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8 January 2008

Online at <https://mpra.ub.uni-muenchen.de/19488/>
MPRA Paper No. 19488, posted 22 Dec 2009 06:18 UTC

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Paper presented at 26th International Symposium on Money, Banking and Finance (Orléans, France)

We are grateful to **Prof. Christian Bordes (Université Paris 1)** for his continuous guidance at the various stages of the research that eventually helped us to bring this paper in its final shape. We would also like to thank **Prof. Philippe Rous (Université de Limoges)** and **Prof. Samuel Maveyraud (Université Montesquieu - Bordeaux IV)** for their detailed comments and valuable suggestions, which greatly improved the quality of this research.

ASYMMETRIC BEHAVIOR OF INFLATION UNCERTAINTY AND FRIEDMAN-BALL HYPOTHESIS: EVIDENCE FROM PAKISTAN

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Abstract This paper is first attempt to measure and analyze inflation uncertainty in Pakistan and it provides several contributions. Using quarterly data from 1976:01 to 2008:02, at first stage we model inflation uncertainty as time varying process through GARCH framework. At second stage asymmetric behavior of inflation uncertainty is analyzed by using GJR-GARCH and EGARCH models, for further analysis of asymmetry and leverage effects, we developed news impact curves proposed by Pagan and Schwert (1990). Finally we investigate the causality and its direction between inflation and inflation uncertainty by using bivariate Granger-Causality test to know which inflation uncertainty hypothesis (Friedman-Ball or Cukierman-Meltzer) holds true for Pakistani data.

We get two important results. First, GJR-GARCH and EGARCH models are more successful in capturing inflation uncertainty and its asymmetric behavior as compared to simple GARCH model. This can also be seen from news impact curves. Second, there is strong evidence that Friedman-Ball inflation uncertainty hypothesis holds true for Pakistan.

Key-words: Inflation, Uncertainty, GJR-GARCH, EGARCH,

Field of Research: Monetary and Financial Economics

JEL Classification: C22, E31, E37

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1. Introduction

Inflation is undoubtedly one of the most largely observed and tested economic variable both theoretically and empirically. Its causes, impacts on other economic variables and cost to the overall economy are well known and understood. One cannot say with certainty whether the Inflation is good or bad for an economy but if the debate focuses on inflation uncertainty or inflation variability instead of just inflation, economists have almost consensus about its negative impact over some of the most important economic variables, like output and growth rate via different channels.

Inflation uncertainty is considered as one of the major cost of Inflation as it not only distort the decisions regarding the future saving and investment due to less predictability of real value of future nominal payments, but also extends the adverse affects of these distortions on the efficiency of resource allocation and the level of real activity. (Fischer 1981, Golob 1993, Holland 1993b).

One can divide the consequences of Inflation uncertainty in two categories, Ex-ante consequences and Ex-Post consequences. Ex-ante consequences are primarily based upon decisions in which an economic agent rationally anticipate about future inflation and its transmission can be performed via three different channels; Financial market Channel where Inflation uncertainty makes Investment in long tem debt more riskier which increases expected return and long term interest rates. High long term interest rate reduces Investment in both Business and Household sector via reduction in investment in Plant & Equipment and Housing & Durable goods. Second channel is Decision Variables Channel where Inflation uncertainty leads to uncertainty about interest rate and other economic variables, due to which economic agents would not be able to index contractual payments according to Inflation, which in turn increases uncertainty about wages, rent, taxes, depreciation and profits and firms will be forced to delay their hiring, production and mainly investment because these decisions are unlikely to reverse, thus reducing the overall economic activity. Third channel is Productive vs. Protective Strategies channel where Inflation uncertainty forced firms to shift their allocation of resources from more productive to less productive uses such as improved forecast about inflation and hedging activities via derivatives to cop up increased uncertainty. Firm's resources will divert from productive strategies to protective actions which are more costly for small enterprises and households (Golob

1994). Ex-post effects of inflation uncertainty include transfer of wealth due to under or over valuation of real payments versus nominal payments which disturbs the status quo between Employer and Employee, Lender and borrower. (Blanchard 1997)

However, the relationship between Inflation and Inflation uncertainty is still debatable as high inflation cause uncertainty or uncertainty cause high inflation. Friedman (1977) was the first who formalized the relationship between Inflation and Inflation Uncertainty and he strongly supported the causality running from inflation to inflation uncertainty which is generally known as Friedman-Ball Hypothesis. This hypothesis has also been extensively studied by many authors and the overall results are mixed. Ball and Cecchetti (1990), Cukierman and Wachtel (1979), Evans (1991), and Grier and Perry (1998), among others, provide evidence in support of a positive impact of the average rate of inflation on inflation uncertainty. Grier and Perry (1998) found that in all G7 countries inflation has a significant and positive effect on inflation uncertainty. Hafer(1985) also tested the Friedman's hypothesis that high inflation uncertainty leads to higher level of unemployment, lower level of output and slower growth in employment, by considering standard deviation of quarterly inflation forecasts obtained through the ASA-NBER survey of professional forecasters, as a proxy for Inflation uncertainty.

On the other hand the causality running in opposite direction from Inflation uncertainty to Inflation can be considered as Cukierman-Meltzer hypothesis. (Cukierman-Meltzer 1986, Holland 1995). There are, however, some evidences in support of this hypotheses as well, like Baillie et al (1996) for UK, Argentina, Brazil and Israel and Grier and Perry (1998) for Japan and France.

There is also a debate on the origin of Inflation uncertainty. One school of thought believe that monetary policy has an important role in determining inflation uncertainty as it comes in fact from the uncertainty of monetary policy regime, which they called as "Regime Uncertainty". According to Ball (1990) when there is high inflation, the policymakers face a dilemma; on the one hand they would like to reduce inflation but on the other hand they fear that it would trigger the recession in the economy, and because the general public is unaware about the taste of policymakers, they will be highly uncertain about the future course of inflation (Ball's 1992, Okun 1971, Friedman 1977). This uncertainty increases further, due to the announcement of

unrealistic stabilization programs by governments when there is a surge of high inflation (Fischer and Modigliani 1978). Second school of thought believes that inflation uncertainty arises because of unknown magnitude of a change in price level due to a given change in money supply (Holland 1993a).

First objective of this study is to model inflation uncertainty for Pakistan. Primarily we focus on the question that what should be that the suitable proxy for inflation uncertainty. Most common way to estimate inflation uncertainty is from surveys of expectations, such as Livingston survey in the United States. Given point estimates of inflation forecasts obtained from different individual forecasters, we can proxy inflation uncertainty as variance of inflation forecasts across cross sectional data. However, in his remarkable contribution, Engle (1983) first modeled inflation uncertainty as autoregressive or time varying conditional heteroscedasticity (ARCH), in which he used conventional inflation equation with fixed parameters but allowed the conditional variance of inflation shocks (forecast errors) to vary overtime, suggesting that this variance could be used as a proxy for inflation uncertainty.

Empirical research on ARCH model often identified long lag processes for the squared residuals, showing persistent effects of shocks on inflation uncertainty. To model this persistence many researchers subsequently suggested variations or extensions to the simple ARCH model to test the inflation uncertainty hypothesis. Bollerslev (1986) and Taylor (1986) independently developed the generalized ARCH (GARCH) model, in which the conditional variance is a function of lagged values of forecast errors and the conditional variance. Beside Bollerslev (1986) there are several studies which modeled inflation uncertainty through GARCH frameworks, such as Bruner and Hess (1993) for US CPI data, Joyce (1995) for UK retail prices, Della Mea and Peña (1996) for Uruguay, Corporal and McKiernan (1997) for the annualized US inflation rate, Grier and Perry (1998) for G7 countries, Grier and Grier (1998) for Mexican Inflation, Magendzo (1998) for Inflation in Chile, Fountas et al (2000) for G7 countries , and Kontonikas (2004) for UK. All these studies modeled inflation uncertainty through GARCH model in one or other way.

The major drawback of ARCH or GARCH models is that both models assume symmetric response of conditional variance (uncertainty) to positive and negative shocks. However, it has been argued that the behavior of inflation uncertainty is

asymmetric rather than symmetric. Brunner and Hess (1993), Joyce (1995), Fountas et al (2006), Bordes et al (2007) are of the view that positive inflation shocks increases inflation uncertainty more than the negative inflation shocks of equal magnitude. If this is correct, the symmetric ARCH and GARCH models may provide misleading estimates of inflation uncertainty [Crawford and Kasumovich, 1996]. The three most commonly used GARCH formulations to capture asymmetric behavior of conditional variance, are the GJR or Threshold GARCH (TGARCH) models of Glosten, Jagannathan and Runkle (1993) and Zakoian (1994), the Asymmetric GARCH (AGARCH) model of Engle and Ng (1993), and the Exponential GARCH (EGARCH) model of Nelson (1991).

The second objective of this study is to model and analyze asymmetric behavior of inflation uncertainty in Pakistan, if it exists, at all. We use GRJ-GARCH and EGARCH models to capture leverage effects and also estimate “news impact curve” for further analysis of asymmetric behavior of inflation uncertainty.

Third purpose of this study is to check the causality and its direction between inflation and inflation uncertainty by using bivariate Granger-Causality test. This portion is carried out specifically to know which inflation uncertainty hypothesis (Friedman-Ball or Cukierman-Meltzer) holds true for Pakistani data. We follow the two step procedure suggested by Grier and Perry (1998) in which they first estimate the conditional variance by GARCH and component GARCH methods and then conduct the Granger-Causality test between these conditional variances and the inflation series.

This paper is first attempt to measure and analyze inflation uncertainty in Pakistan and it provides several contributions. We model inflation uncertainty as time varying conditional variance through GARCH framework. By following Fountas and Karanasos (2007), Bordes and Maveyraud (2008), we also extract inflation uncertainty using GJR-GARCH (TGARCH) and EGARCH models to analyze and capture asymmetric behavior of inflation uncertainty (leverage effects) if it exist, at all. We also present “News Impact Curves” proposed by Pagan and Schwert (1990), for different GARCH models to estimate the degree of asymmetry of volatility to positive and negative shocks of previous periods. And finally, we test Friedman-Ball and Cukierman-Meltzer inflation uncertainty hypotheses through bivariate Granger-Causality test.

The paper is organized as follows: description of data and preliminary analysis of time series is provided in section 2; section 3 presents the theoretical framework; section 4 provides estimation and results. Section 5 concludes.

2. Description and Preliminary Analysis of Data

2.1 Data Set

Data availability and authenticity of available data are among few major hurdles which one can possibly have while working on Pakistan. There are two possible sources to find data with reference to Pakistan, internal sources that include State Bank of Pakistan and Federal Bureau of Statistics; and external sources that include IMF, World Bank and other databases. For this paper we have taken all the data from International Financial Statistics Database of IMF due to a relatively broader coverage of different time series variables. Following variables are included in our data set.

DATA	IFS Series
CPI	ifs:s56464000zfq
GDP(Nominal)	ifs:s56499b00zfa
GDP Deflator	ifs:s56499bipzfa
M2	ifs:s56435100zfq

We used quarterly data because of its additional relevance and usability in the context of Inflation in less developed countries as observed by Ryan and Milne (1994) and calculated quarterly growth rates on Year-on-Year basis for different variables by taking fourth lagged difference of their natural logarithms, in other words we calculate the percentage change in concerned variable with its value from the corresponding quarter in previous year.

For Y_t , where t represents number of Quarters of each year

Quarterly Growth rate of Y_t on Y – o – Y basis = $\ln Y_t - \ln Y_{t-4}$

There are several advantages of using this method for the calculation of growth rates as compared to traditional Annualized Q-o-Q growth rates. First of all the growth rates calculated on Y-o-Y basis are implicitly seasonally adjusted as each quarter is compared with the corresponding quarter in previous year, thus the growth rates not only show the underlying trend but remains sensitive to irregular shocks as well as

capable to capture deviations from expected seasonal behavior (Neo Poh Cheem 2003).

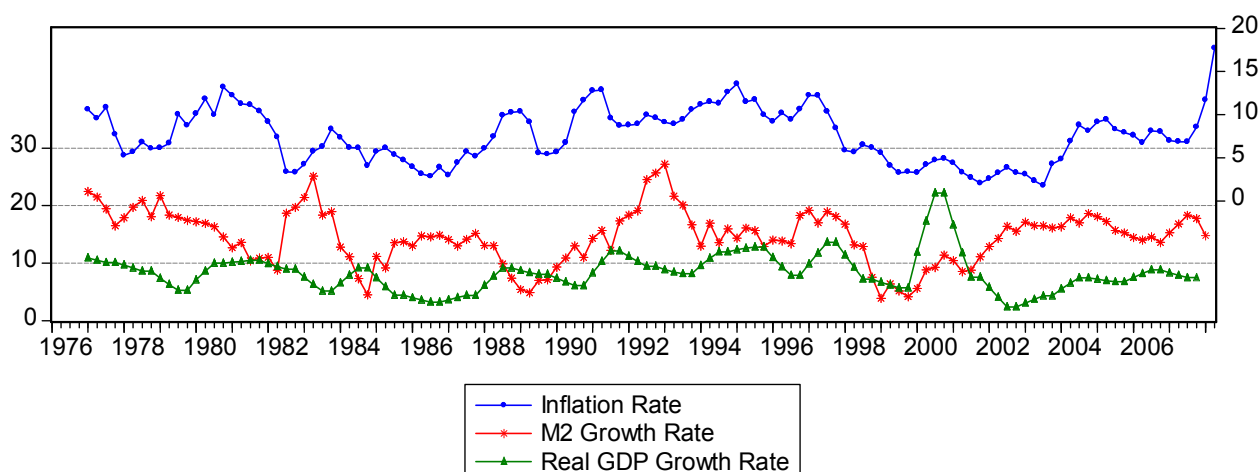
Our sample ranges from 1976:1 to 2008:2. The reason to drop the data of before 1976 is, to avoid some of the major Structural breaks exist in large time series reflecting some major policy changes and historical events that are difficult to model empirically, like First Martial Law by General Ayub Khan (1958), War between India and Pakistan (1965), Second Martial Law by General Yahya Khan (1969), Fall of Dhaka and Separation of East Pakistan (1971).

Although, in Pakistan four different types of price indicators are available, CPI (Consumer Price Index), WPI (Wholesale Price Index), SPI (Sensitive Price Index) and GDP deflator, but for our analysis we have taken CPI (Consumer Price Index) as it not only represents more accurately the cost of living in Pakistan but also because it has been regularly updated in its composition and calculations (Bokhari and Faridun 2006).

2.2 Descriptive statistics of Data

Using quarterly CPI data obtained from IFS [ifs:s56464000zfq] we calculated quarterly inflation on Y-o-Y basis. The figure 1 shows clearly that Inflation in Pakistan has been constantly high (above 5 percent) except for a very short period of times between 1982 to 1984 and 1999 to 2003. There is also a clear increasing trend in inflation from 2003 and onwards which became extremely sharp near the end of our sample (2008Q2).

Figure 1: Graphical Representation of Inflation, M2 Growth and Real GDP Growth



For further insight we broke the data into seven sub-samples each consist of 20- quarters, except the first and last sub-samples which are consist of 12 and 14 quarters respectively (Table 1).

Table 1: (Breakup of Inflation in different Sub-sample periods)

TIME PERIOD	MEAN	MEDIAN	STANDARD DEVIATION
1977Q1 TO 1979Q4	7.8363%	7.2573%	2.0237%
1980Q1 TO 1984Q4	8.0773%	7.8391%	3.1100%
1985Q1 TO 1989Q4	5.9010%	5.4854%	2.3643%
1990Q1 TO 1994Q4	10.0005%	9.7697%	1.8899%
1995Q1 TO 1999Q4	8.4914%	9.3256%	3.1891%
2000Q1 TO 2004Q4	4.1264%	3.5828%	1.8980%
2005Q1 TO 2008Q2	8.8458%	8.0588%	2.8640%

From the over all sample statistics and sub-samples statistics, it is evident that average rate of Inflation in Pakistan is always above 7.5% which is quite high as compared to the world wide acceptable range of suitable inflation rate of 1 – 3 percent, pointed out by David E.Altig (2003).

There are however, two sub-periods, 1985 to 1989 and 2000 to 2004 when average inflation rate is remarkably less than the overall sample average of 7.5% as well as the comparative sub-sample averages. But unfortunately the authenticity of these sub-samples averages is questionable and subject to argument as not only being fallen under the dictatorship regime, but especially after the statement issued by the officials of newly democratic government in April 2008 about the gross misrepresentation and rigging of economic data and manipulation of economic activities by previous prime minister Mr. Shokat Aziz, under the supervision of Army Chief turned President General Parvez Musharraf.**

Table 2 provides the descriptive statistics of concerned variables, showing high variability in all three variables, despite of implicit smoothing due to calculation of Y-o-Y rates. We are unable to reject the null of normality under Jarque-Bera statistics for inflation and M2 growth rate, but we can reject the same for RGDP growth with high significance. The non normal distribution of RGDP growth is also evident by its

** Source: <http://www.newslines.com.pk/NewsApr2008/coverapr2008.htm>

high values of skewness and kurtosis, from the normal bench marks of 0 and 3 respectively.

Table 2: Descriptive Statistics of Variables

	INFLATIO N	M2_GROWTH	RGDP_GROWT H
Mean	7.538174	14.62328	8.410792
Median	7.410908	14.77869	8.167464
Maximum	17.68546	27.25119	22.22579
Minimum	1.764722	3.931652	2.432601
Std. Dev.	3.134167	4.660667	3.318138
Skewness	0.228954	-0.135944	1.230382
Kurtosis	2.521129	3.079432	6.636765
Jarque-Bera	2.304730	0.417877	99.62063
Probability	0.315889	0.811445	0.000000
Observations	126	125	124

2.3 Stationarity of Variables and Preliminary Cointegration Analysis

To check the order of integration in considered time series, we conduct the unit root tests in this section. Augmented Dickey-Fuller (ADF) and Phillips-Perron(PP) tests were used and the results (Table 3) shows that Inflation is seriously affected by the problem of unit root and thus Non stationary. On the other hand, for M2 Growth, we have strong evidences to reject the presence of unit root forcing us to believe on its stationary behavior. The values of Durbon Watson statistic also strengthen our conclusion about stationarity of M2 Growth. However the results for Real GDP growth are somewhat persuasive rather than conclusive. ADF tests clearly reject the possibility of its stationarity showing strong presence of unit root. But on the other hand Philliip Perron tests reject the null of unit root at 10% and 5% but this rejection is itself questionable due to low values of Durbon Watson statistics pointing out us towards the possible deterioration of results due to serial correlation. Interestingly if we rely on Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test to check the stationarity of Inflation, M2 Growth and Real GDP growth, we won't be able to have enough evidences to reject the null hypotheses of stationarity for all variables (results not reported) which is contradictory to the results of ADF and PP test for Inflation and Real GDP growth.

Table 3: Unit root testing

INFLATION	Statistic	Prob	Lags/BW	AIC	SIC	DW Stats
ADF (constant term)	-1.519847	0.5203	4(SIC)	3.402107	3.540742	1.791038
ADF (constant, trend)	-1.370435	0.8648	4(SIC)	3.414736	3.576476	1.798311
PHILLIP PERRON (constant term)	-2.200326	0.2073	6	3.600122	3.645375	1.338362
PHILLIP PERRON (constant, trend)	-1.918631	0.6389	7	3.605208	3.673088	1.362273
MONEY GROWTH	Statistic	Prob	Lags/BW	AIC	SIC	DW Stats
ADF (constant term)	-3.560129	0.0080	4(SIC)	4.471723	4.611098	2.014176
ADF (constant, trend)	-3.546606	0.0390	4(SIC)	4.487793	4.650396	2.013185
PHILLIP PERRON (constant term)	-3.344702	0.0149	1	4.621648	4.667137	2.006133
PHILLIP PERRON (constant, trend)	-3.290910	0.0726	1	4.637686	4.705918	2.007551
RGDP GROWTH	Statistic	Prob	Lags/BW	AIC	SIC	DW Stats
ADF (constant term)	-2.461377	0.1276	6(SIC)	2.372044	2.560910	1.943435
ADF (constant, trend)	-2.477490	0.3387	6(SIC)	2.387854	2.600329	1.943356
PHILLIP PERRON (constant term)	-3.301906	0.0169	6	3.621104	3.666831	0.657080
PHILLIP PERRON (constant, trend)	-3.299109	0.0712	6	3.636733	3.705323	0.657271

Note:***,**,* respectively indicates rejection of the null at 1%, 5% and 10% significance levels.

The above mentioned results prompt us to conduct Cointegration test, under the assumption of I(1) covariance stationarity of all variables, to estimate any long run relationship among them, if it exist.

Table 4: Johansen Cointegration Test for π , M2G and RG

No. of Cointegrating Vectors under the Null Hypothesis	Trace Test			Maximum Eigenvalue Test		
	λ_{trace}	5% Critical Value	Prob.	λ_{max}	5% Critical Value	Prob.
None	44.54070	35.19275	0.0037	22.66782	22.29962	0.0444
At most 1	21.87288	20.26184	0.0298	18.03823	15.89210	0.0227
At most 2	3.834646	9.164546	0.4373	3.834646	9.164546	0.4373

The Johansen test statistics (Table 4) show rejection for the null hypothesis of no cointegrating vectors under both the trace and maximal eigenvalue forms of the test. Moving on to test the null of at most 1 cointegrating vectors, the trace statistics is 21.87, while the 5% critical value is 20.26, so the null is just rejected at 5% (and not rejected at 1%). Finally examining the null that there are at most 2 cointegrating vectors, the trace statistic is now well below the 5% critical value, suggesting that the null should not be rejected, i.e. there are at most two cointegrating vectors. ($1 \leq r \leq 2$).

We also applied Engle-Granger(EG) approach to test the cointegrating relationship among variables, according to which equilibrium errors of cointegrating regression must be stationary for the variables to be cointegrated in long run.

$$\pi_t = \lambda + \theta M2G_t + \varphi RG_t + \varepsilon_t \quad \text{Equation 1}$$

Estimated long run coefficients of $M2G_t$ and RG_t calculated from equation 1 are reported in table 5.

Table 5: Regression Results of Equation 1

Variables	Coefficients
Constant	2.116196**
M2 growth rate ($M2G$)	0.167641***
Real GDP growth rate (RG)	0.339489***
Adjusted R-Square	0.183155
D-W stat	0.286444
Akaike info criterion	4.855724
Schwartz info criterion	4.923956
F-statistics	14.78970***

Note:***,**, * respectively indicates rejection of the null at 1%, 5% and 10% significance levels.

Unit root tests of ε_t , obtained from equation 1, are given in Table 6 indicating that residuals of cointegrating regression are I(0) according to ADF and PP test at 10% and 5% respectively. However we cannot reject the presence of unit root in the residuals of cointegrating regression if we introduce trend term.

Table 6: Unit Root Test for residuals of cointegrating regression

	Statistic
ADF (constant)	-2.605347*
ADF (constant, trend)	-2.710422
PHILLIP PERRON (constant)	-3.027887**
PHILLIP PERRON (constant, trend)	-3.023582

Note:***, **, * respectively indicates rejection of the null at 1%, 5% and 10% significance levels.

3. Inflation Uncertainty Framework

In this section we discussed ARCH model and its extensions such as GARCH, Asymmetric GARCH (AGARCH), Threshold GARCH (TGARCH) and Exponential GARCH (EGARCH) to analyze the relationship between Inflation and Inflation Uncertainty. The formal presentation of ARCH(q) model given by Engel (1982) is

$$\pi_t | \psi_{t-1} \sim N(\kappa X_{t-1}, h_t) \quad \text{Equation 2}$$

$$E_{t-1} \varepsilon_t^2 = h_t = \alpha_o + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 \quad \text{Equation 3}$$

Where equation 2 represents conditional mean of Inflation at time t which depends upon the information set at time period t-1 (ψ_{t-1}). Equation 3 is conditional variance of unanticipated shocks to inflation which is equal to $\varepsilon_t = \pi_t - \kappa X_{t-1}$ and is actually expected value of conditional variance at time t-1, conditioned upon the information set available at time t-1.

If $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_q = 0$ then conditional variance of errors is constant, however to allow conditional variance as time varying measure of inflation uncertainty (presence of ARCH) at least one of the $\alpha_i \geq 0$ where ($i = 1, 2, \dots, q$). By applying the restriction $\sum_{i=1}^q \alpha_i < 1$ we ensure that ARCH process is covariance stationary. Non negativity of all ARCH parameters α_i is sufficient but not necessary condition to ensure that conditional variance doesn't become negative.

However, evidence of long lag processes of Squared residuals in ARCH model suggested that shocks have persistence affects on inflation uncertainty, thus Bollerslev (1986) and Taylor (1986) independently suggested alternative GARCH approach for modeling persistence, according to which the linear GARCH(p,q) process in Equation 4 represents the conditional variance of inflation forecast error which is a function of lagged values of both one period forecast error and the conditional variance.

$$h_t = \alpha_o + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j h_{t-j} \quad \text{Equation 4}$$

Where $\alpha_o > 0, \alpha_i \geq 0$ and $i = 1, 2, \dots, q$

$\beta_j \geq 0$ and $j = 1, 2, \dots, p$

GARCH is more parsimonious compared to ARCH as with only three parameters it allows an infinite number of past squared errors to influence the current conditional variance, Chris Brooks (2002), and is less likely to breach non-negativity constraints, but the primary restriction of GARCH is that it enforces a symmetric response of volatility to positive and negative shocks. According to Brunner and Hess (1993) and Joyce (1995), a positive inflation shock is more likely to increase Inflation uncertainty via monetary policy mechanism, as compared to negative inflation shock of equal size. If it is true then we cannot rely on the estimates of symmetric ARCH and GARCH models and will have to go for asymmetric GARCH models. Two popular asymmetric formulations are GJR model, named after the authors Glosten, Jagannathan and Runkle (1993) and the exponential GARCH (EGARCH) model proposed by Nelson (1991).

GJR-GARCH is simply an extension of GARCH(p,q) with an additional term to capture the possible asymmetries (leverage effects). The conditional variance is now

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma \varepsilon_{t-1}^2 I_{t-1} \quad \text{Equation 5}$$

Where $I_{t-1} = 1$, if $\varepsilon_{t-1} < 0$, otherwise $I_{t-1} = 0$. If the asymmetry parameter γ is negative then negative inflationary shocks result in the reduction of inflation uncertainty. (Bordes et al. 2007)

The exponential GARCH model was proposed by Nelson (1991). There are various ways to express the conditional variance equation, but one possible specification is

$$\log h_t = \alpha_0 + \sum_{j=1}^q \beta_j \log h_{t-j} + \sum_{i=1}^p \alpha_i \left| \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \right| + \sum_{k=1}^r \gamma_k \frac{\varepsilon_{t-k}}{\sqrt{h_{t-k}}} \quad \text{Equation 6}$$

EGARCH model has several advantages over the traditional ARCH and GARCH specifications. First, variance specification represented in equation 6 makes it able to capture the asymmetric effects of good news and bad news on volatility, which is preferable in the context of Inflation and Inflation uncertainty. Second, since the $\log h_t$ is modeled, then even in the presence of negative parameters, h_t will be positive thus relieving the non-negativity constraints artificially imposed on GARCH parameters.

4. Estimation and Results

4.1 Construction of Mean Equation

Though the initial unit root tests and cointegration analysis show that π_t , $M2G_t$ and RG_t are stationary and they might be cointegrated in the long run, still the results are not highly significant and we have equal reasons (rejection of null of unit root at 10% significance level) to formulate a model in the original form of variables instead of their detrended series. We choose to model inflation in autoregressive distributed lag (ADL) form:

$$\delta(L)\pi_t = \lambda + \theta(L)M2G_t + \varphi(L)RG_t + \varepsilon_t \quad \text{Equation 7}$$

Where $\delta(L)$, $\theta(L)$, and $\varphi(L)$ are appropriate lag polynomials of π_t , $M2G_t$, and RG_t respectively. There are strong evidences that Inflation in Pakistan is a monetary phenomenon, Qayyum (2006), Kemal(2006) strongly suggested that excess money supply growth has been a significant contributor to the rise in inflation in Pakistan. Khalid (2005) used Bivariate VAR analysis to conclude that seigniorage and money depth may be considered among the major determinants of Inflation in Pakistan. Ahmad et al(1991) found that major determinants of Inflation among others are, lagged inflation and nominal money growth. In an IMF working paper, Axel Schimmelpfennig et al(2005) developed three different models to forecast inflation, Univariate model (ARIMA based), Unrestricted VAR model and Leading Indicators Model (LIM), and they found LIM based on broad money growth, private sector credit growth and lags in Inflation, best for ex-post inflation forecast in Pakistan. π_t and $M2G_t$ has correlation of 0.23 which increases to 0.29, 0.34 and 0.36 if we take $M2G_{t-1}$, $M2G_{t-2}$ and $M2G_{t-3}$ instead of $M2G_t$, which clearly indicates the transmission delay in monetary stance, thus making us more confident about the selection of ADL model. In this scenario we expect θ_s to be positive and significant.

The bidirectional relationship between Inflation and growth is widely accepted, however according to classical Quantity theory of money, under the assumption of constant velocity and M2 growth, real GDP growth should have a negative impact on Inflation. Domac and Elbrit (1998) did cointegration analysis and developed ECM for Albanian data and found evidence in support of classical supply shocks theory that growth, through structural reforms and improved infrastructure, can significantly reduce inflation. Handerson (1999), Becker and Gordon (2005), Murphy (2007),

Robert McTeer (2007) are among many, who strongly believe that increasing growth have strong impacts of inflation in an opposite direction. Recently in 2008, ECB's and Bundesbank presidents said that "Slowing growth may not be sufficient to reduce inflation in Eurozone" thus negating as well the positive relationship between inflation and growth therefore despite of obtaining strong positive and significant relationship found between π_t and RG_t from cointegrating regression (equation 1), we still expect negative sign of φ_s in our model explaining the negative impact of supply shocks on inflation, especially with lagged values of RG_t .

The reason for the inclusion of autoregressive term $\delta(L)\pi_t$ is straight forward. Inflation, like many other economic variables, has shown strong inertia in various studies. There may be many reasons for this inertia like inability of market agent to interpret and respond timely after an arrival of a particular announcement or news, or the probability of uncertainty attached with that news or the overreaction of market participants by following the herd behavior. In case of presence of strong inflationary inertia, as it is evident from many studies, we expect δ_s to be positive and highly significant.

The optimal number of lags is obtained by using Akaike and Schwartz information criteria (AIC) and (BIC) and in that case it is one, both for autoregressive term and distributed lag term, so we finalized ADL(1, 1) model to estimate mean inflation.

$$\pi_t = \lambda + \delta_1\pi_{t-1} + \theta_1M2G_{t-1} + \varphi_1RG_{t-1} + \varepsilon_t \quad \text{Equation 8}$$

Regression results of equation 8 are reported in table 7:

Table 7: Regression results of ADL(1,1) model

Variables	Coefficients
λ	0.335366
δ_1	0.897731***
θ_1	0.058195**
φ_1	-0.049717
Adjusted R-Square 0.810313	AIC = 3.410951, BIC = 3.501928
F-Statistic 176.1451***	DW-Stat 1.5883
Breusch-Godfrey Serial Correlation LM Test: Lag 4 = 20.1297***	ARCH LM Test: Lag 4 = 6.2354

Note:***,**,* respectively indicates rejection of the null at 1%, 5% and 10% significance levels.

Due to presence of significant serial correlation in residuals of above model as indicated by Breusch-Godfrey test and Ljung-Box Q statistics, we introduced AR(1) and AR(4) error term in equation 7. Lag orders of error term identified through partial autocorrelogram function (PAF) of residuals. So the model becomes:

$$\pi_t = \lambda + \delta_1 \pi_{t-1} + \theta_1 M2G_{t-1} + \varphi_1 RG_{t-1} + u_t$$

$$u_t = \rho_1 u_{t-1} + \rho_4 u_{t-4} + \varepsilon_t \quad \text{Equation 9}$$

Table 8: Results of equation 9

Variables	Coefficients
λ	0.130386
δ_1	0.929164***
θ_1	0.051121**
φ_1	-0.037501
ρ_1	0.168262*
ρ_4	-0.373843***
Adjusted R-Square 0.850537	AIC=3.203545, BIC=3.342919
F-Statistic 136.43681***	DW-Stat 1.914897
Breusch-Godfrey Serial Correlation LM Test: Lag 4=5.75716	ARCH LM Test: Lag 4=5.14009

Note:***,**,* respectively indicates rejection of the null at 1%, 5% and 10% significance levels.

After introducing AR specification of residuals, we found no evidence of serial correlation in DW Stat, Breusch-Godfrey test and Ljung Box Q-Statistics (reported in table 9). R-Square also improved by about 4% due to inclusion of autoregressive components of errors.

Table 9: Q-Stat table for Residuals

Lag	Q-Stat	Prob.
3	0.7523	0.386
5	2.1809	0.536
10	5.1320	0.743
15	14.800	0.320
20	19.225	0.378
25	20.991	0.582
30	22.747	0.746
35	25.970	0.803

4.2 Estimation of Uncertainty

As far as variance equation is concerned, we didn't find any ARCH model from ARCH(1) to ARCH(4) with significant estimated parameters along with conformity of constraints imposed on ARCH(p) process, so we decided to go for GARCH estimation. Table 10 provides the results of 2 different models.

Table 10: GARCH estimations of conditional variance		
	Model 1	Model 2
Mean Equation		
Variables	GARCH(1,1)	GARCH(1,1)
λ	0.147506	-0.235069
δ_1	0.937117***	0.936293***
θ_1	0.045557*	0.047618**
φ_1	-0.031433	
ρ_1	0.175788	0.201809*
ρ_4	-0.411784***	-0.419355***
Variance Equation		
α_0	1.645441***	0.207634
α_1	0.235475*	0.315353***
β_1	-0.438056	0.608708***
γ		
R-Square	0.845660	0.831154
DW Stat	1.926282	1.685223
Akaike criterion	3.214446	3.316416
Schwarz criterion	3.423507	3.501262
F-Stat	82.50290***	85.38659***

Note:***, **, * respectively indicates rejection of the null at 1%, 5% and 10% significance levels.

4.3 Tests for Asymmetries in Volatility:

Engle and Ng (1993) have devised a set of tests to confirm the asymmetry present in volatility, if any. These tests are generally known as Sign and Size bias tests. We used these tests to determine whether an asymmetric model is required to capture the inflation uncertainty or whether the GARCH model can be an adequate model.

We applied sign and size bias tests on the residuals of GARCH(1, 1) (Model 02) whose mean and variance equations are given below

Mean Equation:

$$\pi_t = \lambda + \delta_1 \pi_{t-1} + \theta_1 M2G_{t-1} + u_t$$

$$u_t = \rho_1 u_{t-1} + \rho_4 u_{t-4} + \varepsilon_t$$

Variance Equation:

$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j h_{t-j}$$

Where $\alpha_0 > 0, \alpha_i \geq 0$ and $i = 1, 2, \dots, q$

$$\beta_j \geq 0 \text{ and } j = 1, 2, \dots, p$$

The test for sign bias is based on the significance or otherwise of ϕ_1 in equation 10.

$$\hat{\varepsilon}_t^2 = \phi_0 + \phi_1 S_{t-1}^- + v_t \quad \text{Equation 10}$$

$$S_{t-1}^- \text{ is 1 if } \varepsilon_{t-1} < 0 \text{ and 0 otherwise}$$

Where v_t is an iid error term. If the impact of positive and negative inflation shocks is different on conditional variance, then ϕ_1 will be statistically significant.

It is most likely, especially in case of inflation that the magnitude or size of the inflation shock will affect whether the response of volatility to shock is symmetric or not. Engle and Ng originally suggested a negative sign bias test, based on a regression where S_{t-1}^- is now used as a slope dummy variable. Negative sign bias is argued to be present if ϕ_1 is statistically significant in the equation 11.

$$\hat{\varepsilon}_t^2 = \phi_0 + \phi_1 S_{t-1}^- \varepsilon_{t-1} + v_t \quad \text{Equation 11}$$

However we made little change in that and conducted the above test as positive sign bias test additionally.

$$\hat{\varepsilon}_t^2 = \phi_0 + \phi_1 S_{t-1}^+ \varepsilon_{t-1} + v_t \quad \text{Equation 12}$$

$$S_{t-1}^+ \text{ is 1 if } \varepsilon_{t-1} > 0 \text{ and 0 otherwise}$$

Finally Setting $S_{t-1}^+ = 1 - S_{t-1}^-$ so that S_{t-1}^+ would become the dummy to capture positive inflation shocks, Engle and Ng (1993) proposed a joint test for size and sign bias based on following regression;

$$\hat{\varepsilon}_t^2 = \phi_0 + \phi_1 S_{t-1}^- + \phi_2 S_{t-1}^- \varepsilon_{t-1} + \phi_3 S_{t-1}^+ \varepsilon_{t-1} + v_t \quad \text{Equation 13}$$

Significant value of ϕ_1 in equation 13 indicates the presence of sign bias i.e. positive and negative inflation shocks have different impacts upon future uncertainty. On the other hand, the significant values of ϕ_2 and ϕ_3 would suggest the presence of size bias, where the sign and the magnitude of shock, both are important. A joint test statistics is TR^2 which will asymptotically follow a χ^2 distribution with 3 degrees of freedom under the null hypothesis of no asymmetric effects.

Table 11: Tests for Asymmetries in Volatility

	Sign Bias Test Eq. 10	Negative Sign Bias Test Eq. 11	Positive Sign Bias Test Eq. 12	Joint test for Sign and Size Bias Eq. 13
ϕ_0	1.901442***	1.681014***	1.001339***	0.481507
ϕ_1	-0.661602	0.224811	1.230697***	0.557517
ϕ_2				-0.228534
ϕ_3				1.566024***
TR^2				8.92332**

Note:***,**,* respectively indicates rejection of the null at 1%, 5% and 10% significance levels.

The individual regression results of Sign bias test and negative sign bias test doesn't reveal any evidence of asymmetry as the value of ϕ_1 is insignificant. But we can see that the coefficient indicating the positive sign bias is significant in individual as well as in joint test. In addition, although none of the other coefficients except ϕ_3 are significant in the joint regression, the χ^2 test statistic is significant at 5%, suggesting a rejection of the null hypothesis of no asymmetries.

The above results lead us to go for asymmetric GARCH models instead of symmetric and in table 12 we report the results of 3 asymmetric GARCH models.

Table 12: GJR-GARCH and EGARCH estimations of conditional variance

	Model 3	Model 4	Model 5
Variables	GJR-GARCH	GJR-GARCH	EGARCH
Mean Equation			
λ	-0.024369	-0.236679	0.065636
δ_1	0.913173***	0.914421***	0.917033***
θ_1	0.064182**	0.062802	0.053746***
φ_1	-0.030109		-0.036433*
ρ_1	0.203838**	0.188266	0.160722***
ρ_4	-0.424543***	-0.339855**	-0.401705***
Variance Equation			
α_0	0.414841*	1.436776	0.220033
α_1	0.071345	0.077708	0.265016***
β_1	0.671568***	0.477734	-0.954307***
γ	-0.151450	-0.293339**	0.139627**
R-Square	0.843248	0.829570	0.842640
DW Stat	1.932040	1.648933	1.844275
Akaike criterion	3.218947	3.490593	3.160134
Schwarz criterion	3.452486	3.699655	3.392425
F-Stat	71.53131***	73.40415***	71.80327***

Note:***,**,* respectively indicates rejection of the null at 1%, 5% and 10% significance levels.

Results from GJR-GARCH (Model 3 and 4) confirmed that these models are successful in modeling asymmetric (leverage effects) of lagged inflation shocks on one period ahead conditional variance. From both models we obtained the negative values of γ as expected, thus concluding that negative inflation shocks (good news) reduce inflation uncertainty. On the other hand the value of γ is positive and significant in EGARCH estimation (Model 5) suggesting that when there is an unexpected increase in inflation, resulting positive inflation shocks (bad news), inflation uncertainty increases more than when there is a unanticipated decrease in inflation.

4.4 News Impact Curves

For further investigation of asymmetric behavior of inflation uncertainty, we analyzed the effects of news on volatility or inflation uncertainty with the help of “News Impact Curve”. By keeping constant all the information at t-2 and earlier, we can examine the implied relation between ε_{t-1} and h_t which we called as “News Impact Curve”. It is a pictorial representation of the degree of asymmetry of volatility to

positive and negative shocks and it plots next period uncertainty h_t that would arise from various positive and negative values (news) of past inflation shocks (ε_{t-1}) [Pagan and Schwert, 1990]. For the GARCH model, this curve is a quadratic function centered at $\varepsilon_{t-1} = 0$. The equations of News impact curve for the GARCH, GJR-GARCH and EGARCH models are provided in table 13.

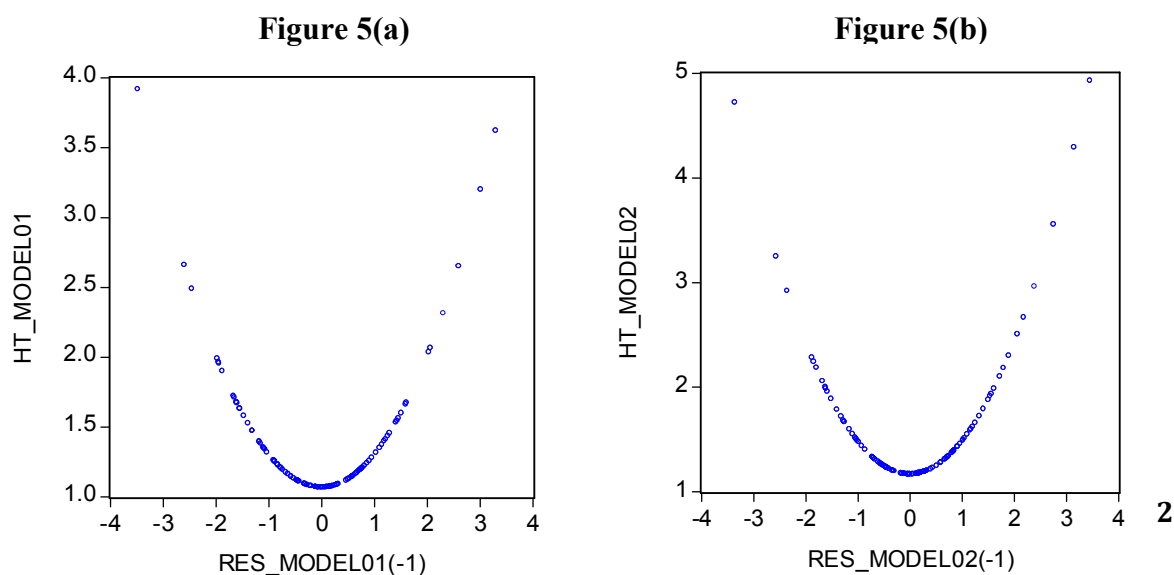
Table 13: News Impact Curve for different GARCH processes

GARCH(1,1)	$h_t = A + \alpha_1 \varepsilon_{t-1}^2$ <p>Where $A = \alpha_0 + \beta_1 \bar{\sigma}^2$ And $\bar{\sigma}^2 = \alpha_0 / [1 - \alpha_1 - \beta_1]$</p>
GJR-GARCH(1,1) Or TGARCH(1,1)	$h_t = A + (\alpha_1 + \gamma_1 I_{t-1}) \varepsilon_{t-1}^2$ <p>Where $A = \alpha_0 + \beta_1 \bar{\sigma}^2$ And $\bar{\sigma}^2 = \alpha_0 / [1 - \alpha_1 - \beta_1 - (\frac{\gamma_1}{2})]$</p>
EGARCH(1,1)	$h_t = A \exp \left\{ \frac{\alpha_1 (\varepsilon_{t-1} + \gamma_1 \varepsilon_{t-1})}{\bar{\sigma}} \right\}$ <p>Where $A = \bar{\sigma}^{2\beta_1} \exp \{ \alpha_0 \}$ $\bar{\sigma}^2 = \exp \left\{ \frac{\alpha_0 + \alpha_1 \sqrt{2/\pi}}{1 - \beta_1} \right\}$</p>

Source: Eric Zivot (2008), “Practical Issues in the Analysis of Univariate GARCH Models”

Where h_t is the conditional variance at time t, \hat{a}_{t-1} is inflation shock at time t-1, $\bar{\sigma}$ is the unconditional standard deviation of inflation shocks, \hat{a}_0 and \hat{a}_1 are constant term and parameter corresponding to h_{t-1} in GARCH variance equation respectively.

The resulting news impact curves for GARCH, GJR-GARCH and EGARCH models are given in figure 5.



It can be seen in figure 5(a) and 5(b), that GARCH news impact curves are of course symmetrical about zero, so that a shock of given magnitude will have the same impact on the future volatility, irrespective of its sign. On the other hand GJR news impact curves [figure 5(c) and 5(d)] are asymmetric where negative inflation shocks are in fact reducing the future volatility exactly as it was aimed to model through equation 5.

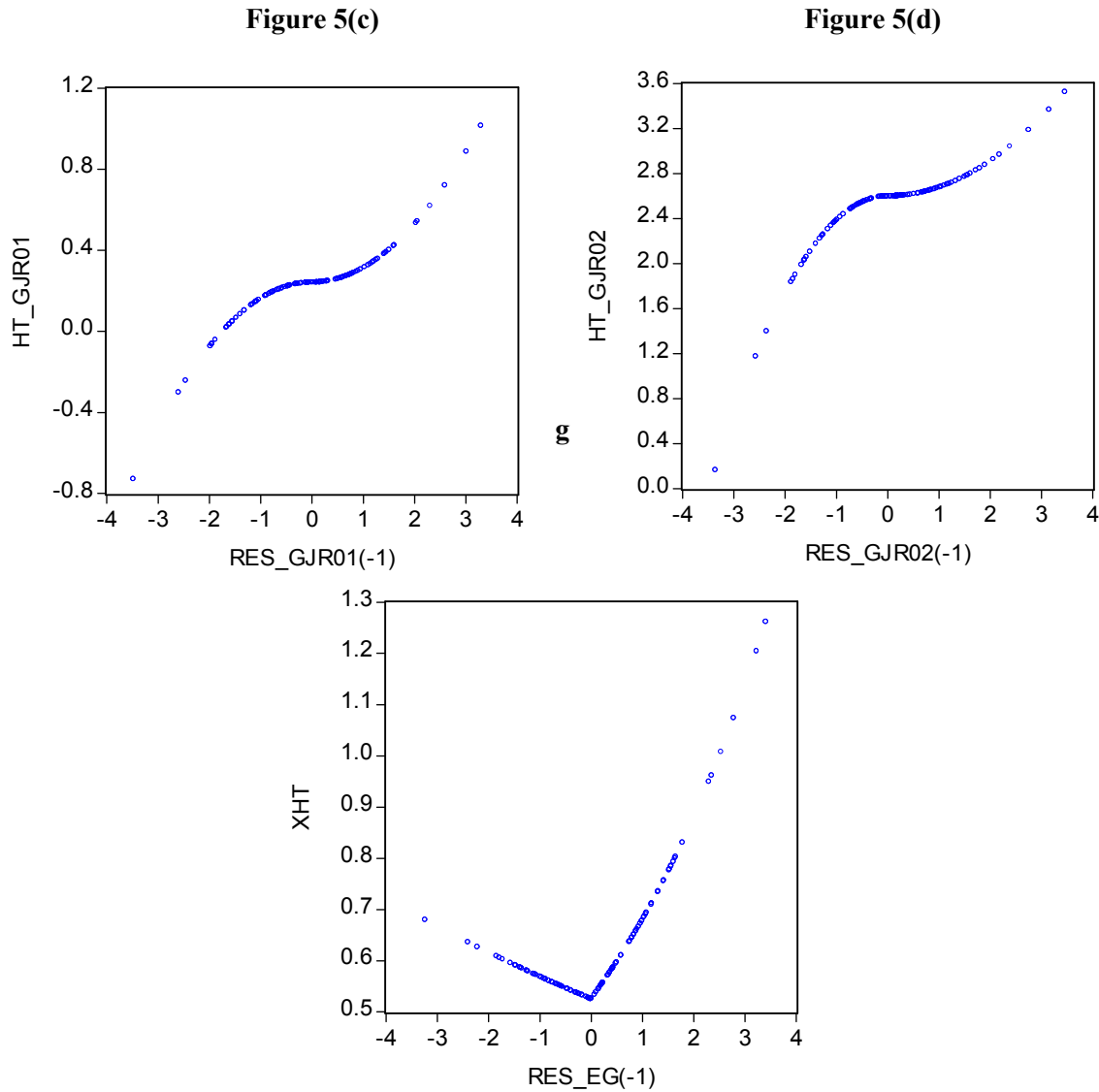


Figure 5(e) is also according to our expectation where we see that unexpected increase in inflation (positive inflation shocks) increases volatility more than when there is a decrease in inflation that is what we can also interpret from the positive and significant value of γ reported for EGARCH model in table 12.

4.4 Testing of Friedman-Ball Hypothesis (Granger causality)

In order to assess Friedman-Ball and Cukierman-Meltzer hypotheses, we implement Bivariate Granger-Causality test up to 10 lags, between inflation and inflation uncertainty (one period ahead conditional forecast of variance), derived from model 1 to model 5. The results for GARCH models (model 1 and 2) are reported in table 14(a). We report only p-values of Wald statistics for the null hypothesis that “Inflation does not cause Uncertainty” in the first column and that “Uncertainty does not cause Inflation” in the second column for each model. The results reported in table 14(a) are not very encouraging and they refused almost both Friedman-Ball and Cukierman-Meltzer hypotheses, and it appears that neither of inflation or inflation uncertainty causes each other.

Table 14(a): Granger Causality test (P-values of Wald Statistics)

Lags	GARCH (Model 01)		GARCH (Model 02)	
	π does not cause h_t	h_t does not cause π	π does not cause h_t	h_t does not cause π
1	0.26888	0.72597	0.08924	0.62038
2	0.56460	0.25638	0.07732	0.72482
3	0.73427	0.38953	0.18948	0.51783
4	0.64214	0.46390	0.09205	0.29570
5	0.91466	0.30105	0.17072	0.12520
6	0.95092	0.12722	0.29456	0.10380
7	0.48360	0.18771	0.42834	0.21033
8	0.61851	0.37005	0.45173	0.18022
9	0.42338	0.53233	0.31722	0.21285
10	0.43627	0.31679	0.37353	0.21144

However results which we report in table 14(b) for GJR-GARCH (model 3 and 4) and EGARCH (model 5), are consistent and strongly reject the null of “Inflation does not cause uncertainty” thus supporting Friedman-Ball hypothesis.

Table 14(b): Granger Causality test (P-values of Wald Statistics)

Lags	GJR-GARCH (Model 03)		GJR-GARCH (Model 04)		EGARCH (Model 05)	
	π does not cause h_t	h_t does not cause π	π does not cause h_t	h_t does not cause π	π does not cause h_t	h_t does not cause π
1	2.6E-05	0.41844	0.00446	0.63392	0.00058	0.07367
2	2.2E-25	0.84589	3.0E-17	0.54390	9.9E-08	0.02533
3	4.3E-27	0.84114	7.4E-20	0.17518	1.5E-08	0.07124
4	1.3E-27	0.00128	9.4E-24	0.08609	1.2E-08	0.00387
5	6.7E-33	0.94750	1.2E-25	0.99978	4.9E-08	0.27712
6	1.5E-35	0.39302	4.7E-26	0.85809	2.1E-09	0.52711
7	1.4E-33	0.08357	2.5E-25	0.69109	7.5E-08	0.17706
8	1.7E-32	0.18487	1.2E-23	0.08138	1.4E-07	0.21410
9	1.4E-30	0.02934	1.3E-22	0.16555	3.7E-06	0.45088
10	9.3E-32	0.11950	1.6E-23	0.33863	1.3E-05	0.45551

5. Conclusion

This study provides several interesting results. First of all we estimated inflation uncertainty as time varying conditional variance of inflation shocks and found performance of asymmetric GARCH models (GJR-GARCH and EGARCH) better than simple GARCH models. GJR-GARCH estimates negative and significant value of “leverage effect” parameter which suggests that negative shocks of inflation tends to decrease next period uncertainty, this conclusion is also supported by the results of EGARCH models.. News Impact curves graphically reflect the asymmetric behavior of inflation uncertainty from GJR-GARCH and EGARCH models. Finally bivariate Granger-Causality test strongly support Friedman-Ball hypothesis for GJR-GARCH and EGARCH models, i.e. high inflation causes inflation uncertainty and that the causality is running from inflation to inflation uncertainty. We do not find any evidence in support of Cukierman-Meltzer hypotheses.

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Appendix

Figure 6: Forecast of Conditional Variance (Inflation Uncertainty)

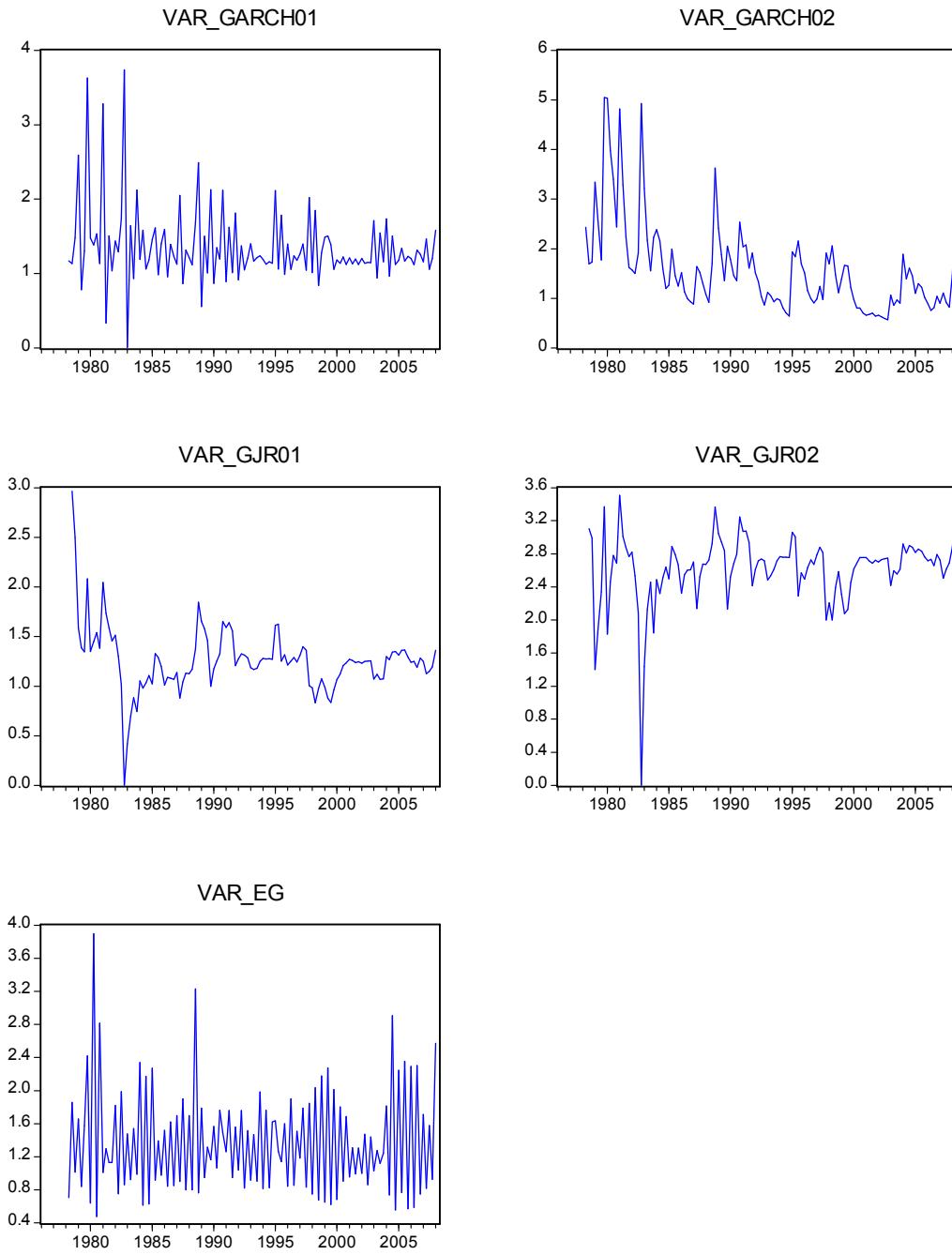


Figure 7: Impulse Response Functions of Uncertainty to Inflation

Response to Cholesky One S.D. Innovations ± 2 S.E.

