane, D.M., and Lakshmi R. (2002). Dynamics of inflation in India-A P-Star Approach. *Applied Economics*, 34, 101-110.

Nas, T. F., and Perry, M. J. (2000). Inflation uncertainty and monetary policy in Turkey: 1960-1998. *Contemporary Economic Policy*, 18(2), 170-180.

Nazar D., Farshid, P. and Mojtaba, K. Z. M. (2010). Asymmetry effects of inflation on inflation uncertainty in Iran: Using from EGARCH model, 1959-2009", *American Journal of Applied Sciences*, 7, 535-539.

Neanidis, K., C., and Savva, C., S. (2011). Nominal uncertainty and inflation: The role of European Union membership. *Economics Letters,* 112, 26–30.

Neanidisa, K.C., & Savvab, C.S. (2010). *Macroeconomic uncertainty, inflation and growth regime-dependent effects in the G7*. Centre for Growth and Business Cycle Research, Economic Studies, No.145,University of Manchester, Manchester,

Nelson, C.R. and Ploser, C.I. (1982). Trends and random walks in macroeconomics time series: some evidence and implications. *Journal of Monetary Economics*. 10, 139-162.

Nelson, D.B. (1991) Conditional heteroscedasticity in asset returns: A new aproach. *Econometrica*, 59:2, str. 347-70

Norrbin,S.C. and Pinar,Y.F.(2005). The robustness of the link between volatility and growth of output. *Review of World Economics*, 141,343–356.

Oehlert, G. W. (1992). A note on the delta method. *American Statistician*, 46: 27–29.

Okun, A., (1971). The mirage of steady inflation. *Brookings Papers on Economic Activity 2*, 485- 498.

Ozer M, and Tu rkyilmaz, S.A. (2005). Time series analysis of inflation and inflation variability in Turkey. *Journal of Economic Management and Finance*, 200:229

Pagan, A. (1984). Econometric issues in analysis of regressions with generated regressors, *International Economic Review*, 25(1), 221-247.

Patton, A. J., and Timmermann, A.G. (2008). *The resolution of macroeconomic uncertainty: Evidence from survey forecast.* CREATES Research Paper No. 2008-5

Payne, J., E. (2008). Inflation and inflation uncertainty: Evidence from the Caribbean region. *Journal of Economic Studies*, 35, 501-511.

Perron, P. (1989). The great crash, the oil price shock and the unit root hypothesis. *Econometrica*, 57:1361–1401.

Phillips, P.C.D., Perron, P.P. (1988) Testing for a unit root in time series regression. *Biometrika*, 75, 2, 335-346

Pindyck, R., (1991). Irreversibility, uncertainty, and investment. *Journal of Economic Literature 29*, 1110–1148.

Pourgerami, A., & Maskus, K. E. (1987). The effects of inflation on the predictability of price changes in Latin America - Some estimates and policy implications. *World Development, 15*, No. 2, 287-290.

Rafferty , M. (2005) The ef fects of expected and unexpected volatility on long-run growth:

Rafferty, M. (2005). The effects of expected and unexpected volatility on long-run growth: Evidence from 18 developed economies. *Southern Economic Journal*, 71, 582-591.

Ram, R. (1985). Level and variability of inflation: Time-series and cross-section evidence from 117 countries, *Economica*, 52, 209-223.

Ramey, G. and Ramey, V. (1991). Technology Commitment and the Cost of Economic Fluctuations, NBER Working Paper 3755.

Ramey, G. and V.A. Ramey, 1995. Cross-country evidence on the link between volatility and growth. *American Economic Review* 85, 1138-1152.

Rangarajan, C. and Arif, R. R. (1990). Money, output and prices: A macro econometric model. *Economic and Political Weekly*, 21, 837- 852.

Rangarajan, C. (1983). Conflict between employment and inflation *in A. Robinson et al Ed: Employment Policy in a developing country, A case study of India*, McMillan, London

Rebello, S.(2005). *Real Business Cycle models: past, present, and future*. NBER Working pa-per, No. 11401

Rizvi., K. A. and Naqvi, B.(2009). Inflation volatility: An Asian perspective. University Library of Munich, Germany, *MPRA paper No. 19489*

Romer, R.M., (1986). Increasing returns and long-run growth. *Journal of Political Economy* 94, 1002-10037.

Saint-Paul, G. (1993) Productivity growth and the structure of the business cycle. *European Economic Review,* 37, 861-890.

Sandmo, A. (1970). The effect of uncertainty on saving decisions. *The Review of Economic Studies 37*(3), 353-360

Sarel, M. (1996). Nonlinear effects of inflation on economic growth, *IMF Staff Papers,* 43, 199–215.

Schumpeter, J. A.(1939). *Business cycle: A theoretical, historical, and statistical analysis of the capitalist process*. McGraw-Hill, New York.

Shephard, N. (1996). *Statistical Aspects of ARCH and Stochastic Volatility Models*. In *Time Series Models in Econometrics, Finance and Other Fields*, D.R. Cox, D.V. Hinkley, and O.E. Bandorff-Nielsen (ed.) Chapman & Hall, London, pp. 1-67.

Shields, K., Olekalns, N., Henry, O.T. and Brooks, C. (2005). Measuring the response of macroeconomic uncertainty to shocks. *The Review of Economics and Statistics*, 87, 362-370.

Sidrauski, M., (1967). Inflation and economic growth. *Journal of Political Economy 75*, 796–810.

Solow,R.(1956). A contribution to the theory of economic growth. *Quarterly Journal of Economics*,70,.65–94.

Speight, A. E. H. (1999). UK output variability and growth some further evidence. *Scottish Journal of Political Economy*, 46, 175–184.

Stiglitz,J.E.(1993).*Endogenous growth and cycles* .NBER Working Papers 4286,

Taylor, J. (1979). Estimation and control of a macroeconomic model with rational expectations. *Econometrica*, 47, 1267–1286.

Telatar, F.,and Telatar, E. (2003) The relationship between inflation and different sources of inflation uncertainty in Turkey. *Applied Economics Letters*, 10(7): 431

Temple, J. (2000). Inflation and growth: stories short and tall. *Journal of Economic Surveys*, 4, 395–426.

Thornton, J. (2006) High and variable inflation: Further evidence on the Friedman hypothesis. *South African Journal of Economics*, 74, 167

Thornton, J. (2006). Inflation and inflation uncertainty in India. *Indian Economic review,* Vol.XXX, No.1, 1-8

Thornton, J. (2007) The relationship between inflation and inflation uncertainty in emerging market economies. *Southern Economic Journal*, 73, 4, 858-870

Thornton, J. (2008). Inflation and inflation uncertainty in Argentina, 1810-2005, *Economics Letters*, 98, 247-252.

Thornton, J.(1988). Inflation and output growth: Some time series evidence, a note. *American Economist* 32, 55–58.

Turnovsky, S. and Chattopadhyay, P. (1998). *Volatility and growth in developing economies: Some numerical results and empirical evidence*. Working Papers 0055, University of Washington, Department of Economics.

Turnovsky, S. and Chattopadhyay, P. (2003). Volatility and growth in developing economies: some numerical results and empirical evidence. *Journal of International Economics*, 59, 267-295.

Ungar, M. and Zilberfarb, B. Z.(1993). Inflation and its unpredictability: Theory and empirical evidence. *Journal of Money, Credit and Banking*, *25*, No. 4. 709–720.

Varvarigos, D. (2008).Inflation, variability, and the evolution of human capital in a model with transactions costs. *Economics Letters*, 98, 320-326.

Weiss A. (1986). Asymptotic theory for ARCH models: Estimation and testing. *Econometric Theory*, 2, 107–131.

Wilson, B. K. (2006). The link between inflation, inflation uncertainty and output: newtime series evidence from Japan, *Journal of Macroeconomics*, 28, 609-620.

Wooldridge JM (1991). On the applications of robust, regression-based diagnostics to models of conditional means and conditional variances. Journal of Econometrics 47:5–46

Zakoian, J. (1994). Threshold heteroskedastic models, *Journal of Economic Dynamics and Control*, 18, 931-944.

Zarnowitz, V. and Lambros, L.,(1987). Consensus and uncertainty in economic prediction. *Journal of Political Economy*, 95, 591-621.

Zarnowitz, V. and Moore. G.(1986). *Major changes in Cyclical Behavior*. In: Gordon, R.J.(Ed.),*The American Business Cycle: Continuity and Change*. University of Chicago Press, Chicago, .519–572.

Zhang, C.(2010). Inflation Uncertainty and Monetary Policy in China. *China & World Economy*, 18, 40-55.