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Inflation and Inflation Uncertainty in Pakistan

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Abstract
This study estimates inflation and inflation uncertainty in Pakistan. To quantify the disparity in inflation levels, the average point is defined as the point at which positive and negative disruptions have an impact. The response to them can also influence the measures of positive and negative shocks in the fluctuation of inflation. The secondary data from 1983: Q1 to 2020: Q4 is derived from the IMF-IFS data series. The ARCH families of models are employed to calculate and analyze the inflation uncertainty in Pakistan. The ARCH and GARCH models capture the symmetric response of inflationary innovations. The Friedman-Ball hypothesis posits that inflation in the present day exacerbates the uncertainty surrounding inflation in the future. This investigation investigates this hypothesis and ascertains its validity for Pakistan.
Keywords: Inflation rate, Inflation Uncertainty, Granger Causality, ARMA-ARCH and ARMA-GARCH models.

1. Introduction

Since it is essential for monetary policy implementation, the precise estimate of the money demand function (MDF) is highly prized in the academic literature of macroeconomics. Since 1973, researchers and policymakers have primarily focused on MDF stability because it is a prerequisite for selecting a monetary policy instrument (Poole, 1970). The income velocity of money is unstable due to interest rates and other factors unrelated to income; parameters are unstable; and there is a short-term mismatch between the money stock kept and the expected money demand. These three sources of instability were highlighted by Andersen (1985). So, to solve the stability problem of MDF, we need to pick an estimating method that takes parameter instability and determinant selection into account. Researchers looking into what drives money demand have considered a wide range of variables in their investigations. Money demand stability is strongly affected by economic uncertainty and pricing expectations for the future, according to Hossain (2019). Not only that, but new studies have shown that economic uncertainty has a major impact on how and where money demand functions (Kuncoro, 2022; Mandeya & Sin-Yu, 2022; Hossain & Arwatchanakarn, 2020). In their analysis of the stable money demand function, Huellen et al. (2020) consider the effect of trade openness on opportunity costs. Consequently, the conduct of money demand is significantly influenced by the uncertainty resulting from anticipated inflation and exchange rates.

Several studies have been conducted in the empirical literature that have examined either inflation rate uncertainty or exchange rate volatility as potential determinants, in addition to other conventional factors of the money demand function. Nevertheless, the results of these studies are ambiguous because the findings are inconsistent across different countries.

Inflation is perhaps the most widespread process that is in constant observation within the world economy. The unpredictable future prices are one of the devastating results of inflation (G. Ackley 1978; Odintsov et al., 2023). In the event of unexpected inflation, economic agents are uncertain about the future prices of products, as the rise in prices is distinct from the forecast level. Unpredictable inflation (uncertainty) is the result of incomplete information regarding the determination of future price levels (Holland 1995). Nevertheless, the concept of inflation uncertainty was first introduced by Okun (1971) and Milton Friedman (1977). Milton Friedman (1977) contended that inflationary pressures induce an increase in price volatility, which in turn generates substantial uncertainty regarding future pricing. The price system's efficacy is diminished by inflation uncertainty, which also distorts future investment and saving decisions. An attempt to identify the causality between inflation and inflation uncertainty, in the context of Pakistan, is the primary concern of the present research.

2. Literature Review

Inflation uncertainty and inflation dynamics have been critical subjects of economic research for an extended period, particularly in developing economies like Pakistan. It is essential to comprehend these dynamics, as inflation can erode purchasing power, distort resource allocation, and impact macroeconomic stability. Additionally, inflation uncertainty can result in increased risk premiums and impede investment. Numerous studies have been conducted over the years to investigate the causes and consequences of inflation and its uncertainty. These studies have identified a diverse array of influencing factors, such as fiscal imbalances, monetary policy, and exogenous shocks. The objective of this literature review is to comprehensively summarize the results of these and other significant studies, thereby offering a comprehensive overview of the current state of knowledge regarding inflation and inflation uncertainty in Pakistan. Additionally, it will identify voids and potential areas for further investigation.

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Arabi (2010) and Sharaf & Shahen (2023) observed that inflation has a moderately positive correlation with the ambiguity of the Sudanese reality from 1960 to 2005. Their inflation gauge was the consumer price index. The inflation uncertainty is estimated using a variety of GARCH-type models. The outcomes of time-varying GARCH models demonstrate that the ARCH-M, EGARCH, and GARCH models are capable of effectively predicting unemployment uncertainty. The EGARCH model can be employed to quantify the impact of leverage and demonstrate that the three models exhibit unequal behavior about news and disturbances. Boero et al. (2008) investigated the stability and unpredictability of inflation in the United Kingdom from 1958 to 2006 under the lens of inflationary policy changes. The ARCH model can be implemented by dividing the dataset into sub-periods, which capitalizes on structural gaps in the mean and variance equations of the sub-periods. The data from the early period is consistent with the principle of "Monetary policy neglects," which suggests that the ARCH effect has had an impact on UK inflation rates since the 1980s.

Through an examination of three Caribbean economies Barbados, Jamaica, and the Bahamas Payne (2008) and Galindo & As for inflation and inflation uncertainty, Nuguer (2023) investigates both of them. That relationship could be done by employing the CPI, the level of inflation, and inflation uncertainty for all three countries using the monthly data from IFS. The information seems that inflationary innovations are making things much more unstable in Jamaica and the Bahamas. Still, Barbados shows less unpredictability than before. Uncertainty regarding inflation in every kingdom grows as inflation rates rise, according to the Granger causality test. With more people worried about future inflation, Jamaica's inflation rate fell. Results of Granger causality studies indicate that the Friedman-ball hypothesis is true in the Bahamas as well as in Barbados. However, Jamaica is among the countries that are affected by the Holland stabilization hypothesis. Caporal and Kontonikas (2006) and Pantovic et al. (12 EMU member states) investigated how monetary policy and the Euro affected inflation and future inflation uncertainty in the year 2023 by using an empirical investigation. This group includes the following nations: Greece, Ireland, Portugal, Spain, Italy, and Portugal herself. At the beginning of the year 1999, the idea of the EURO was formed, and the policy framework was changed. This policy regime is represented by a fictitious variable. The volatility of inflation is measured using a GARCH pattern, which is applied to monthly data for EMU economies that span the period from 1973 to 2004. The investigation also distinguishes between stable state uncertainty and structural and impulse lack of clarity. Empirical studies reveal that for steady state inflation, this is the only country that has a positive trend. The rest of the countries in the example also indicate no changes. Germany, Ireland, and Greece have not only followed the above-mentioned conditions but have also broken the association between inflation and inflation uncertainty. The authors of the work under study, Henry et al. (2006) and Jiang et al. (2022) explore this relation and establish that the inflation uncertainty affecting G-7 countries follows an asymmetric pattern of positive and negative shocks. Proper utilization of archived prices by reactivating or updating selected prices through the mixed strategy resulted in an overall increase of 17.14 percent as average countries are obtained by initiating the IMF-IFS. The data is divided into distinct periods for each nation, with each country generating over 500 observations. The GARCH model generates inflation uncertainty, which is substantially correlated with the inflation rate in the United States, the United Kingdom, and Canada Cheng and Hou (2022). Daal et al. (2005). apply the Power GARCH type to analyze the relationship between inflation and inflation uncertainty in developed and developing countries. In the same way, they develop a precise specification that ensures the deterrent effect of inflations varying temporal volatility, clustering, and asymmetric impacts on conditional variances. One way to gauge inflation is by looking at the consumer price index (CPI). We look at 23 countries throughout different periods using data from the International Financial Statistics (IFS). Members of this group include the G-7 and other developing economies in Asia, Latin America, and the Middle East. Many different countries call Asia home. Some examples are Pakistan, India, Sri Lanka, Indonesia, Korea, and Thailand. All nations, rich and poor alike, should use the Friedman-Ball hypothesis, according to the study's findings.

Two empirical studies, one by Berument and Dincer (2005) and the other by Beckmann et al. (2022), find out how the inflation growth and inflation uncertainty of the G-7 economies are related. A Comprehensive Report For this research, we used the Maximum Likelihood method. Using empirical analysis, every state's findings support the Friedman-Ball theory. Furthermore, America, France, Japan, and the UK all back the Cukierman-Meltzer theory. Despite this, four nations Canada, France, the UK, and the US have seen lower inflation as a consequence of elevated uncertainty, while Japan shows the opposite. U.S., Japanese, and British empirical research on inflation and inflation uncertainty was carried out by Chapman (2020) and Conrad and Karanasos (2005). Inflation is represented in this study by the monthly consumer price index (CPI) from the OECD Statistical Compendium. Two significant conclusions can be derived from the practical application of the ARFIMA FIGARCH model. Initially, the Friedman hypothesis is implemented throughout the entire nation.

Another point is that less important data back up the Cukierman-Meltzer theory. For the US, the study yields no conclusions, but for the UK, it presents contradictory evidence that works. Study results at 12 delays contradict the Cukierman-Meltzer hypothesis. Kontonikas (2004) and Hassani et al. (2020) assess the consequences of inflation and inflation uncertainty on the UK economy through the use of an inflation-targeting monetary policy framework. To show inflation uncertainty, the study employs a range of GARCH approaches, including component GARCH and GARCH in the mean. The mean-variance GARCH model allows us to simultaneously verify the reality of inflation and the uncertainty feedback it generates. Divided into two parts, temporary and permanent, the

Component GARCH model examines how previous inflation and inflation targeting affected long-term uncertainty. Evidence gathered from 1972 to 2002 in the UK is used in the study. The empirical investigation has determined that the implementation of an inflation-targeting policy framework results in a direct negative impact on long-term uncertainty.

3. Data and Methodology

3.1. Sources of Data

The IMF-IFS database is employed in the study due to its regular updates, reliability, and accessibility of desirable variables in its composition and calculation. Variables that are employed in the analysis are briefly described below.

The data for the Consumer Price Index (CPI) time series variable, which covers the years 1983 and 2020, is taken from the IMF-IFS database. Every three months, data from the Consumer Price Index is released. To determine the rate of inflation, the consumer price index (CPI) is used every three months.

$$\pi_t = \left[\left(p_t - p_{t-1} \right) / \, p_{t-1} \right] * 100 \qquad (1)$$

Where π_t is used for the inflation rate, p_t indicates current prices while representing last period prices.

Inflation uncertainty is the term used to describe the lack of certainty regarding the future prices of products by an economic agent, as future inflation differs from anticipated inflation. Mainly, we look at two proxies for inflation uncertainty the conditional variance of inflation and the distributions of individual expectations derived from survey data. This variable cannot be derived from any reliable source in Pakistan.

3.2. Inflation and Inflation Uncertainty: Empirical Models

Uncertainty about inflation and macroeconomic stability can only be understood by looking at these rates. Empirical models, which help researchers to measure the effect of different economic variables on the dynamics of inflation and to predict its future tendencies, have a major impact on this investigation. These models range from advanced frameworks that incorporate regime-switching and time-varying parameter techniques to more traditional econometric methodologies such as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Autoregressive Conditional Heteroskedasticity (ARCH) models. As an example, Bollerslev’s (1986) GARCH model has been widely used to describe inflation data volatility clustering. Furthermore, the Markov-Switching GARCH (MS-GARCH) model has been implemented to identify periods of high and low inflation uncertainty (Hamilton & Susmel, 1994). These empirical models not only inform the design of effective monetary policies but also provide insights into the underlying mechanisms fuelling inflation and its uncertainty. The objective of this review is to offer a thorough overview of the primary empirical models employed in the literature, emphasizing their applications, strengths, and constraints in the context of inflation and inflation uncertainty. The most critical aspect of empirical analysis is the selection of an appropriate model to observe the association between inflation and inflation uncertainty. The focal point of any research study is the implementation of an appropriate technique. The study’s impact appears to be a futile endeavor in the absence of a proper empirical analysis. Consequently, it is crucial to implement an appropriate methodology. Recent research employs two distinct methodologies to approximate inflation uncertainty.

3.2.1. Survey-based Proxies for Inflation Uncertainty

The first thing that inflation expectations surveys do is check the spread of people’s forecasts across different periods. One study that utilized expectations surveys to develop inflation uncertainty proxies is the Livingstone survey in the US. The anticipated inflation rate for the Livingstone survey was recorded by approximately fifty forecasters. The range of discrepancy among individual predictors on a specific location in time was summarized by survey-based procedures. Nevertheless, they are unable to offer insight into the variability of all individuals about their predictions. Every forecaster is likely to be highly uncertain about their prospective actions; however, they must provide identical point estimates. Therefore, the survey calculations would be ineffective in reducing the uncertainty. In their research employing this methodology, Odintsov et al. (2023); Hafer (1986), and Davis & Kanago (1996) corroborated Friedman’s hypothesis. This type of proxy is also employed by Jiang et al. (2022); Fischer (1981), and Jaffee & Kleiman (1977), to determine whether inflation and uncertainty are related (Golob, 1994). The discovery of a positive correlation between inflation and uncertainty is equally crucial. Since 2009, Pakistan has been conducting the Pakistan Inflation Expectations Survey (PIDE) every quarter.

3.2.2. Econometric Measures of Inflation Uncertainty

The econometric forecasting models are the second method for calculating inflation uncertainty. To forecast future inflation, researchers implemented an econometric model. Forecasted error terms with large values indicate a high level of uncertainty, while those with minor forecasted errors indicate a low level of uncertainty. An autoregressive conditional heteroscedasticity (ARCH) model’s conditional variance of the residuals is a time-varying variable process. As an alternative to inflation uncertainty, this estimated variance will be implemented. These are the reasons ARCH techniques are beneficial. Financial time series data demonstrates conditional heteroscedasticity. Inconsistent and inefficient behavior is observed in the OLS estimation of a time series variable equation. In the presence of substantial and substantial conditional heteroscedasticity, Engle (1982) demonstrated that efficiency gains can be achieved by employing ARCH instead of OLS. When estimating the production (or unemployment) equation, ordinary least squares (OLS) are used in all survey-based empirical studies on the actual impacts of inflation uncertainty, including Golob (1993). These papers contain coefficients that are estimated to be exceedingly inefficient.

3.3. Inflation Uncertainty Framework

The majority of time series exhibit volatility and lack a constant mean and variance, as revealed by advanced research in the financial sector. ARCH and GARCH-type models are employed in a diverse array of time series analyses; however, their most successful implementations are in the financial sector. Financial decisions are typically perceived as a trade-off between risk and return. Consequently, asset pricing, portfolio optimization, and risk management are all contingent upon the risk.

3.3.1. Autoregressive Conditional Heteroscedasticity (ARCH) Model

The Autoregressive conditional heteroscedasticity (ARCH) method, first introduced by Engle (1982), uses a mean inflation equation to keep the parametric values but permits the conditional variance to change with time. To stand in for the unpredictability of inflation, the variance is used. As a method, the ARCH process might change over time. The following is the general outline of the ARCH (q) model:

$$\pi_t = \beta_o + \sum_{i=1}^{n} \beta_i \pi_{t-1} + \varepsilon_t \qquad (2)$$

$$\varepsilon_t \approx \text{iidN}(o, h_t)$$

Where shows a zero mean and conditional variance is identically, and independently distributed.

$$\sigma_{\varepsilon t}^2 = \alpha_o + \sum_{i=1}^{q} \alpha_1 \varepsilon_{t-i}^2 \qquad (3)$$

As $\sigma_{\varepsilon t}^2 = h_t$

Then

$$h_t = \alpha_o + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \qquad (4)$$

The conditional mean of inflation is defined in Eq. (2), where inflation is a function of explanatory variables. The conditional variance equation is delineated in Eq. (3). Since this conditional variance depends on the values of the squared error term that were immediately preceding it, the impact of a new or existing shock depends on the size of the one-lag period shock. For the squared error factors, the ARCH model is empirically applied in a long-lag process, showing how disruptions affect inflation uncertainty persistently.

3.3.2. Generalized ARCH (GARCH) Model

In the extended ARCH model, the conditional variance equation uses components of both moving averages and autoregressives. A first-order ARCH model is equivalent to a GARCH (0, 1) model when p=0 and q=1. According to Enders (2003), GARCH is a more frugal alternative to a high-order lagged ARCH model. Bollerslev (1986) suggested another method. A lagged squared residual term and its prior delays can impact the conditional variance in the GARCH model. A linear GARCH (p, q) process in its general form looks like this:

$$h_t = \alpha_o + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \delta_j h_{t-j} \qquad (5)$$

By Eq. (5), the squared residual components capture the prior values of news (shocks), whereas the lagged variance terms record their values; the latter determines the value of conditional variance. If the inflation uncertainty is not negative and the coefficient meets the requirements, then the GARCH (1, 1) model is sufficient. If one wants to quantify the symmetric effect in conditional variance, one can use either Bollerslev's (1986) or Engel's (1982) ARCH model. The main problem with both models is that they don't tell us how good or bad news affects uncertainty. Both the ARCH and GARCH models have shown that shocks of equal magnitude, whether positive or negative, produce the same amount of volatility.

3.3.3. The Granger Causality Test

The final test in this study's research method is the examination of the causality relationship between inflation rate and inflation uncertainty through the aid of a Granger non-causality test. The simple test that was designed by Granger (1969) was used to examine the efficiency of the given variables in inferring causality. For two stationary variables, the Granger causality test is carried out using the following VAR model:

$$h_t = \partial_0 + \sum_{i-1}^{n} \lambda_{1i} h_{t-i} + \sum_{i=1}^{m} \beta_{1i} \pi_{t-1} + e_{1t} \qquad (6)$$

$$\pi_t = \partial_1 + \sum_{i-1}^{n} \lambda_{2i} h_{t-i} + \sum_{i=1}^{m} \beta_{2i} \pi_{t-1} + e_{2t} \qquad (7)$$

(1) HoA: Inflation uncertainty is not Granger-caused by inflation.

(2) HoB: Inflation uncertainty does not induce inflation through Granger causality.

4. Results and Discussions

4.1. Unit Root Test

Verifying the order of integration is a critical component of the estimation process. Based on the results of the level and first difference Dickey-Fuller (DF), Phillips Perren (PP) tests, and Augmented Dickey-Fuller (ADF), it is possible to identify the sequence of integration. Table 1 displays the results of the following tests: Phillips Perren (PP), Augmented Perren Fiszer (ADF), and Dickey-Fuller (DF). Since we have excluded the probability of having a unit root, the results will reveal that inflation is, in fact, stationary at the level or combined of order I (0).

Table 1: Unit Root Test for Inflation

Inflation Rate	Test Statistic	Lags/BW	AIC	SIC	DW Stats	Level of Significance
DF-GLS (constant)	-5.13	3/SIC	11.2	11.41	5.63	10%
DF-GLS (constant, trend)	-7.66	3/SIC	11.08	11.3	5.55	10%
ADF (constant)	-14.57	3/SIC	10.79	11.12	5.5	5%
ADF (constant, trend)	-13.8	3/SIC	10.82	11.15	5.52	5%
PP (constant)	-25.36	1/NW	12.39	12.5	5.84	1%
PP (constant, trend)	-25.56	1/NW	12.42	12.6	5.81	1%

The nature of the variables in the analysis is demonstrated by plotting all series of variables against the time. The vertical axis in Figure (1) represents the quarterly inflation rate, which is seen on the horizontal axis, and spans the years 1983 to 2020. You can see that Pakistan's inflation rate fluctuates over time and follows a normal distribution with a constant variance and mean in the quarterly graph of inflation rates. The series is thus stationary, meaning there is no unit root.

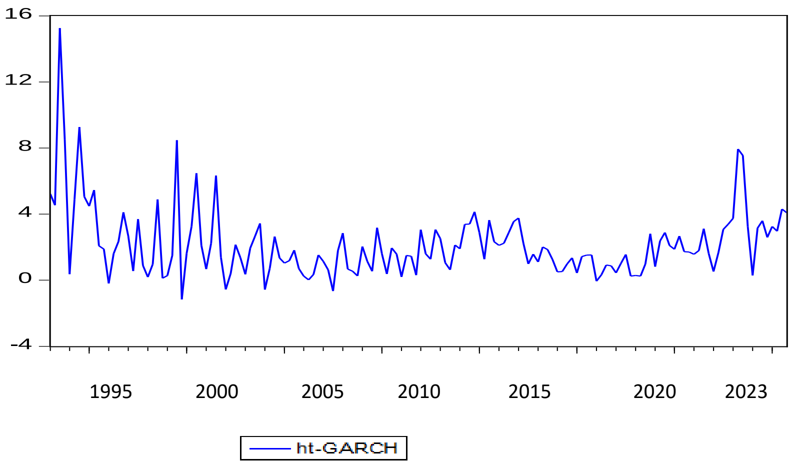

Figure 1: Inflation Rate

4.2. Empirical Assessments of Inflation and Inflation Uncertainty

4.2.1. Mean Equation Construction

In ARCH-type models, the first step is to prove that there is no serial connection by creating an inflation mean equation. Here is another way to express the mean equation:

$$\pi_t = \beta_o + \sum_{i=1}^{n} \beta_1 \pi_{t-i} + \varepsilon_t \qquad (8)$$

It is important to apply the Akaike Information Criterion (AIC) and the Schwartz Bayesian Criterion (SBC) to find the AR and MA periods, and the LM-ARCH test to confirm that ARCH effects are present. As well as the highest possible R2 and lowest possible SBC and AIC values are used to add the maximum four delays of inflation. Kochonikas used the minimum SBC and AIC values as well as the greatest R2, Vork (1999) utilized 10 lags of inflation, and Erkam & Cavusoglu (2008) and Grier & Perry (2000) employed 12 inflation lags. In contrast, Vork (2004) utilized 12 lags of inflation. Below are the predicted results of the equation:

$$\pi_t = \beta_o + \beta_1 \pi_{t-1} + \beta_2 \pi_{t-2} + \beta_3 \pi_{t-3} + \beta_4 \pi_{t-4} + ut_t \qquad (9)$$

The estimations of quantity and quality indicators based on the AR(4) models are shown in Table 2 from the established AR(4) model, it is quite apparent that lag values of the current condition of inflation have considerable influences on the present situation. Therefore, at the 1% level of significance, the findings of the calculated model are suggestive of a positive and significant relationship between the variables πt and πt-1. Should the first-order lagged inflation rate be one percent higher, then the current actual rate of inflation would be one percent higher as well. 25 percentage points.

Table 2: Regression results AR(4) Model

Variables	Coefficient	p-value
0.82***(3.72)	2.44***(11.06)	0.22
0.25***(3.22)	0.74***(9.57)	0.077
-0.14***(-2.06)	-0.42***(-6.12)	0.069
0.15***(2.14)	0.45***(6.36)	0.071
0.31***(4.69)	0.92***(13.92)	0.065
R-squared	**Adjusted R-squared**	
1.03	0.91	
D-W	**AIC**	
4.87	10.8	
F-statistics	**SBC**	
49.24***	11.1	
Serial Correlation LM test: Lags (5)	**Heteroskedasticity Test: ARCH Lags(6)**	
66.22	60.14	

Note: ***, **, * respectively stands for reject the null at 1%, 5%, and 10% significance level. Z-statistics are in parentheses. Breusch-Godfrey serial correlation LM test is employed.

The present πt decreased by 0.14 units as a result of the second latent inflation, which demonstrates a negative relationship. In the same vein, the third and fourth lagged previous inflation exhibits a substantial positive impact on πt. All lag inflation rates have a positive and statistically significant cumulative effect. Godfrey Breusch Linking Multiple Series LM As the test statistic of 66.22 shows, the residuals seem to be serially correlated. A high degree of correlation hides the ARCH impact in residuals. The addition of the MA term reduced the significance of serial correlation. Autoregressive conditional heteroskedasticity in residuals can only be appropriately evaluated if the mean inflation equation does not contain serial correlation. Cassimano and Jensen (1988) state that the ARCH effect and serial correlation are inversely related.

Table 3: Regression results ARMA(4,1) Model

Variables	Coefficient	p-value
0.09***(3.31)	0.27***(9.83)	0.0012
0.31***(3.80)	0.92***(11.29)	0.0002
-0.03(-0.40)	-0.09(-1.19)	0.6865
0.10(1.58)	0.30(4.69)	0.116
0.06(0.41)	0.18(1.22)	0.6791
μ	0.86*(5.14)	0.0858
R-squared	**Adjusted R-squared**	
1.6	1.43	
D-W	**AIC**	
5.67	10.69	
F-statistics	**SBC**	
44.97***	11.06	
Serial Correlation LM Test: Lags(6)	**Heteroskedasticity Test: ARCH Lags(6)**	
28.98***	121.97	

Note: ***, **, * Hence, H0 being rejected at the respective 1%, 5%, and 10% significance levels. Z-statistics are in parentheses. Breusch-Godfrey Serial Correlation LM Test is used.

The ARMA-GARCH model was implemented by Nas and Perry (2000) and Payne (2007). Nas and Perry (2000) employed AR (8) and MA (12) as delays, whereas Payne (2007) incorporated AR (12) and MA (12). ARMA (7, (1, 12))-PGARCH (1, 1) was implemented by Daal et al. (2005). A {AR (p) MA (1, 12)-GARCH (1, 1)} model was also used by Henry, Olekalns, and Suardi (2006), who followed Daal (2005). The loss of the degree of freedom of variables is also prevented by the inclusion of lagged residues in the mean equation. The ARMA (4,1) model is illustrated in Eq 10. The ARCH-type model's mean equation is generally expressed as follows:

$$\pi_t = \beta_o + \beta_1\pi_{t-1} + \beta_2\pi_{t-2} + \beta_3\pi_{t-3} + \beta_4\pi_{t-4} + \mu ut_{t-1} + \varepsilon_t \qquad (10)$$

Table 3 displays the estimated results of equation 10; adding the MA term to the mean equation improved the R-squared and D-W values. Additionally, the value of the serial correlation has been decreased from 22.23 to 9.75. With an ARCH impact of 40.73, we can confidently say that homoskedasticity is not true. As a result, using ARCH-type models instead of a simple OLS regression yields better results. Hence, A first-order moving average term, which is defined by the minimal values of SBC and AIC, four inflation rate delays, and an ARCH-type model to establish the average inflation equation.

4.2.2. Regression Results of ARCH (3) Model

The mean equation indicates that all lagged inflation coefficients are significant, as illustrated in Table 4. The autoregressive coefficients' estimated values are both significant and positive. Conditional variance changes by 0.52

units in response to a substantial disturbance, as shown by AR(4), MA(1), and ARCH (3) models. At the 1% level of significance, the total of the ARCH coefficients is noteworthy. Pakistan uses this conditional variance to stand in for inflation uncertainty. A goodness-of-fit of about 55% is confirmed by the conventional set of regression statistics, and the D-W statistics are about 1.94, which indicates that there is no autocorrelation. Since standardized residuals do not include the ARCH effect, the variance equation can be defined with precision. Based on the results of the ARCH (3) model, Figure 4.3 shows the conditional variance.

Table 4: ARCH (3) Model Regression Results

Variables	Coefficient	p-value
o	0.86(3.06)	0.316
	1.37***(16.88)	0
	-0.53***(-8.50)	0.042
	0.39**(5.82)	0.053
	1.01***(7.85)	0.081
µ	-0.74***(-7.63)	0.012
	Variance Equation	
Variables	**Coefficient**	**p-value**
α0	2.76***(13.96)	0
	1.55***(12.02)	0.05
	Summary Statistics	
Statistic	**Value**	
R-squared	1.64	
Adjusted R-squared	1.28	
D-W	5.76	
AIC	10.28	
F-statistics	12.24	
SBC	10.54	

Note: ***, **, * respectively mean the null hypothesis is rejected at 1 percent, 5 percent, and 10 percent levels of significance. Z-statistics are in parentheses.

4.2.3. GARCH (1,1) Model Regression Results

Data from the AR(4), MA(1), and GARCH(1,1) models, as well as their projected values, are illustrated in Table 4. The stochastic model works well with Pakistani data when looking at variation and mean. Individual 1 The ARCH coefficient is determined to have a positive relation with the variance equation when this test is conducted at the 1% level of significance. Therefore, in the model, the coefficient δ1 represents the term GARCH. The fact that shocks still control the conditional variance (h t) of inflation in the system is implied by a highly significant and positive value of δ. A nada. The estimated GARCH coefficient value is "Ŵ," which indicates that shocks are responsible for the 75-unit rise in the conditional variance of inflation.

Concerning the conventional set of regression statistics the R square is around 0. 67% and the D W statistic is 1. The level of autocorrelation in the residuals, shown by cross-tabulation of the residual values with the sequence number 94, having no autocorrelation. This is because of the ARCH effect which is not detected on the squared standardized residuals, hence the variance equation can be stated with much precision. With this expected conditional variance of inflation, we can supplant inflation as the measure of variability over time. To determine the direction of causality between inflation uncertainty and inflation rate, the calculated conditional variance is also utilized in a subsequent Granger causality test. See Figure 2 for a visual representation of the GARCH(1,1) model's conditional variance plot. Due to their symmetrical pattern, the AR(4) and MA(1) GARCH(1,1) models' computed outputs do not reveal which shocks cause the most inflationary variability.

4.2.4. ARCH Family Models of Inflation Uncertainties (conditional variance) ht series

To quantify the uncertainty associated with inflation, the ARCH family of models is utilized (conditional variance). Figures 2 and 3 show the graphs for these subjects. As seen in Figure 2, the ARCH(3) model yielded conditional variance. Based on the results of the GARCH(1,1) model, Figure 3 shows the conditional variance.

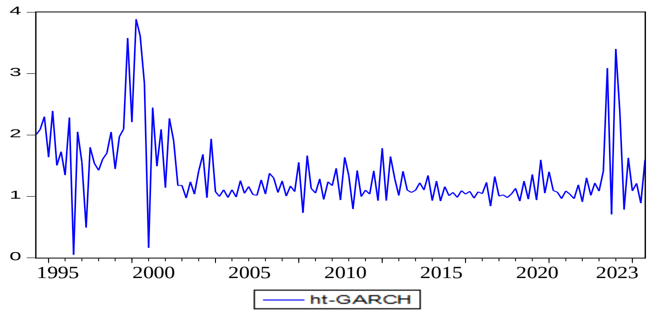

Figure 2: The ARCH Model Inflation uncertainty

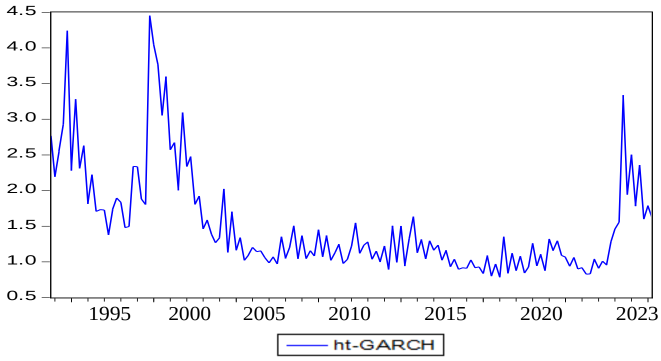

Figure 3: The GARCH Model Inflation Uncertainty

4.3. Inflation and Inflation Uncertainty Bivariate Granger-Causality Tests

To test the relationship between inflation and inflation uncertainty in Pakistan this paper uses the bivariate Granger causality test. Thus, taking not more than sixteen connotations, we can determine the effects of the outcomes. If we use the AIC and SBC values one more time we will be able to determine the optimal length of the latency. The F-statistics are presented in figures and are the results of the Granger causality test which indicates how inflation and uncertainty are. Even though the name includes GARCH, varieties of ARCH-GARCH models generate unknowns. In both the cases of inflation uncertainty as well as inflation direction the pair-wise Granger causality test of the ARCH(3) model is depicted by the results as shown in Figure 3. When the inflation uncertainty leads the inflation at 1, 2, 5, and 16 steps, the null hypothesis is Inflation uncertainty does not guarantee cause inflation is rejected. Because the p-values are, in this case, concordant with these delays, this rejection offers only very limited support for the Cukierman-Meltzer hypothesis. The following claim was tested in the regressions inflation does not Granger cause inflation uncertainty and the null hypothesis is rejected even with the longest lag times in the analysis.

Table 5: Granger Causality Test (p-values of F-statistic)

Lags	ARCH (3) Model		GARCH (1,1) Model	
	πt does not cause ht	ht does not cause πt	πt does not cause ht	ht does not cause πt
1	0.003	0.2071	5.94.E-07	0.2174
2	0.0098	0.2429	5.94.E-07	0.1096
3	1.5.E-04	0.0285	1.78.E-06	0.767
4	1.5.E-04	0.9851	8.91.E-07	2.27
5	0.0006	1.7826	8.91.E-06	1.26
6	1.5.E-05	1.9602	2.08.E-05	2.07
7	2.1.E-05	1.9746	2.08.E-05	1.83
8	8.9.E-05	1.2959	1.19.E-05	1.8
9	1.5.E-05	1.246	2.38.E-07	1.53
10	2.7.E-05	1.4879	2.38.E-07	1.73
11	1.5.E-05	1.8247	2.97.E-08	1.98
12	8.9.E-05	2.0484	8.91.E-08	2.31
13	3.0E-05	1.4222	1.49.E-07	2.34
14	1.2.E-04	0.8084	5.94.E-07	2.31
15	2.4.E-04	0.4041	2.67.E-06	1.28
16	0.0006	0.5356	1.49.E-05	0.47

The p-values for “uncertainty cause inflation” are inconsistent, while those for “inflation cause uncertainty” are consistent. In light of recent innovations that aim to increase inflation, the State Bank of Pakistan should make efforts to lower the inflation rate. The Granger causality test for inflation and uncertainties, which was carried out using the GARCH(1,1) model, is similarly related, and supports the hypothesis that “inflation increases inflation uncertainty.”

5. Conclusions and Policy Recommendations

This study seeks to shed light on the causes, consequences, and potential outcomes of the correlation between inflation uncertainty and actual economic activity. This analysis uses the IMF-IFS data set, which is updated quarterly from 1983 to 2020, to capture the effects of inflation uncertainty and the welfare loss it imposes on Pakistan’s actual economic activities. We use a family of ARCH models to investigate uncertainty’s function in this research. The study’s empirical investigation is divided into two phases. Inflation uncertainty is estimated using CPI inflation rates in the first fold, while the second fold considers the effects of inflation uncertainty on inflation rates. The symmetry of news is defined by an ARCH and GARCH model. The ARCH model is capable of calculating uncertainty; however, it is subject to numerous constraints. The GARCH model’s estimated result offers insight into the behavior of symmetric shocks, but it does not provide a significant amount of information regarding how news, whether positive or negative, can cause significant volatility in uncertainty (Hartmann et al., 2022; Abaidoo & Agyapong, 2023; Akbar, 2023; Kassouri, 2022).

In light of the findings of the investigation, the subsequent policy recommendations are proposed.

- An evaluation of the country's current monetary policy is necessary to identify the underlying causes of persistent inflation.
- To achieve political stability, it is imperative to enhance the distribution network and good governance. Complicated political and economic environments necessitate the implementation of measures that guarantee central bank transparency and the establishment of robust fiscal, financial, and monetary institutions by approved policies.
- To manage unanticipated inflation, it is imperative that the government comprehend the factors that contribute to inflation. Consequently, the utility cost of inflation uncertainty in the country is mitigated by the monitoring of a reasonable forecasting mechanism.

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